Potato Disease Prediction This project is a Potato Disease Prediction System using Deep Learning and Convolutional Neural Networks (CNNs). The model is trained on the PlantVillage dataset and classifies potato leaf images into three categories:

- Potato Early Blight
- Potato Late Blight
- Healthy Leaf

Libraries

```
import tensorflow as tf
from tensorflow import keras
from keras import models, layers
import numpy as np
import matplotlib.pyplot as plt
import os
import pathlib
```

```
2025-09-26 23:44:21.072098: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] 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 00:00:1758930261.270973      36 cuda_dnn.cc:8310] Unable to
register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
E0000 00:00:1758930261.323144      36 cuda_blas.cc:1418] Unable to
register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
```

```
# importing dataset
dir = os.listdir('../input/plant-village/PlantVillage')
for filenames in dir:
    print(filenames)
```

```
Pepper__bell___Bacterial_spot
Potato___healthy
Tomato_Leaf_Mold
Tomato__Tomato_YellowLeaf__Curl_Virus
Tomato_Bacterial_spot
Tomato_Septoria_leaf_spot
Tomato_healthy
Tomato_Spider_mites_Two_spotted_spider_mite
Tomato_Early_blight
Tomato__Target_Spot
Pepper__bell___healthy
Potato___Late_blight
Tomato_Late_blight
```

```
Potato___Early_blight
Tomato__Tomato_mosaic_virus
```

```
!cp -rf ../input/plant-
village/PlantVillage/Potato___Early_blight ./Potato___Early_blight
!cp -rf ../input/plant-
village/PlantVillage/Potato___Late_blight ./Potato___Late_blight
!cp -rf ../input/plant-
village/PlantVillage/Potato___healthy ./Potato___healthy
```

```
Current_Dir = os.getcwd()
dataset_dir = pathlib.Path(Current_Dir)
print(dataset_dir)
```

```
/kaggle/working
```

```
IMG_SIZE = 256 # image size
BATCH_SIZE = 32 # batch size
CHANNELS = 3
EPOCHS = 50
```

```
dataset = tf.keras.preprocessing.image_dataset_from_directory(
    dataset_dir,
    shuffle=True,
    image_size = IMG_SIZE,
    batch_size = BATCH_SIZE,
)
dataset
```

```
Found 2152 files belonging to 3 classes.
```

```
I0000 00:00:1758930288.599259      36 gpu_device.cc:2022] Created
device /job:localhost/replica:0/task:0/device:GPU:0 with 15513 MB
memory:  -> device: 0, name: Tesla P100-PCIE-16GB, pci bus id:
0000:00:04.0, compute capability: 6.0
```

```
<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 256, 256, 3),
dtype=tf.float32, name=None), TensorSpec(shape=(None,),
dtype=tf.int32, name=None))>
```

