Mount Google Drive and Set Path

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount(
```

```
import os
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from collections import Counter

# Define path
base_dir = '/content/drive/MyDrive/Assessment/Assessment_1/dataset'
train_dir = os.path.join(base_dir, 'train')
test_dir = os.path.join(base_dir, 'test')
```

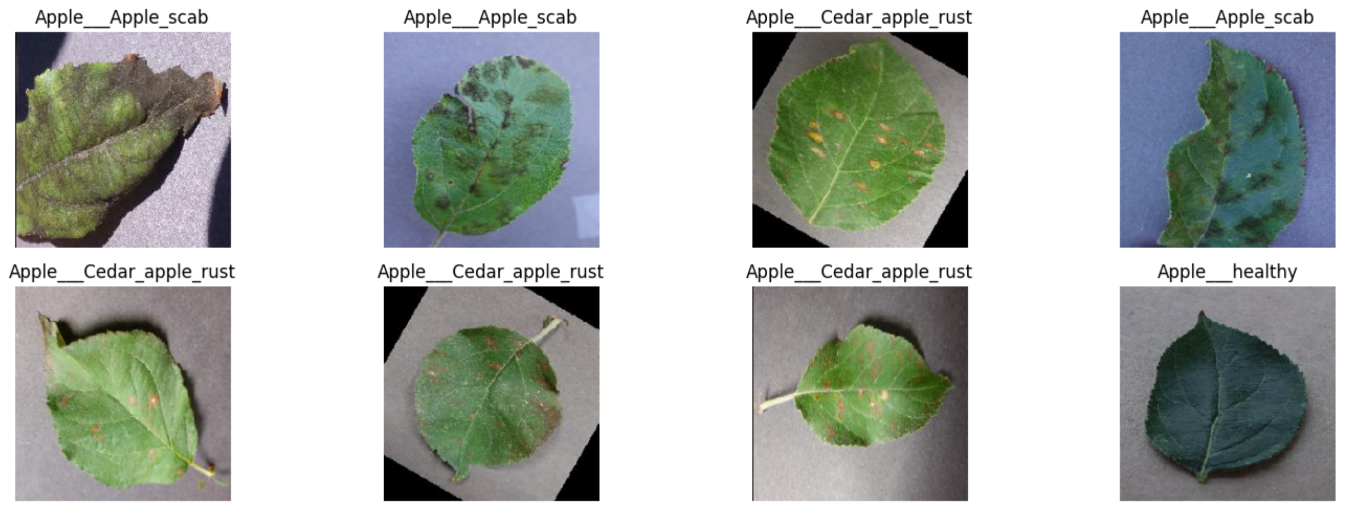
Set Parameters and Create Data Generators

```
IMG_SIZE = (224, 224)
BATCH_SIZE = 32

# No augmentation
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

# Load images
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=IMG_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    shuffle=False
)
```

```
Found 6218 images belonging to 4 classes.
Found 1553 images belonging to 4 classes.
```

Visualize Sample Images

```
def plot_images(generator, class_indices, num_images=8):
    class_names = list(class_indices.keys())
    x_batch, y_batch = next(generator)
    plt.figure(figsize=(15, 5))
    for i in range(num_images):
        ax = plt.subplot(2, 4, i + 1)
        plt.imshow(x_batch[i])
        label_index = np.argmax(y_batch[i])
        plt.title(class_names[label_index])
        plt.axis("off")
    plt.tight_layout()
    plt.show()

plot_images(train_generator, train_generator.class_indices)
```



Dataset Analysis

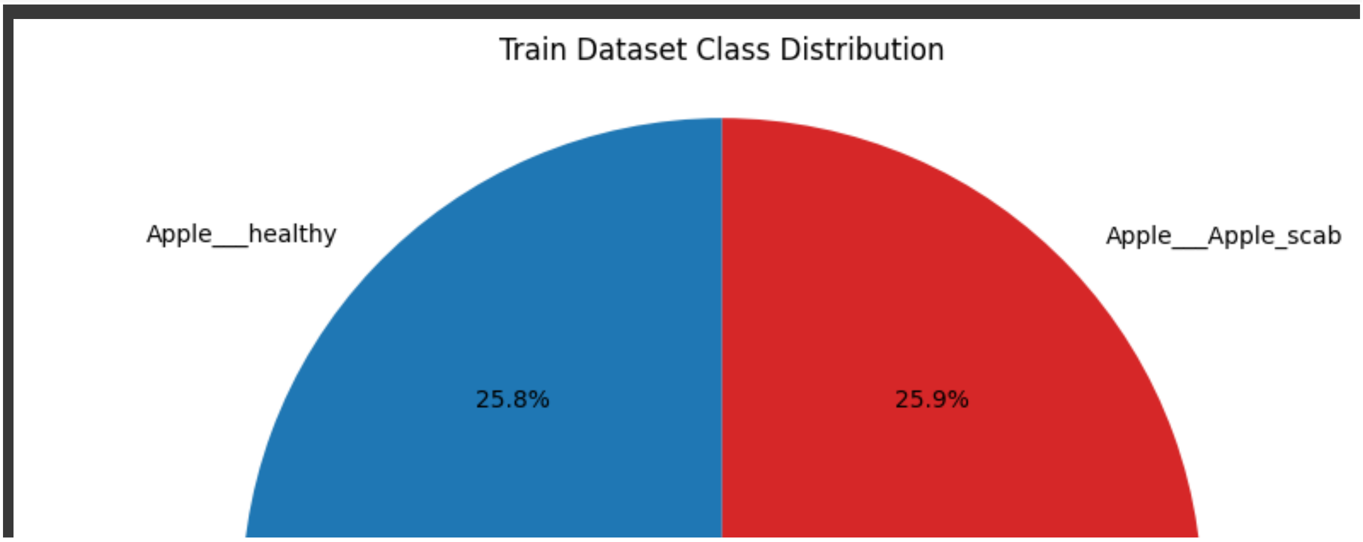
```
# Count total images per class
def count_images(directory):
    class_counts = {}
    for class_name in os.listdir(directory):
        class_path = os.path.join(directory, class_name)
        if os.path.isdir(class_path):
            class_counts[class_name] = len(os.listdir(class_path))
    return class_counts

train_counts = count_images(train_dir)
test_counts = count_images(test_dir)