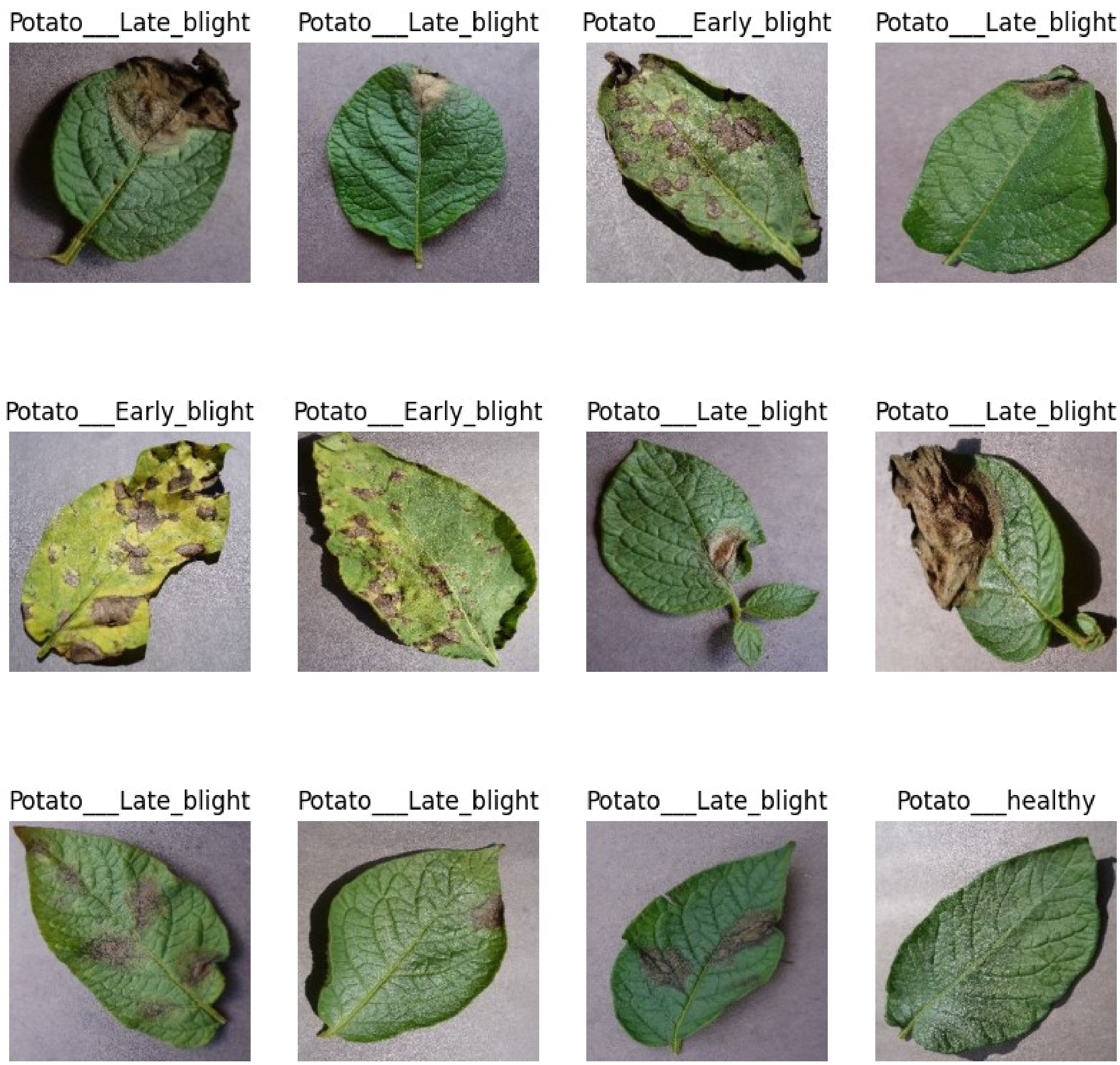
```
print(len(dataset))
```

```
class_names = dataset.class_names
print(class_names)
```

```
68
['Potato___Early_blight', 'Potato___Late_blight', 'Potato___healthy']
```

Some Random Images Shows

```python
plt.figure(figsize=(10,10))
for image_batch,label_batch in dataset.take(1):
  for i in range(12):
    plt.subplot(3,4,i+1)
    plt.imshow(image_batch[i].numpy().astype('uint8'))
    plt.title(class_names[label_batch[i]])
    plt.axis('off')
```




```python
# 80% data ====> Training
# 10% data ====> Validation
# 10% data ====> Testing
```

Splitting Data

```
def splitting_data(ds, train_split = 0.8, val_split = 0.1, test_split
= 0.1, shuffle = True, shuffle_size=10000):

  if shuffle:
        ds = ds.shuffle(shuffle_size, seed = 12)
  ds_size = len(ds)
  train_size = int(train_split*ds_size)
  val_size = int(val_split*ds_size)

  train_ds = ds.take(train_size)
  val_ds = ds.skip(train_size).take(val_size)
  test_ds = ds.skip(train_size).skip(val_size)


  return train_ds, val_ds, test_ds

train_ds, val_ds, test_ds = splitting_data(dataset)
print(len(train_ds))
print(len(val_ds))
print(len(test_ds))

54
6
8

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size =
tf.data.AUTOTUNE )
val_ds = val_ds.cache().shuffle(1000).prefetch(buffer_size =
tf.data.AUTOTUNE )
test_ds = test_ds.cache().shuffle(1000).prefetch(buffer_size =
tf.data.AUTOTUNE )
```

Data Resizing & Scaling

```
resize_and_rescale = tf.keras.Sequential([
    layers.Resizing(IMG_SIZE, IMG_SIZE),
    layers.Rescaling(1.0/255)
])
```

Data Augmentation

```
data_augmentation = tf.keras.Sequential([
    layers.RandomFlip('horizontal_and_vertical'),
    layers.RandomRotation(0.2)
])
```