print("Train Class Distribution:", train_counts)
print("Test Class Distribution:", test_counts)
print("Total training images:", sum(train_counts.values()))
print("Total testing images:", sum(test_counts.values()))
```

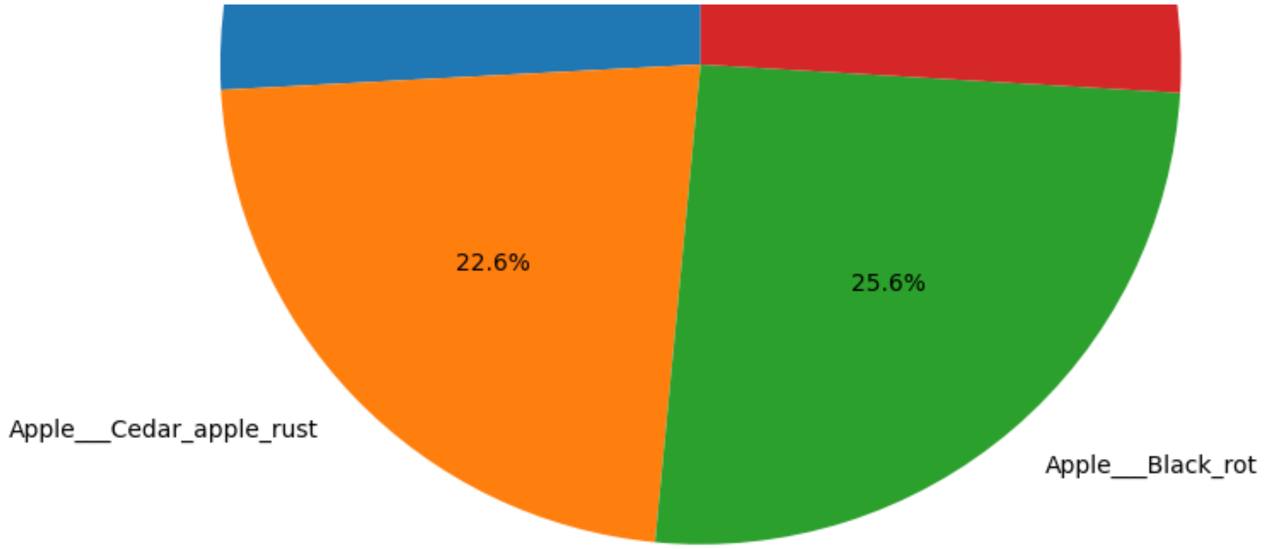
```
Train Class Distribution: {'Apple___healthy': 1607, 'Apple___Cedar_apple_rust': 1408, 'App
Test Class Distribution: {'Apple___healthy': 401, 'Apple___Cedar_apple_rust': 352, 'Apple_
Total training images: 6218
Total testing images: 1553
```

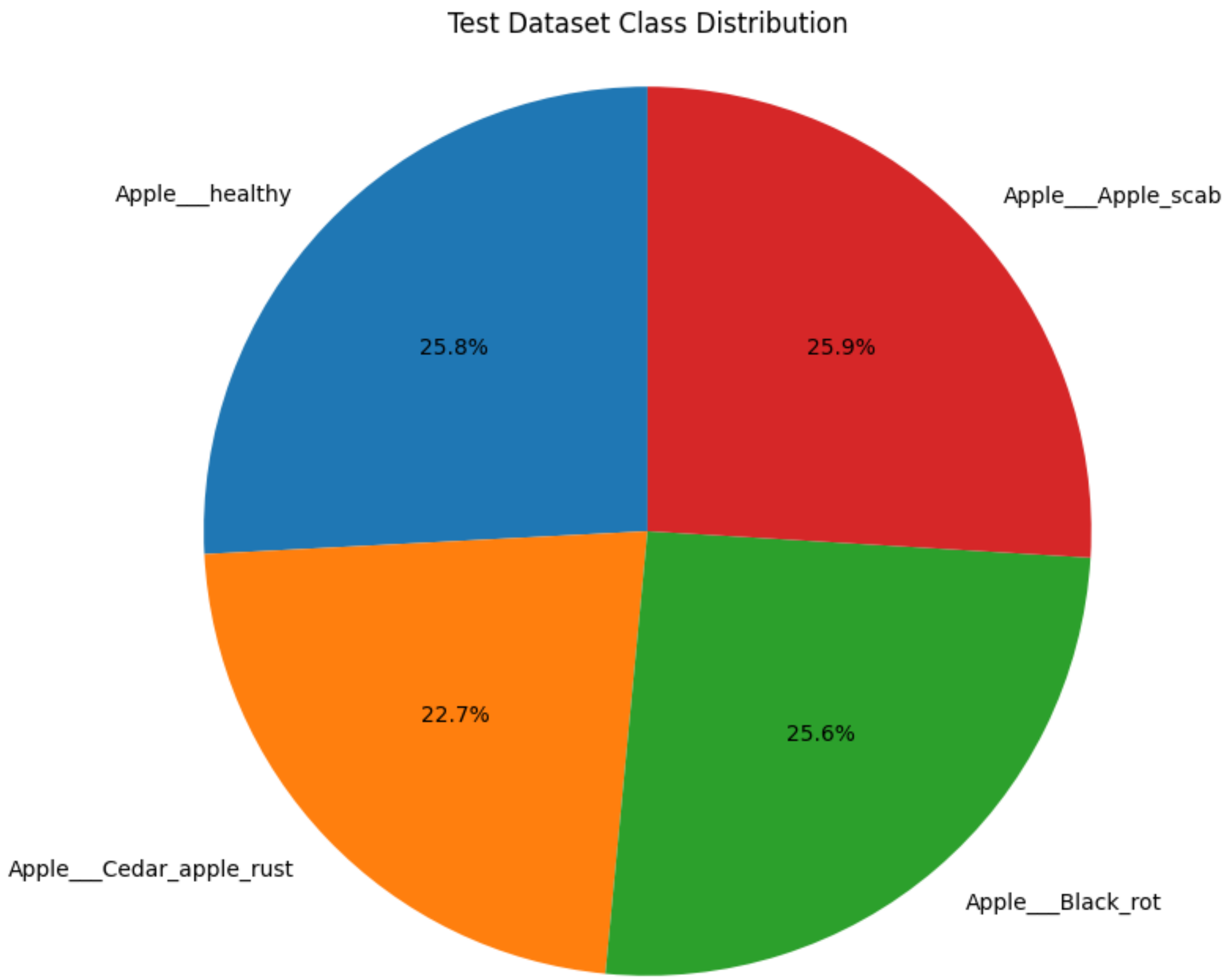
We split the dataset into training and testing sets in a folder-based format. A standard 80/20 split is often applied to ensure sufficient data for training while retaining a portion for unbiased evaluation.**bold text**

Class Distribution Histogram

```
import matplotlib.pyplot as plt

def plot_pie_chart(counts, title):
    labels = list(counts.keys())
    sizes = list(counts.values())
    plt.figure(figsize=(8, 8))
    plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90)
    plt.title(title)
    plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
    plt.show()

plot_pie_chart(train_counts, "Train Dataset Class Distribution")
plot_pie_chart(test_counts, "Test Dataset Class Distribution")
```

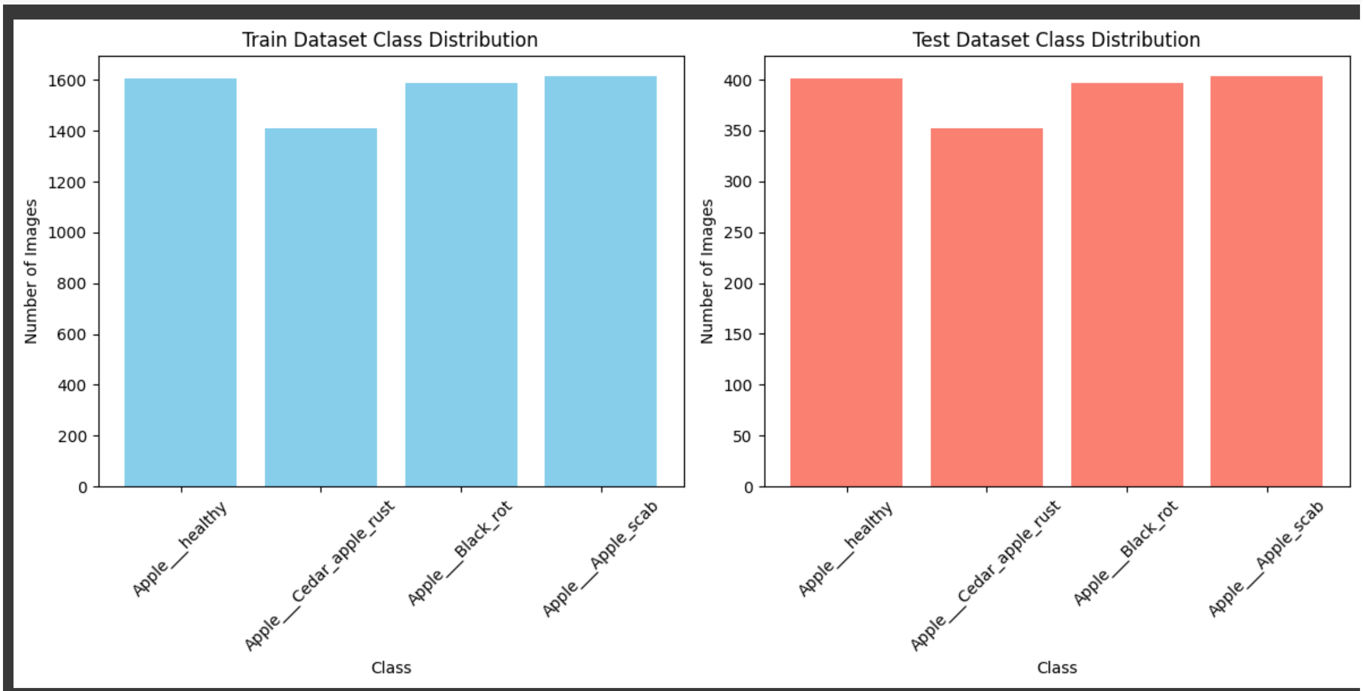






Bar Plot for Class-wise Image Counts

```
# Plot class distribution using bar charts
plt.figure(figsize=(12, 6))

# Train dataset bar plot
plt.subplot(1, 2, 1)
plt.bar(train_counts.keys(), train_class_counts, color='skyblue')
plt.title("Train Dataset Class Distribution")
plt.xlabel("Class")
plt.ylabel("Number of Images")
plt.xticks(rotation=45)

# Test dataset bar plot
plt.subplot(1, 2, 2)
plt.bar(test_counts.keys(), test_class_counts, color='salmon')
plt.title("Test Dataset Class Distribution")
plt.xlabel("Class")
plt.ylabel("Number of Images")
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```



Filter A filter (or feature detector) refers to the set of values (weights) that are applied to the input data during the convolution process.

Kernel A kernel is the actual matrix (the set of weights) that is used to perform the convolution operation on the input image. It is typically smaller than the image (e.g., a 3x3 or 5x5 matrix)

Build the Baseline CNN Architecture

Convolutional Layer: Extracts local features using filters. Activation Layer (ReLU): Introduces non-linearity. Pooling Layer: Reduces spatial dimensions and retains essential features. Flatten Layer: Converts 2D feature maps into 1D vectors. Fully Connected Layer: Learns high-level features for classification or regression. Dropout Layer: Prevents overfitting by randomly deactivating neurons. Batch Normalization: Normalizes layer inputs for more stable training.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam

# Build the model
model = Sequential() #This initializes a Sequential model

# Convolutional Layer 1
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3))) #32 is number of f
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional Layer 2
model.add(Conv2D(64, (3, 3), activation='relu')) #(3, 3): The size of each filter (kernel)
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional Layer 3
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

# Flatten layer
model.add(Flatten())
#flatten the multi-dimensional output from the previous layer (typically the 2D feature maps a
# Fully connected layers
model.add(Dense(512, activation='relu')) #learns the feature
model.add(Dropout(0.5))  # Dropout to prevent overfitting
model.add(Dense(256, activation='relu'))
model.add(Dense(4, activation='softmax'))  # 4 classes

# Model summary
model.summary()
```

```
Model: "sequential_1"

 Layer (type)                         Output Shape                   Param #
 conv2d_3 (Conv2D)                    (None, 222, 222, 32)               896
 max_pooling2d_3 (MaxPooling2D)       (None, 111, 111, 32)                 0
 conv2d_4 (Conv2D)                    (None, 109, 109, 64)            18,496
 max_pooling2d_4 (MaxPooling2D)       (None, 54, 54, 64)                   0
 conv2d_5 (Conv2D)                    (None, 52, 52, 128)             73,856
 max_pooling2d_5 (MaxPooling2D)       (None, 26, 26, 128)                  0
 flatten_1 (Flatten)                  (None, 86528)                        0
 dense_3 (Dense)                      (None, 512)                 44,302,848
 dropout_1 (Dropout)                  (None, 512)                          0
 dense_4 (Dense)                      (None, 256)                    131,328
 dense_5 (Dense)                      (None, 4)                        1,028

 Total params: 44,528,452 (169.86 MB)
 Trainable params: 44,528,452 (169.86 MB)
 Non-trainable params: 0 (0.00 B)
```

A Sequential model is a linear stack of layers where each layer has exactly one input and one output

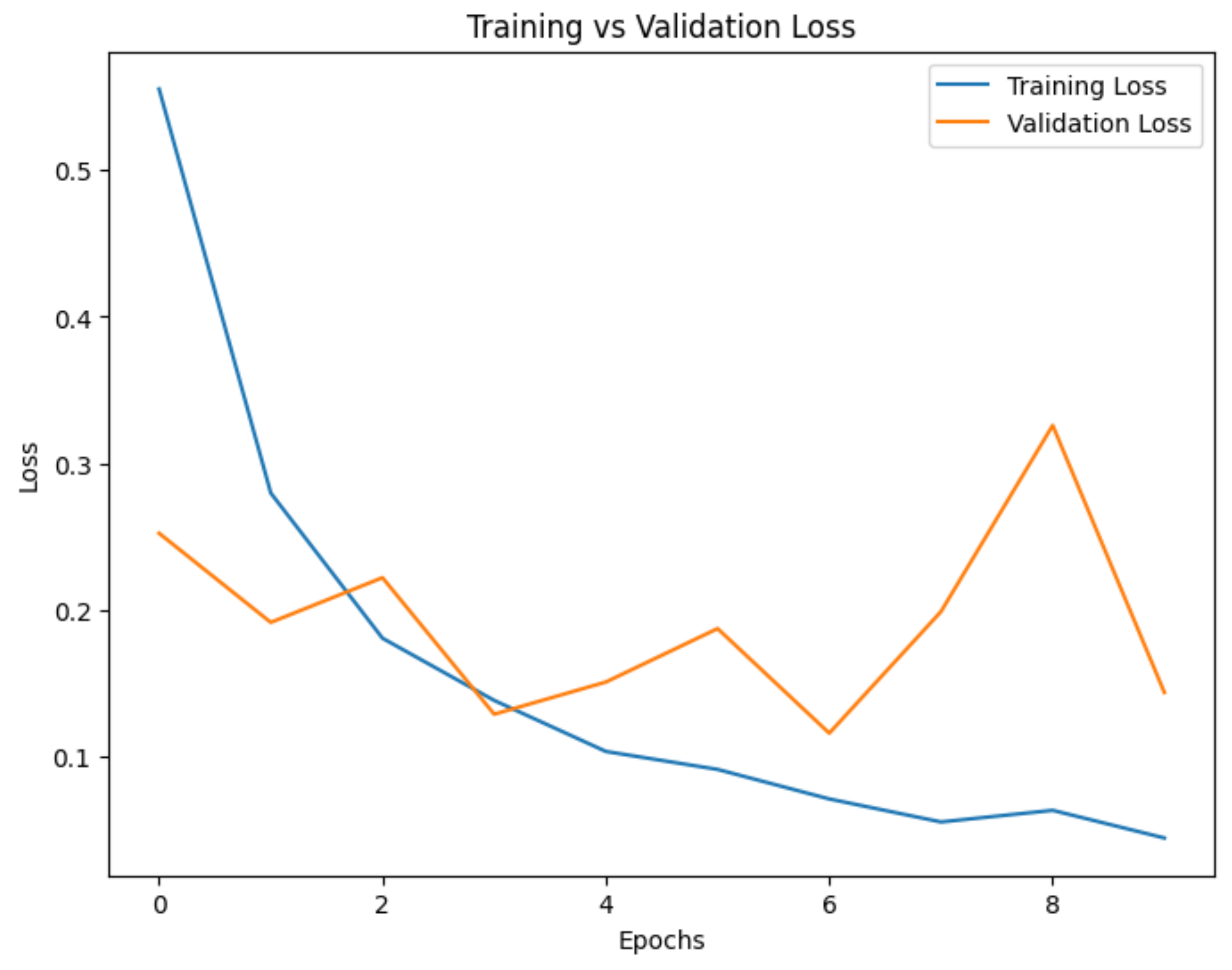
Compile the Model

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

Train the Model

```
history = model.fit(
    train_generator,
    epochs=10,  # Adjust as necessary
    validation_data=test_generator,
    verbose=1 #This controls how much information is shown during training.
)

# Plotting training & validation loss
plt.figure(figsize=(8, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapte
  self._warn_if_super_not_called()
Epoch 1/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 4867s 25s/step - accuracy: 0.6507 - loss: 0.8926 - val_accura
Epoch 2/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 37s 190ms/step - accuracy: 0.8997 - loss: 0.2961 - val_accura
Epoch 3/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 34s 174ms/step - accuracy: 0.9277 - loss: 0.1924 - val_accura
Epoch 4/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 168ms/step - accuracy: 0.9505 - loss: 0.1561 - val_accura
Epoch 5/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 42s 174ms/step - accuracy: 0.9631 - loss: 0.1060 - val_accura
Epoch 6/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 33s 168ms/step - accuracy: 0.9684 - loss: 0.0886 - val_accura
Epoch 7/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 37s 188ms/step - accuracy: 0.9804 - loss: 0.0586 - val_accura
Epoch 8/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 32s 165ms/step - accuracy: 0.9835 - loss: 0.0479 - val_accura
Epoch 9/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 33s 169ms/step - accuracy: 0.9772 - loss: 0.0661 - val_accura
Epoch 10/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 32s 165ms/step - accuracy: 0.9821 - loss: 0.0420 - val_accura
```



Evaluate the Model

```
from sklearn.metrics import classification_report

# Get predictions
predictions = model.predict(test_generator)
y_pred = np.argmax(predictions, axis=1)  #picks the class with the highest probability for eac
y_true = test_generator.classes