Build Neural Networks

```
input_shape = (BATCH_SIZE, IMG_SIZE, IMG_SIZE, CHANNELS)
n_classes = 3
```

```python
model = tf.keras.Sequential([
    resize_and_rescale,
    data_augmentation,
    layers.Conv2D(32, (3,3), activation = 'relu', input_shape =
input_shape),
    layers.MaxPooling2D((2,2)),

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

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

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

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

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

    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax')
])
model.build(input_shape = input_shape)
model.summary()
```

```
/usr/local/lib/python3.11/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 `Input(shape)` object as the first layer in
the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

Model: "sequential_2"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ sequential (Sequential)         │ (32, 256, 256, 3)      │
0 │
├─────────────────────────────────┼────────────────────────┼──────────
─────┤
│ sequential_1 (Sequential)       │ (32, 256, 256, 3)      │
0 │
```

```
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d (Conv2D)                     │ (32, 254, 254, 32)       │
896 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d (MaxPooling2D)        │ (32, 127, 127, 32)       │
0 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_1 (Conv2D)                   │ (32, 125, 125, 64)       │
18,496 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_1 (MaxPooling2D)      │ (32, 62, 62, 64)         │
0 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_2 (Conv2D)                   │ (32, 60, 60, 64)         │
36,928 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_2 (MaxPooling2D)      │ (32, 30, 30, 64)         │
0 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_3 (Conv2D)                   │ (32, 28, 28, 64)         │
36,928 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_3 (MaxPooling2D)      │ (32, 14, 14, 64)         │
0 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_4 (Conv2D)                   │ (32, 12, 12, 64)         │
36,928 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_4 (MaxPooling2D)      │ (32, 6, 6, 64)           │
0 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_5 (Conv2D)                   │ (32, 4, 4, 64)           │
36,928 │
├─────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_5 (MaxPooling2D)      │ (32, 2, 2, 64)           │
0 │
├─────────────────────────────────────┼──────────────────────────┼──────────
```

```
──────┤
│ flatten (Flatten)                  │ (32, 256)                 │
0 │
├──────────────────────────────────┼─────────────────────────┼───────
──────┤
│ dense (Dense)                      │ (32, 64)                  │
16,448 │
├──────────────────────────────────┼─────────────────────────┼───────
──────┤
│ dense_1 (Dense)                    │ (32, 3)                   │
195 │
└──────────────────────────────────┴─────────────────────────┴───────
──────┘

 Total params: 183,747 (717.76 KB)

 Trainable params: 183,747 (717.76 KB)

 Non-trainable params: 0 (0.00 B)
```

Explain the Model Architecture

1. Conv2D

- This is a 2D convolution layer, commonly used for images.
- It applies small filters (also called kernels) to the image to detect patterns (edges, textures, shapes).

2. 32

- This means the layer has 32 filters.
- Each filter learns a different pattern (for example: vertical edges, horizontal edges, circles, etc.).
- Output feature map depth will be 32 channels.

3. (3,3)

- This is the filter size (kernel size).
- A 3×3 filter looks at a small region of the image at a time.
- Smaller kernels (like 3×3) are good at detecting fine details, while larger ones (like 5×5, 7×7) detect broader patterns.

4. activation='relu'

- Activation function applied after convolution.
- ReLU (Rectified Linear Unit) sets all negative values to 0, keeping only positive signals.
- Helps the network learn nonlinear features and prevents gradient vanishing.

5. input_shape=(IMG_SIZE, IMG_SIZE)

- Defines the input image size for the first layer in the model.
- Important: If your images are RGB (color images), you must add the channel dimension → (IMG_SIZE, IMG_SIZE, 3)
- (height, width, channels)

- 3 = Red, Green, Blue.

1. What is MaxPooling?

- Pooling reduces the spatial size (height and width) of the feature maps.
- Instead of looking at every pixel, it summarizes a region.
- With MaxPooling, it takes the maximum value in each region.

2. (2,2)

- This is the pool size → a window of 2×2.
- The layer looks at each 2×2 block of the feature map and keeps only the largest value.
- By default, stride = pool size (2), so the feature map shrinks by half in height and width.