# Print classification report
print(classification_report(y_true, y_pred, target_names=test_generator.class_indices.keys()))
```

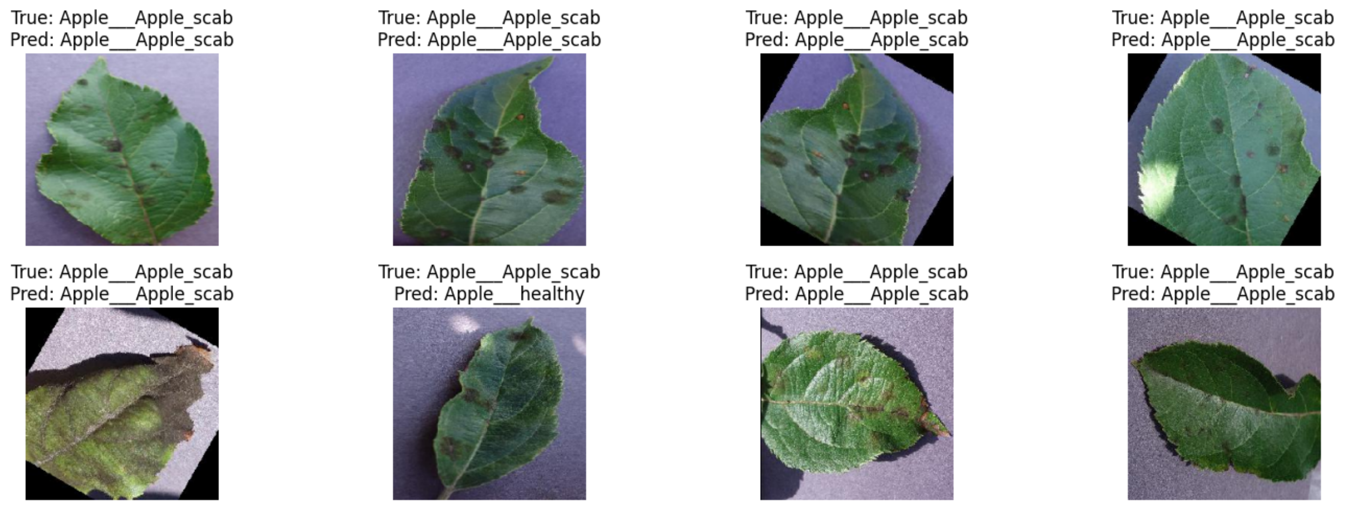
```
49/49 ━━━━━━━━━━━━━━━━━━━━ 7s 141ms/step
                          precision    recall  f1-score   support

      Apple___Apple_scab       0.98      0.90      0.94       403
       Apple___Black_rot       0.93      0.99      0.96       397
Apple___Cedar_apple_rust       0.97      1.00      0.98       352
         Apple___healthy       0.98      0.97      0.97       401

                accuracy                           0.96      1553
               macro avg       0.96      0.97      0.96      1553
            weighted avg       0.96      0.96      0.96      1553
```

Precision measures the accuracy of positive predictions. Recall measures how well the model identifies actual positive instances. F1-Score is the harmonic mean of precision and recall.

Visualize Predictions

```
def plot_predictions(generator, model, num_images=8):
    class_names = list(generator.class_indices.keys())
    x_batch, y_batch = next(generator)
    plt.figure(figsize=(15, 5))

    for i in range(num_images):
        ax = plt.subplot(2, 4, i + 1)
        plt.imshow(x_batch[i])
        predicted_class = class_names[np.argmax(model.predict(x_batch[i:i+1]))]
        true_class = class_names[np.argmax(y_batch[i])]
        plt.title(f"True: {true_class}\nPred: {predicted_class}")
        plt.axis('off')

    plt.tight_layout()
    plt.show()

plot_predictions(test_generator, model)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 936ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
```



True: Apple___Apple_scab
Pred: Apple___Apple_scab

True: Apple___Apple_scab
Pred: Apple___Apple_scab

True: Apple___Apple_scab
Pred: Apple___Apple_scab

True: Apple___Apple_scab
Pred: Apple___Apple_scab

True: Apple___Apple_scab
Pred: Apple___Apple_scab

True: Apple___Apple_scab
Pred: Apple___healthy

True: Apple___Apple_scab
Pred: Apple___Apple_scab

True: Apple___Apple_scab
Pred: Apple___Apple_scab

batch normalization is normalizes the inputs to each layer of the network. This means it adjusts the data so that each input has a mean of 0 and a variance of 1. This makes the training process smoother and faster.

Build the Deeper Model

```
from tensorflow.keras.layers import BatchNormalization

# Build deeper model
model_deeper = Sequential()
```

```
# Convolutional Layer 1
model_deeper.add(Conv2D(64, (3, 3), activation='relu', input_shape=(224, 224, 3)))
model_deeper.add(BatchNormalization())  # Batch normalization
model_deeper.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional Layer 2
model_deeper.add(Conv2D(128, (3, 3), activation='relu'))
model_deeper.add(BatchNormalization())
model_deeper.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional Layer 3
model_deeper.add(Conv2D(256, (3, 3), activation='relu'))
model_deeper.add(BatchNormalization())
model_deeper.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional Layer 4 (Added layer)
model_deeper.add(Conv2D(512, (3, 3), activation='relu'))
model_deeper.add(BatchNormalization())
model_deeper.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional Layer 5 (Added layer)
model_deeper.add(Conv2D(512, (3, 3), activation='relu'))
model_deeper.add(BatchNormalization())
model_deeper.add(MaxPooling2D(pool_size=(2, 2)))

# Flatten layer
model_deeper.add(Flatten())

# Fully connected layers
model_deeper.add(Dense(1024, activation='relu'))
model_deeper.add(Dropout(0.5))  # Dropout for regularization
model_deeper.add(Dense(512, activation='relu'))
model_deeper.add(Dense(4, activation='softmax'))  # 4 classes
#decreasing will neurons to 64, you are decreasing the model's capacity.
# Model summary
model_deeper.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: U
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential_2"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ conv2d_6 (Conv2D)                │ (None, 222, 222, 64)   │         1,792 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ batch_normalization              │ (None, 222, 222, 64)   │           256 │
│ (BatchNormalization)             │                        │               │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_6 (MaxPooling2D)   │ (None, 111, 111, 64)   │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_7 (Conv2D)                │ (None, 109, 109, 128)  │        73,856 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ batch_normalization_1            │ (None, 109, 109, 128)  │           512 │
│ (BatchNormalization)             │                        │               │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_7 (MaxPooling2D)   │ (None, 54, 54, 128)    │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_8 (Conv2D)                │ (None, 52, 52, 256)    │       295,168 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ batch_normalization_2            │ (None, 52, 52, 256)    │         1,024 │
│ (BatchNormalization)             │                        │               │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_8 (MaxPooling2D)   │ (None, 26, 26, 256)    │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_9 (Conv2D)                │ (None, 24, 24, 512)    │     1,180,160 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ batch_normalization_3            │ (None, 24, 24, 512)    │         2,048 │
│ (BatchNormalization)             │                        │               │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_9 (MaxPooling2D)   │ (None, 12, 12, 512)    │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_10 (Conv2D)               │ (None, 10, 10, 512)    │     2,359,808 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ batch_normalization_4            │ (None, 10, 10, 512)    │         2,048 │
│ (BatchNormalization)             │                        │               │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_10 (MaxPooling2D)  │ (None, 5, 5, 512)      │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ flatten_2 (Flatten)              │ (None, 12800)          │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_6 (Dense)                  │ (None, 1024)           │    13,108,224 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ dropout_2 (Dropout)              │ (None, 1024)           │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_7 (Dense)                  │ (None, 512)            │       524,800 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_8 (Dense)                  │ (None, 4)              │         2,052 │
└──────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 17,551,748 (66.95 MB)
 Trainable params: 17,548,804 (66.94 MB)
 Non-trainable params: 2,944 (11.50 KB)
```

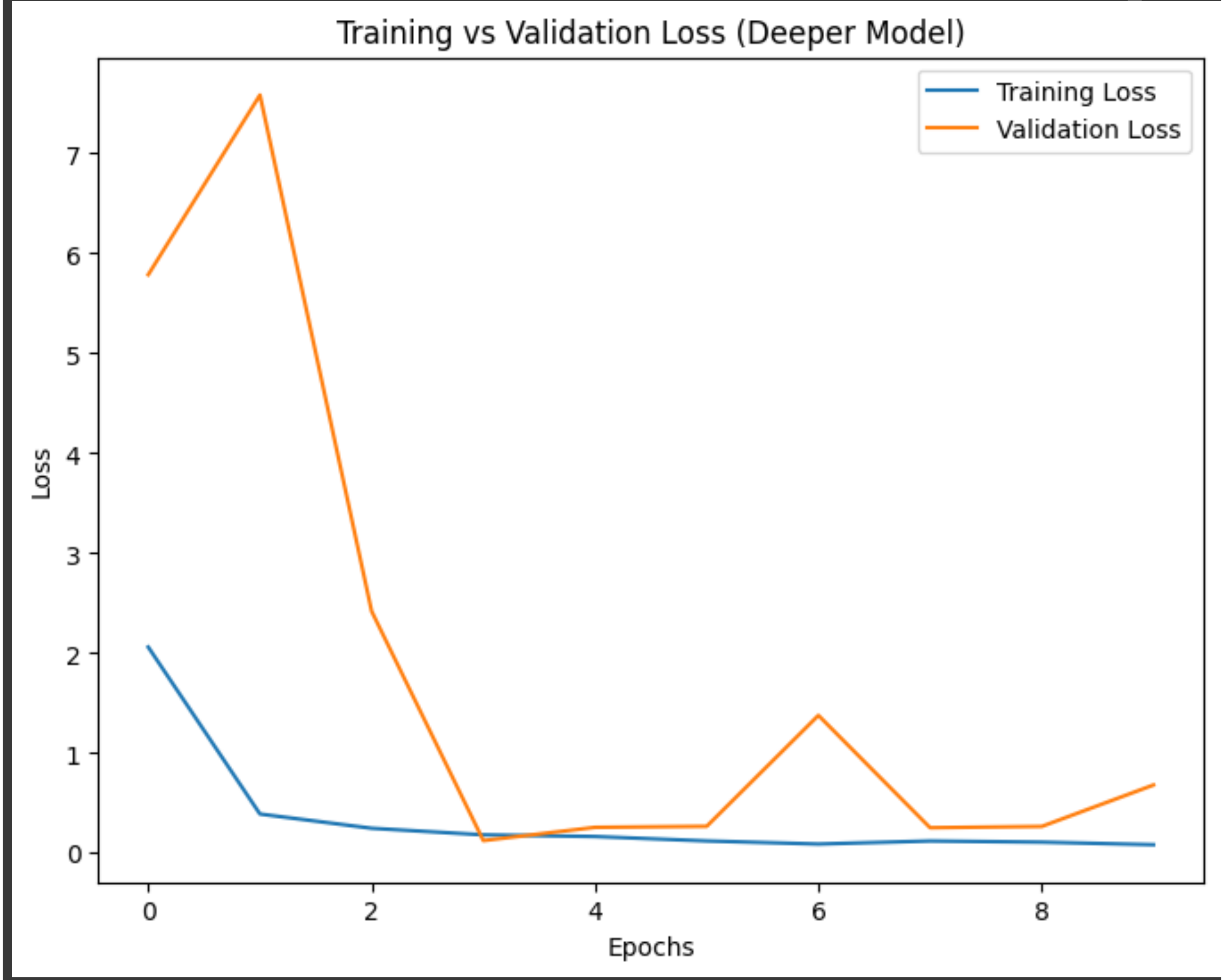
Compile the Model

```
# Compile the deeper model
model_deeper.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
```

Train the Deeper Model

```
history_deeper = model_deeper.fit(
    train_generator,
    epochs=10,  # Adjust as necessary
    validation_data=test_generator,
    verbose=1 #This controls how much information is shown during training
)

# Plotting training & validation loss for deeper model
plt.figure(figsize=(8, 6))
plt.plot(history_deeper.history['loss'], label='Training Loss')
plt.plot(history_deeper.history['val_loss'], label='Validation Loss')
plt.title('Training vs Validation Loss (Deeper Model)')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 69s 263ms/step - accuracy: 0.6703 - loss: 3.8081 - val_accura
Epoch 2/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 186ms/step - accuracy: 0.8610 - loss: 0.4941 - val_accura
Epoch 3/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 38s 194ms/step - accuracy: 0.9216 - loss: 0.2724 - val_accura
Epoch 4/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 185ms/step - accuracy: 0.9310 - loss: 0.2050 - val_accura
Epoch 5/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 184ms/step - accuracy: 0.9500 - loss: 0.1476 - val_accura
Epoch 6/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 181ms/step - accuracy: 0.9663 - loss: 0.1046 - val_accura
Epoch 7/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 185ms/step - accuracy: 0.9709 - loss: 0.0861 - val_accura
Epoch 8/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 182ms/step - accuracy: 0.9645 - loss: 0.1154 - val_accura
Epoch 9/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 35s 181ms/step - accuracy: 0.9729 - loss: 0.0962 - val_accura
Epoch 10/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 39s 201ms/step - accuracy: 0.9694 - loss: 0.0955 - val_accura
```



Evaluate the Deeper Model

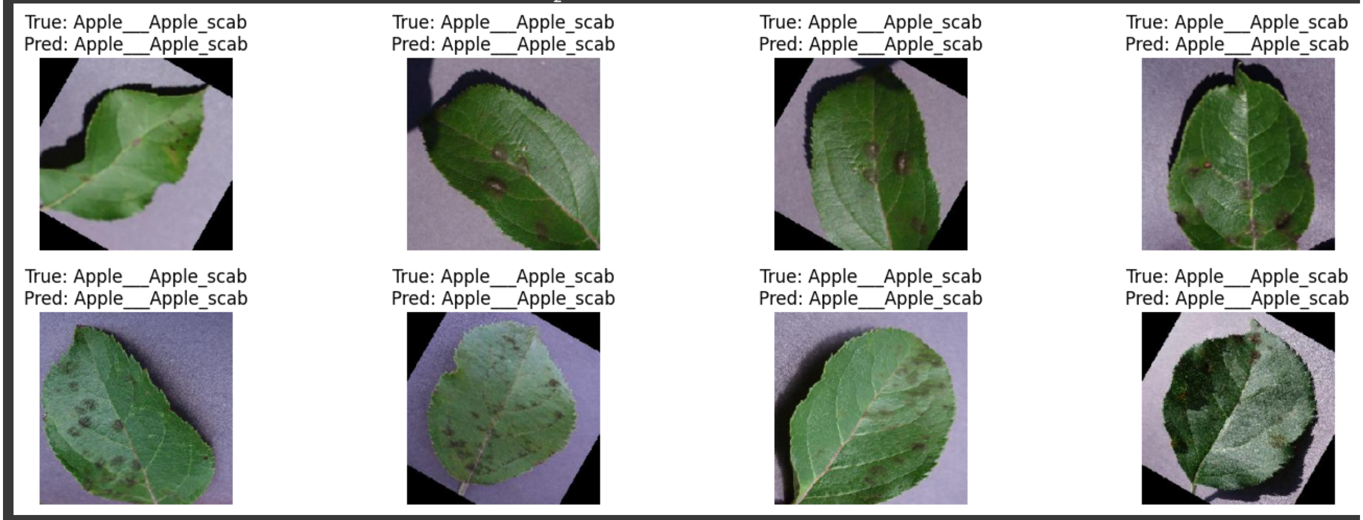
```
# Get predictions from deeper model
predictions_deeper = model_deeper.predict(test_generator)
y_pred_deeper = np.argmax(predictions_deeper, axis=1)

# Print classification report
from sklearn.metrics import classification_report

print(classification_report(y_true, y_pred_deeper, target_names=test_generator.class_indices.k
```

```
49/49 ━━━━━━━━━━━━━━━━━━━━ 8s 144ms/step
                         precision    recall  f1-score   support

     Apple___Apple_scab       0.75      0.95      0.84       403
      Apple___Black_rot       0.96      0.99      0.98       397
Apple___Cedar_apple_rust       0.84      0.82      0.83       352
        Apple___healthy       0.97      0.70      0.81       401

               accuracy                           0.87      1553
              macro avg       0.88      0.87      0.87      1553
           weighted avg       0.88      0.87      0.87      1553
```

Visualize Predictions from the Deeper Model