Example

Suppose we have a small 4×4 feature map:

```
[1, 3, 2, 4]
[5, 6, 1, 2]
[3, 2, 8, 7]
[4, 1, 9, 5]
```

- *Apply MaxPooling (2×2):*
- Top-left block → max(1,3,5,6) = 6
- Top-right block → max(2,4,1,2) = 4
- Bottom-left block → max(3,2,4,1) = 4
- Bottom-right block → max(8,7,9,5) = 9

Result (2×2):

```
[6, 4]
[4, 9]
```

Flatten() → convert CNN features into a long vector. **Dense(64, relu)** → learn complex feature combinations. **Dense(n_classes, softmax)** → output final class probabilities. **model.build(input_shape=...)** → tell Keras what shape of data to expect.

Compiling the Model

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Model Training

```
history = model.fit(train_ds, epochs=EPOCHS, validation_data=val_ds,
batch_size=BATCH_SIZE)

Epoch 1/50
```

```
I0000 00:00:1758930298.684612     105 cuda_dnn.cc:529] Loaded cuDNN
version 90300

54/54 ━━━━━━━━━━━━━━━━━━━━ 12s 77ms/step - accuracy: 0.4794 - loss:
0.9382 - val_accuracy: 0.5885 - val_loss: 0.8457
Epoch 2/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.6654 - loss:
0.6948 - val_accuracy: 0.7083 - val_loss: 0.6389
Epoch 3/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.7804 - loss:
0.5229 - val_accuracy: 0.8594 - val_loss: 0.2987
Epoch 4/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.8798 - loss:
0.3300 - val_accuracy: 0.8594 - val_loss: 0.3115
Epoch 5/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.8924 - loss:
0.2641 - val_accuracy: 0.8750 - val_loss: 0.3809
Epoch 6/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9138 - loss:
0.2722 - val_accuracy: 0.9271 - val_loss: 0.2034
Epoch 7/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9334 - loss:
0.1937 - val_accuracy: 0.8021 - val_loss: 0.4112
Epoch 8/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9254 - loss:
0.1851 - val_accuracy: 0.9323 - val_loss: 0.1644
Epoch 9/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9474 - loss:
0.1448 - val_accuracy: 0.8906 - val_loss: 0.2331
Epoch 10/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9323 - loss:
0.1643 - val_accuracy: 0.9323 - val_loss: 0.1466
Epoch 11/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9547 - loss:
0.1271 - val_accuracy: 0.9010 - val_loss: 0.2140
Epoch 12/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9499 - loss:
0.1271 - val_accuracy: 0.9010 - val_loss: 0.1966
Epoch 13/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9586 - loss:
0.1254 - val_accuracy: 0.9635 - val_loss: 0.0922
Epoch 14/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9610 - loss:
0.1286 - val_accuracy: 0.8802 - val_loss: 0.2925
Epoch 15/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9681 - loss:
0.0855 - val_accuracy: 0.8438 - val_loss: 0.3375
Epoch 16/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9639 - loss:
0.0908 - val_accuracy: 0.9896 - val_loss: 0.0348
```

```
Epoch 17/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9795 - loss:
0.0503 - val_accuracy: 0.9792 - val_loss: 0.0500
Epoch 18/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9570 - loss:
0.1300 - val_accuracy: 0.9427 - val_loss: 0.1413
Epoch 19/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9887 - loss:
0.0398 - val_accuracy: 0.8594 - val_loss: 0.4219
Epoch 20/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9744 - loss:
0.0788 - val_accuracy: 0.9167 - val_loss: 0.1995
Epoch 21/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9885 - loss:
0.0350 - val_accuracy: 0.8750 - val_loss: 0.2619
Epoch 22/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9787 - loss:
0.0592 - val_accuracy: 0.9010 - val_loss: 0.2231
Epoch 23/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9876 - loss:
0.0363 - val_accuracy: 0.9375 - val_loss: 0.1606
Epoch 24/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9860 - loss:
0.0332 - val_accuracy: 0.9115 - val_loss: 0.2528
Epoch 25/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9872 - loss:
0.0307 - val_accuracy: 0.9948 - val_loss: 0.0159
Epoch 26/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9912 - loss:
0.0230 - val_accuracy: 0.9635 - val_loss: 0.0842
Epoch 27/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9896 - loss:
0.0301 - val_accuracy: 0.9792 - val_loss: 0.0541
Epoch 28/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9925 - loss:
0.0255 - val_accuracy: 0.9896 - val_loss: 0.0267
Epoch 29/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9857 - loss:
0.0450 - val_accuracy: 0.8698 - val_loss: 0.3905
Epoch 30/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9725 - loss:
0.0756 - val_accuracy: 1.0000 - val_loss: 0.0097
Epoch 31/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9819 - loss:
0.0444 - val_accuracy: 0.9792 - val_loss: 0.0387
Epoch 32/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9950 - loss:
0.0159 - val_accuracy: 0.9688 - val_loss: 0.0725
Epoch 33/50
```

```
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9910 - loss:
0.0276 - val_accuracy: 1.0000 - val_loss: 0.0200
Epoch 34/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9915 - loss:
0.0260 - val_accuracy: 1.0000 - val_loss: 0.0086
Epoch 35/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9854 - loss:
0.0406 - val_accuracy: 0.9896 - val_loss: 0.0477
Epoch 36/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9858 - loss:
0.0289 - val_accuracy: 0.9792 - val_loss: 0.0571
Epoch 37/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9928 - loss:
0.0210 - val_accuracy: 0.9948 - val_loss: 0.0185
Epoch 38/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9935 - loss:
0.0214 - val_accuracy: 0.9792 - val_loss: 0.0755
Epoch 39/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9841 - loss:
0.0445 - val_accuracy: 0.9427 - val_loss: 0.1529
Epoch 40/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9610 - loss:
0.0914 - val_accuracy: 0.9844 - val_loss: 0.0234
Epoch 41/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9910 - loss:
0.0274 - val_accuracy: 0.9896 - val_loss: 0.0228
Epoch 42/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9950 - loss:
0.0152 - val_accuracy: 0.9844 - val_loss: 0.0462
Epoch 43/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9974 - loss:
0.0083 - val_accuracy: 0.9740 - val_loss: 0.0571
Epoch 44/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9964 - loss:
0.0165 - val_accuracy: 0.9896 - val_loss: 0.0162
Epoch 45/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9886 - loss:
0.0275 - val_accuracy: 0.9740 - val_loss: 0.0422
Epoch 46/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9851 - loss:
0.0548 - val_accuracy: 0.9323 - val_loss: 0.1461
Epoch 47/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 34ms/step - accuracy: 0.9785 - loss:
0.0472 - val_accuracy: 0.9167 - val_loss: 0.1922
Epoch 48/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9914 - loss:
0.0214 - val_accuracy: 0.9948 - val_loss: 0.0114
Epoch 49/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9939 - loss:
```

```
0.0224 - val_accuracy: 0.9844 - val_loss: 0.0429
Epoch 50/50
54/54 ━━━━━━━━━━━━━━━━━━━━ 2s 33ms/step - accuracy: 0.9882 - loss:
0.0333 - val_accuracy: 0.9844 - val_loss: 0.0254
```