```
plot_predictions(test_generator, model_deeper)
```

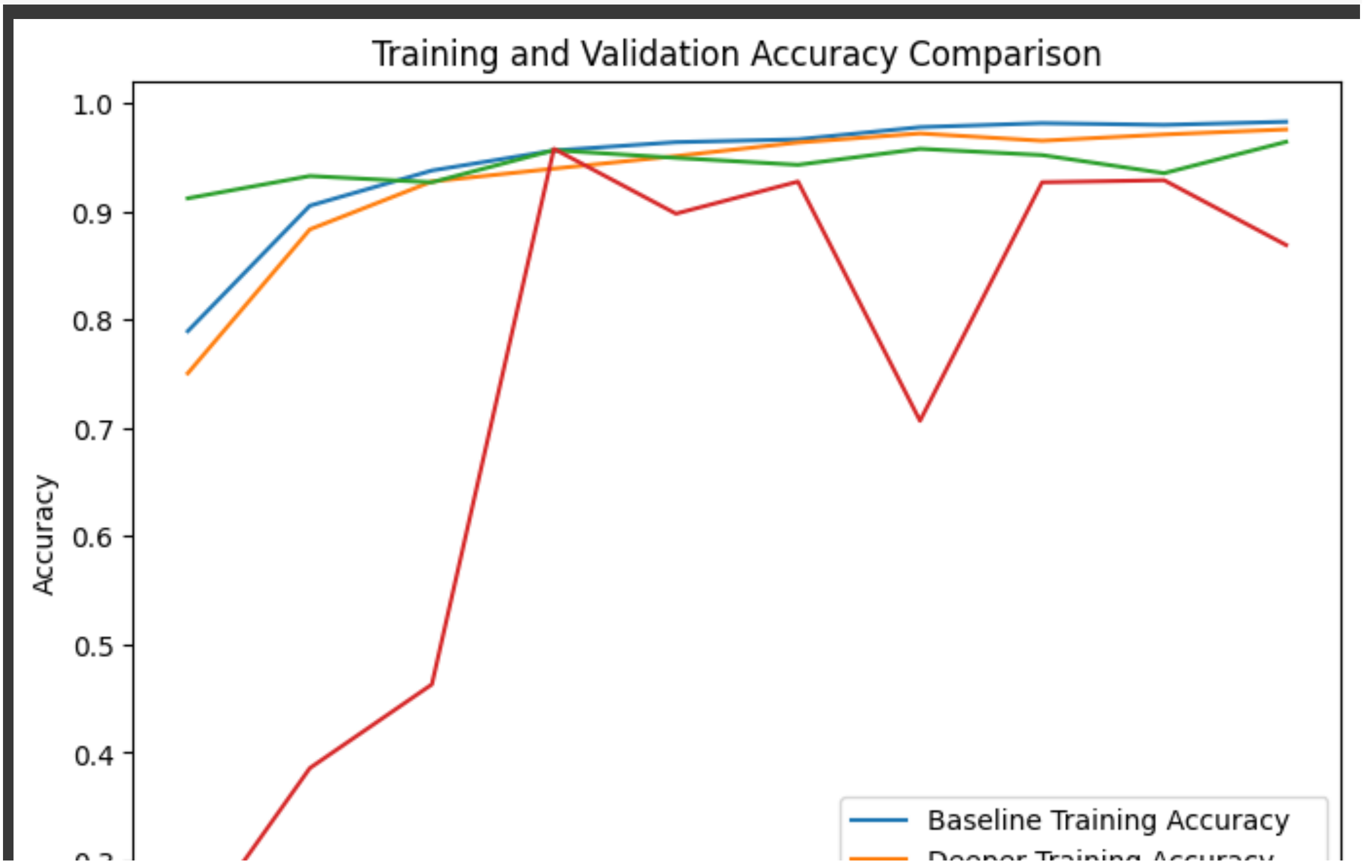
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
```

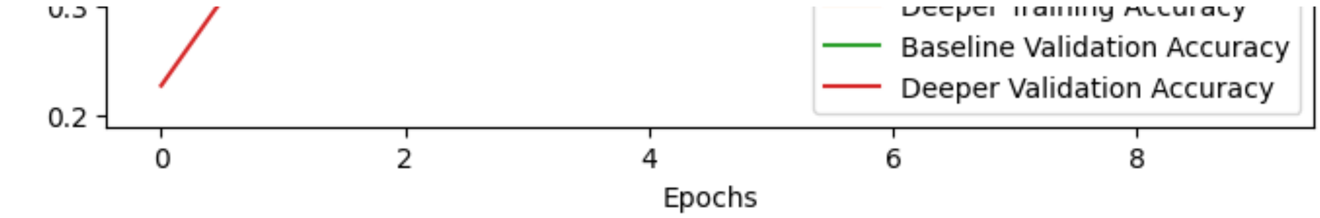


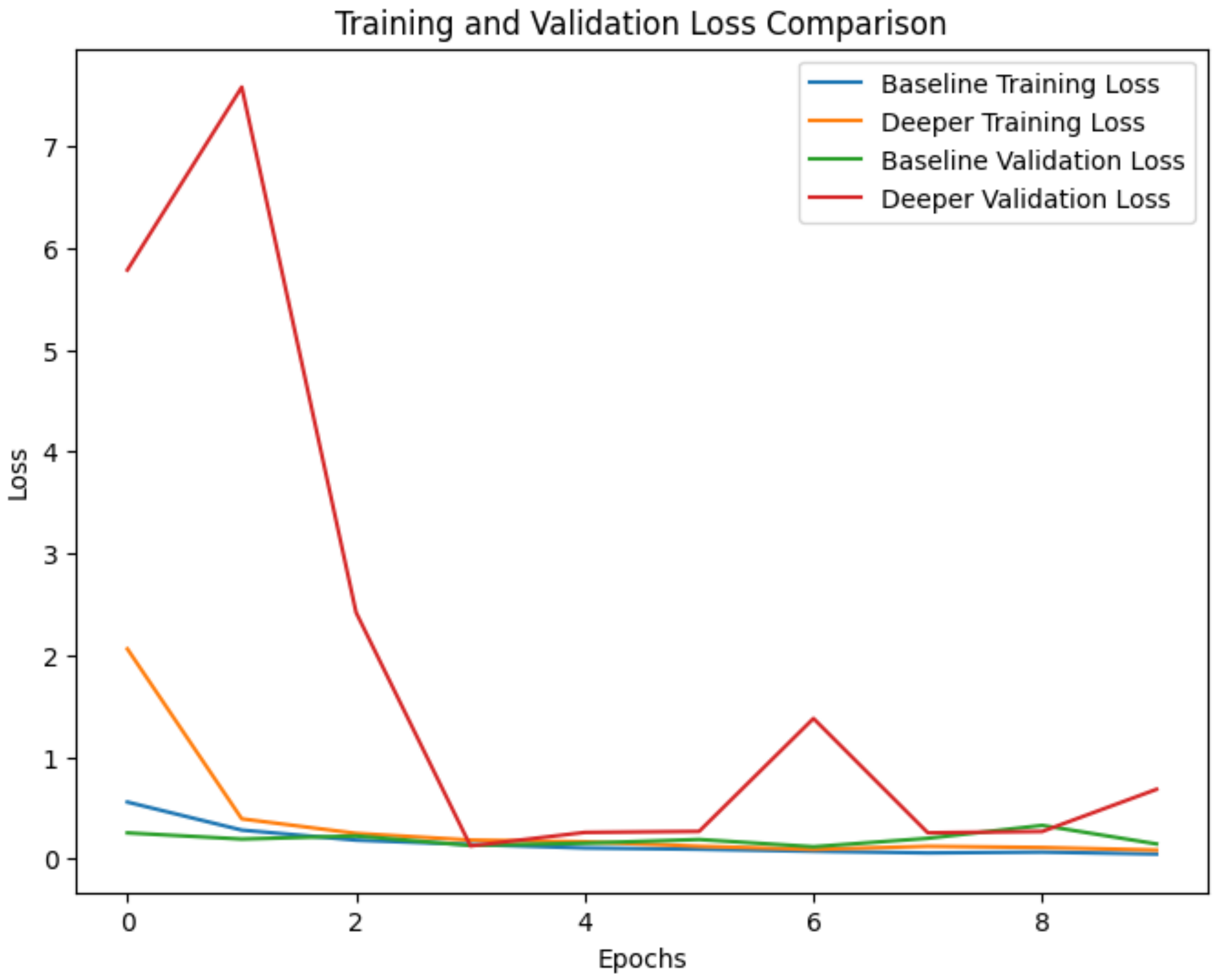
Comparative Analysis of Baseline vs. Deeper Model