Testing the Model

```python
print("Calculating model accuracy")
loss, accuracy = model.evaluate(train_ds)
print(f"Train Accuracy: {accuracy:.4f}")
print(f"Train Loss: {loss:.4f}")
```

```
Calculating model accuracy
54/54 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9961 - loss:
0.0146
Train Accuracy: 0.9936
Train Loss: 0.0170
```

```python
print("Calculating model accuracy")
loss, accuracy = model.evaluate(test_ds)
print(f"Test Accuracy: {accuracy:.4f}")
print(f"Test Loss: {loss:.4f}")
```

```
Calculating model accuracy
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9953 - loss:
0.0442
Test Accuracy: 0.9961
Test Loss: 0.0401
```

Prediction

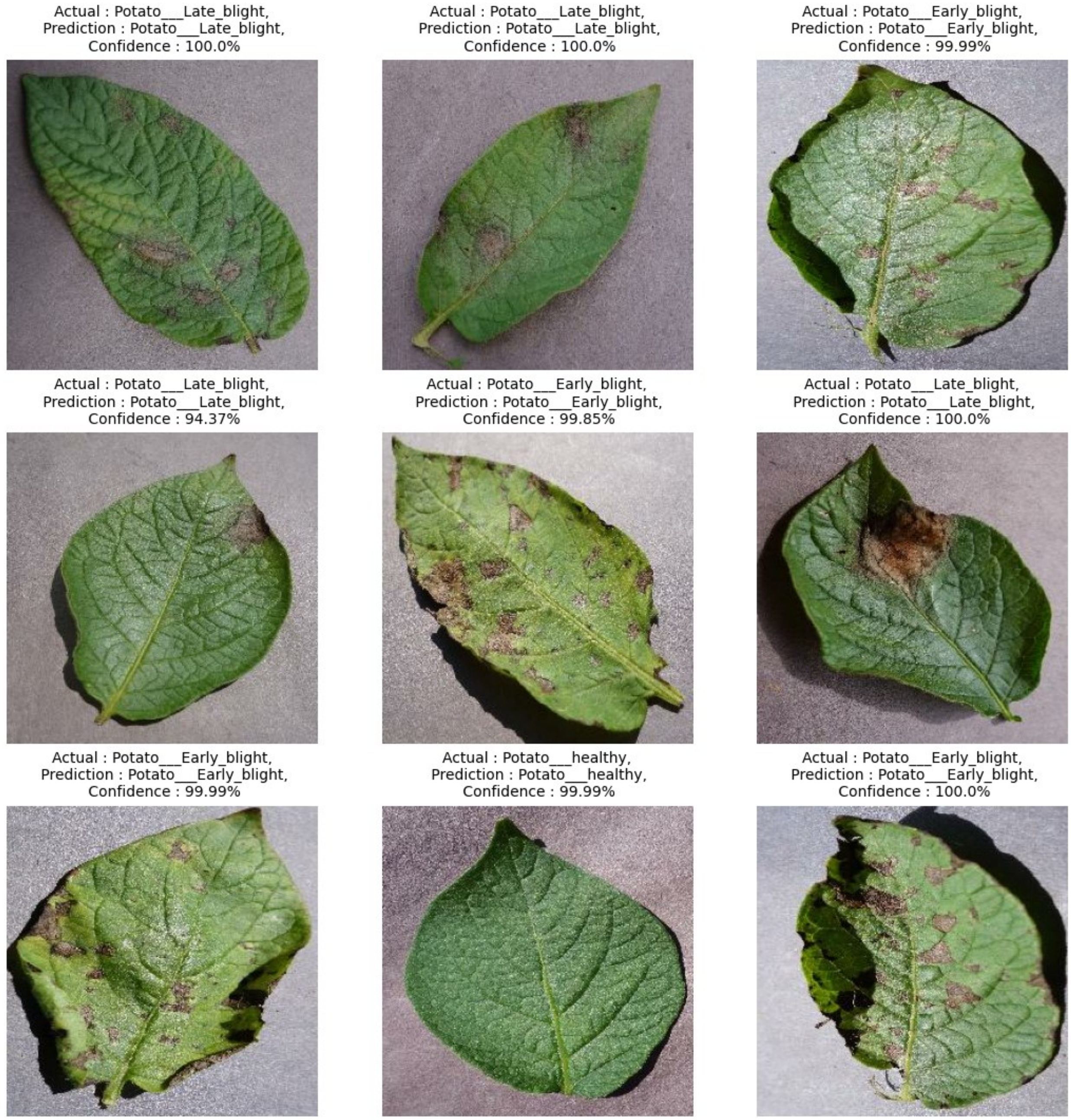
```python
for batch_image, batch_label in train_ds.take(1):
    first_image = batch_image[0].numpy().astype('uint8')
    first_label = class_names[batch_label[0]]


    plt.imshow(first_image)
    print('Actual Label : ', first_label)

    batch_prediction = model.predict(batch_image)
    print('Predicted Label : ',
class_names[np.argmax(batch_prediction[0])])
    plt.axis('off')
```

```
Actual Label :  Potato___Early_blight
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 192ms/step
Predicted Label :  Potato___Early_blight
```

```
# plotting batch of images with its actual label, predicted label and
confidence
plt.figure(figsize = (13,13))
for batch_image, batch_label in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3,3,i+1)
        image = batch_image[i].numpy().astype('uint8')
        label = class_names[batch_label[i]]

        plt.imshow(image)

        batch_prediction = model.predict(batch_image)
        predicted_class = class_names[np.argmax(batch_prediction[i])]
        confidence = round(np.max(batch_prediction[i]) * 100, 2)

        plt.title(f'Actual : {label},\n Prediction :
{predicted_class},\n Confidence : {confidence}%', fontsize=10)
        plt.axis('off')
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
```



Save the Model

```
model.save("potato_disease_clf.keras")
```