Model Performance Comparison

```
# Compare accuracy and loss for baseline and deeper models
baseline_history = history.history
deeper_history = history_deeper.history

# Plot accuracy comparison
plt.figure(figsize=(8, 6))
plt.plot(baseline_history['accuracy'], label='Baseline Training Accuracy')
plt.plot(deeper_history['accuracy'], label='Deeper Training Accuracy')
plt.plot(baseline_history['val_accuracy'], label='Baseline Validation Accuracy')
plt.plot(deeper_history['val_accuracy'], label='Deeper Validation Accuracy')
plt.title('Training and Validation Accuracy Comparison')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot loss comparison
plt.figure(figsize=(8, 6))
plt.plot(baseline_history['loss'], label='Baseline Training Loss')
plt.plot(deeper_history['loss'], label='Deeper Training Loss')
plt.plot(baseline_history['val_loss'], label='Baseline Validation Loss')
plt.plot(deeper_history['val_loss'], label='Deeper Validation Loss')
plt.title('Training and Validation Loss Comparison')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```





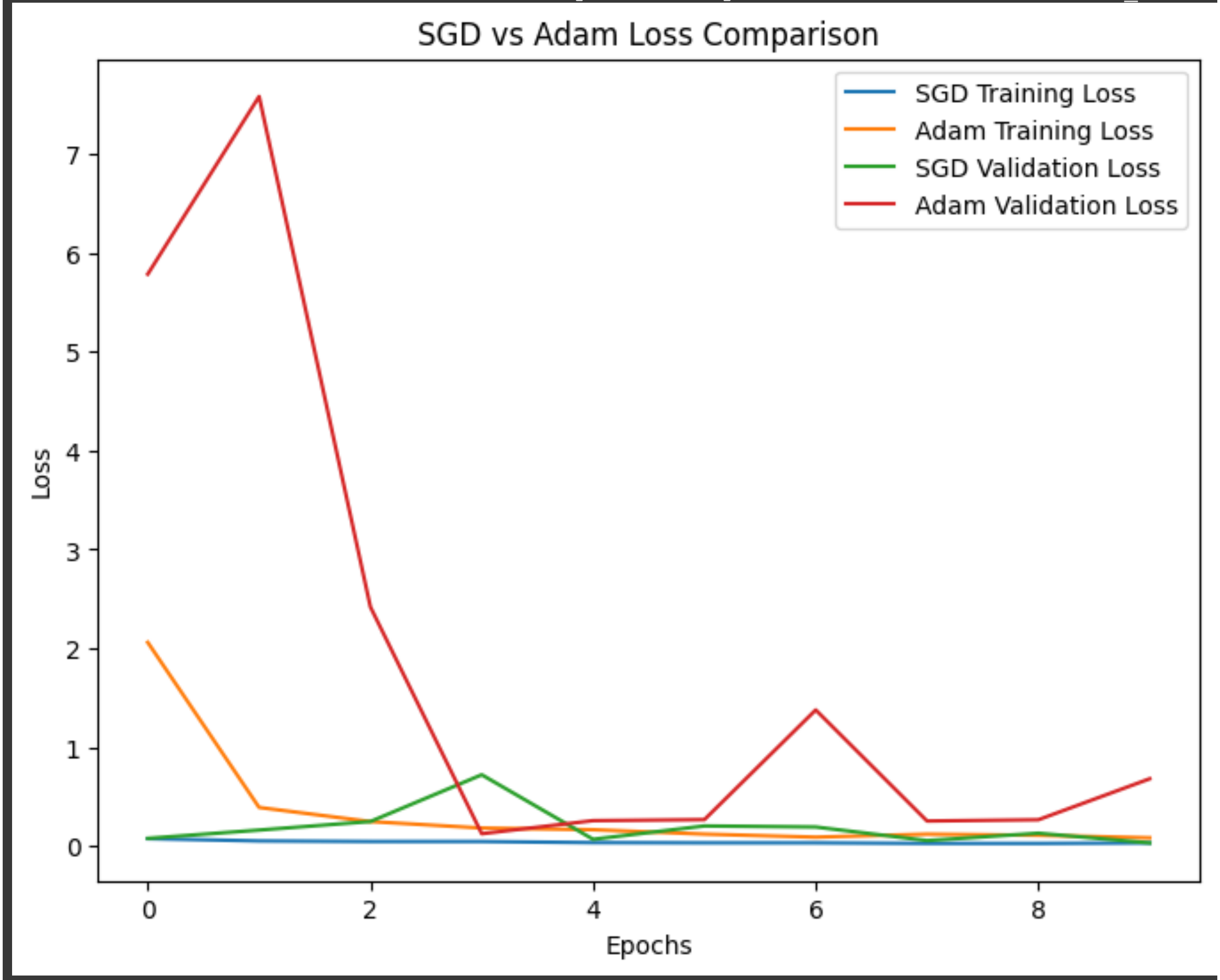


Computational Efficiency Comparison

Optimizer Comparison (SGD vs Adam)

```
# Compile model with SGD optimizer
model_deeper.compile(optimizer='sgd', loss='categorical_crossentropy', metrics=['accuracy'])

# Train with SGD learning rate is 0.01 meanwhile adam is 0.0005
history_sgd = model_deeper.fit(
    train_generator,
    epochs=10, #one complete pass through the entire training dataset during the training proc
    validation_data=test_generator,
    verbose=1
)

# Plot SGD vs Adam Loss
plt.figure(figsize=(8, 6))
plt.plot(history_sgd.history['loss'], label='SGD Training Loss')
plt.plot(deeper_history['loss'], label='Adam Training Loss')
plt.plot(history_sgd.history['val_loss'], label='SGD Validation Loss')
plt.plot(deeper_history['val_loss'], label='Adam Validation Loss')
plt.title('SGD vs Adam Loss Comparison')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 43s 199ms/step - accuracy: 0.9754 - loss: 0.0951 - val_accura
Epoch 2/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 35s 180ms/step - accuracy: 0.9844 - loss: 0.0488 - val_accura
Epoch 3/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 42s 183ms/step - accuracy: 0.9873 - loss: 0.0430 - val_accura
Epoch 4/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 35s 180ms/step - accuracy: 0.9890 - loss: 0.0410 - val_accura
Epoch 5/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 181ms/step - accuracy: 0.9895 - loss: 0.0300 - val_accura
Epoch 6/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 35s 180ms/step - accuracy: 0.9911 - loss: 0.0282 - val_accura
Epoch 7/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 44s 198ms/step - accuracy: 0.9875 - loss: 0.0314 - val_accura
Epoch 8/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 36s 184ms/step - accuracy: 0.9896 - loss: 0.0248 - val_accura
Epoch 9/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 35s 178ms/step - accuracy: 0.9936 - loss: 0.0252 - val_accura
Epoch 10/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 35s 180ms/step - accuracy: 0.9881 - loss: 0.0334 - val_accura
```



Loading and Adapting a Pre-Trained Model

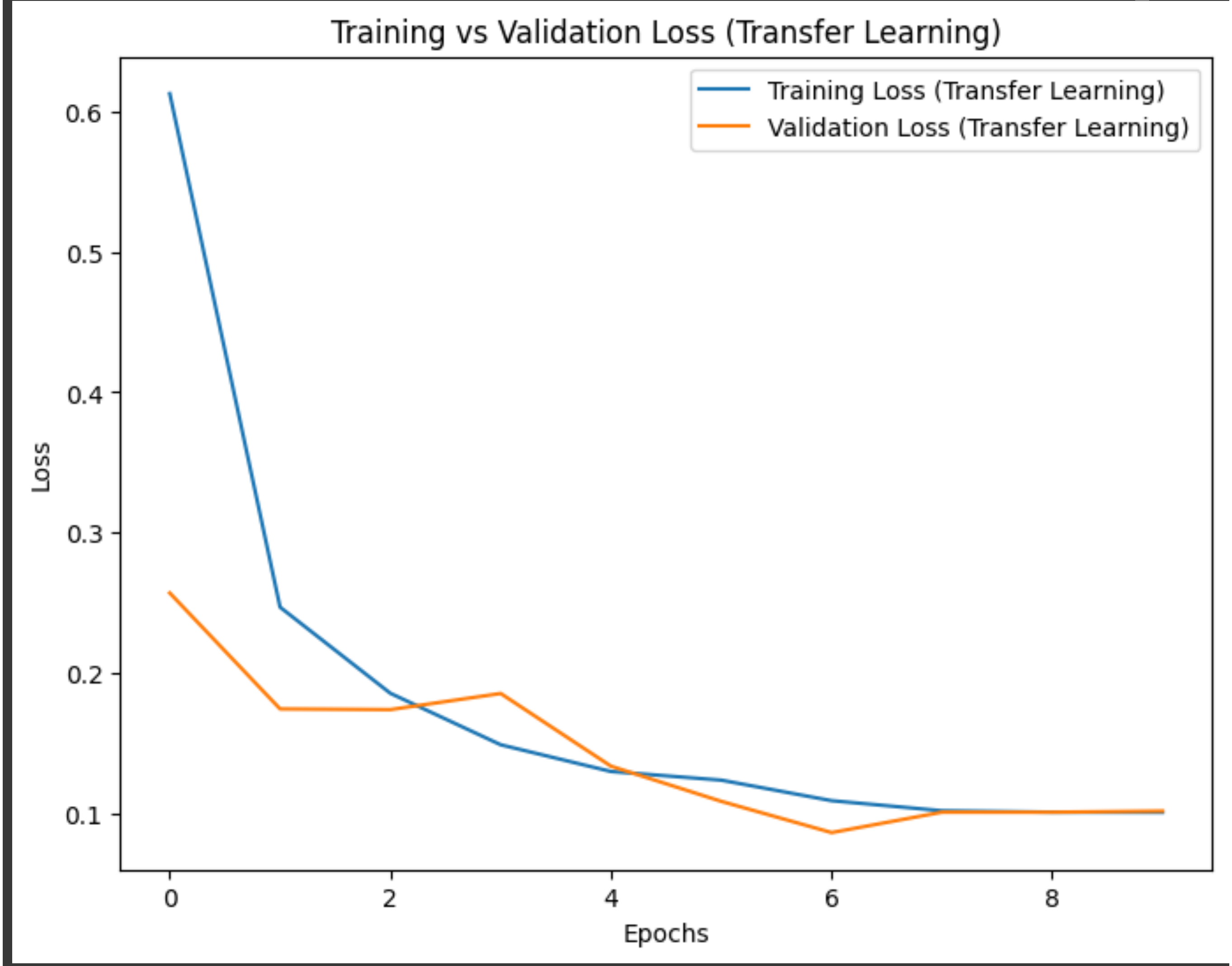
```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.layers import GlobalAveragePooling2D
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam

# Load VGG16 with pre-trained ImageNet weights, without the top fully connected layers
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
#will only retain the convolutional layers and pooling layers, which are responsible for featu
# Freeze the base model (so the weights won't be updated during training)
for layer in base_model.layers:
    layer.trainable = False

# Add a custom top layer for your classification task
x = base_model.output
x = GlobalAveragePooling2D()(x)  # Pooling layer to reduce dimensionality
x = Dense(1024, activation='relu')(x)
x = Dropout(0.5)(x)  # Regularization
x = Dense(4, activation='softmax')(x)  # 4 classes for classification

# Create the final model
model_transfer = Model(inputs=base_model.input, outputs=x)

# Compile the model
model_transfer.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy']
model_transfer.summary()
#Adam(learning_rate=0.0005)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/v
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 4s 0us/step
Model: "functional_42"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ input_layer_3 (InputLayer)      │ (None, 224, 224, 3)    │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block1_conv1 (Conv2D)           │ (None, 224, 224, 64)   │         1,792 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block1_conv2 (Conv2D)           │ (None, 224, 224, 64)   │        36,928 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block1_pool (MaxPooling2D)      │ (None, 112, 112, 64)   │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block2_conv1 (Conv2D)           │ (None, 112, 112, 128)  │        73,856 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block2_conv2 (Conv2D)           │ (None, 112, 112, 128)  │       147,584 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block2_pool (MaxPooling2D)      │ (None, 56, 56, 128)    │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block3_conv1 (Conv2D)           │ (None, 56, 56, 256)    │       295,168 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block3_conv2 (Conv2D)           │ (None, 56, 56, 256)    │       590,080 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block3_conv3 (Conv2D)           │ (None, 56, 56, 256)    │       590,080 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block3_pool (MaxPooling2D)      │ (None, 28, 28, 256)    │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block4_conv1 (Conv2D)           │ (None, 28, 28, 512)    │     1,180,160 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block4_conv2 (Conv2D)           │ (None, 28, 28, 512)    │     2,359,808 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block4_conv3 (Conv2D)           │ (None, 28, 28, 512)    │     2,359,808 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block4_pool (MaxPooling2D)      │ (None, 14, 14, 512)    │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block5_conv1 (Conv2D)           │ (None, 14, 14, 512)    │     2,359,808 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block5_conv2 (Conv2D)           │ (None, 14, 14, 512)    │     2,359,808 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block5_conv3 (Conv2D)           │ (None, 14, 14, 512)    │     2,359,808 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ block5_pool (MaxPooling2D)      │ (None, 7, 7, 512)      │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ global_average_pooling2d        │ (None, 512)            │             0 │
│ (GlobalAveragePooling2D)        │                        │               │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_9 (Dense)                 │ (None, 1024)           │       525,312 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dropout_3 (Dropout)             │ (None, 1024)           │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_10 (Dense)                │ (None, 4)              │         4,100 │
└─────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 15,244,100 (58.15 MB)
 Trainable params: 529,412 (2.02 MB)
 Non-trainable params: 14,714,688 (56.13 MB)
```

Training Strategies

```
# Train only the custom top layers
history_transfer = model_transfer.fit(
    train_generator,
    epochs=10,  # You can adjust this based on training time
    validation_data=test_generator,
    verbose=1 #This controls the level of logging output during training
)

# Plot training vs validation loss for transfer learning
plt.figure(figsize=(8, 6))
plt.plot(history_transfer.history['loss'], label='Training Loss (Transfer Learning)')
plt.plot(history_transfer.history['val_loss'], label='Validation Loss (Transfer Learning)')
plt.title('Training vs Validation Loss (Transfer Learning)')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 70s 287ms/step - accuracy: 0.6281 - loss: 0.9107 - val_accura
Epoch 2/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 55s 212ms/step - accuracy: 0.9059 - loss: 0.2711 - val_accura
Epoch 3/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 82s 210ms/step - accuracy: 0.9387 - loss: 0.1827 - val_accura
Epoch 4/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 206ms/step - accuracy: 0.9494 - loss: 0.1472 - val_accura
Epoch 5/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 206ms/step - accuracy: 0.9425 - loss: 0.1556 - val_accura
Epoch 6/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 206ms/step - accuracy: 0.9548 - loss: 0.1327 - val_accura
Epoch 7/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 205ms/step - accuracy: 0.9632 - loss: 0.1091 - val_accura
Epoch 8/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 41s 206ms/step - accuracy: 0.9691 - loss: 0.0890 - val_accura
Epoch 9/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 205ms/step - accuracy: 0.9610 - loss: 0.1103 - val_accura
Epoch 10/10
195/195 ━━━━━━━━━━━━━━━━━━━━ 40s 206ms/step - accuracy: 0.9621 - loss: 0.1058 - val_accura
```



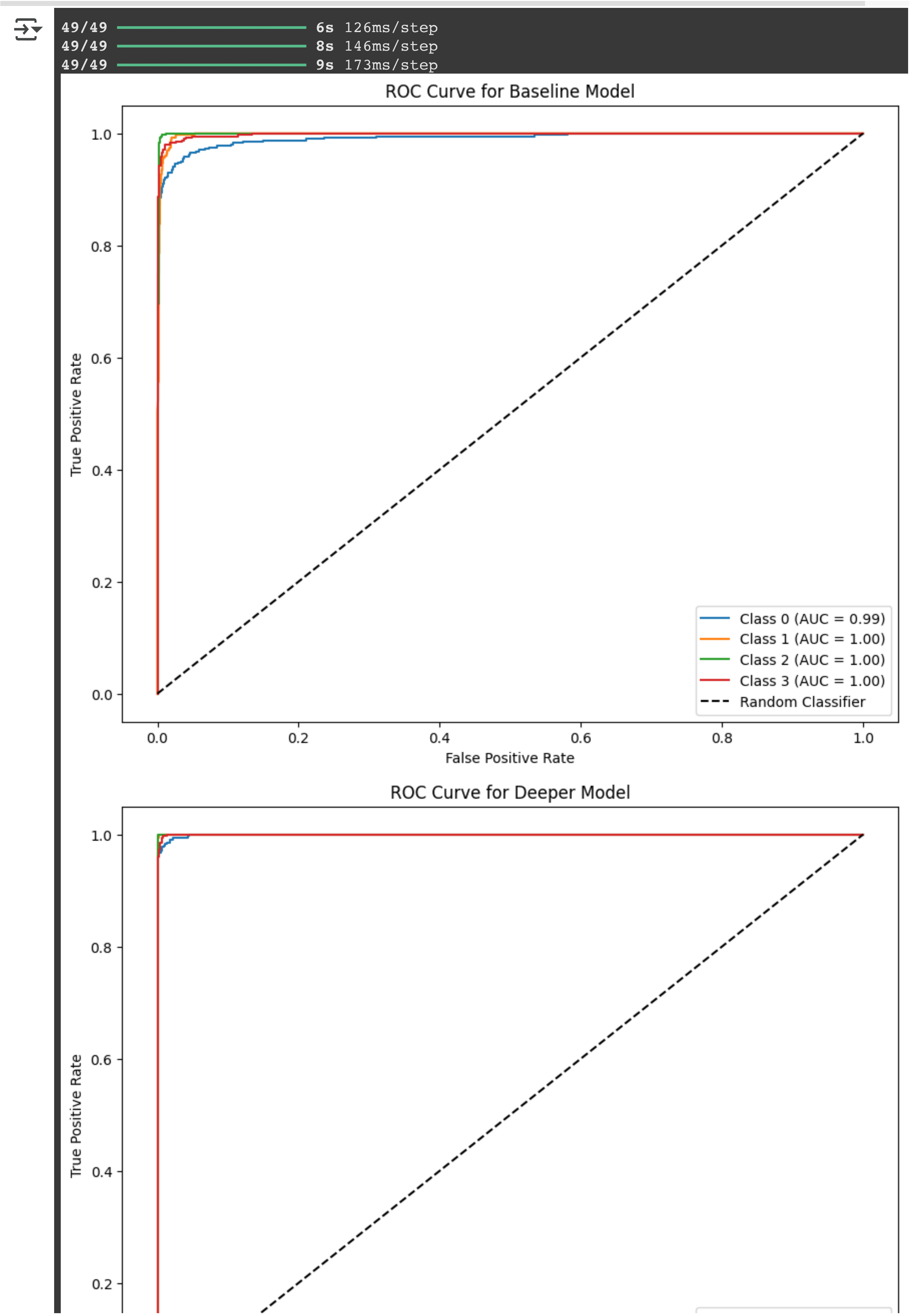
Model Evaluation and Prediction

```
# Get predictions from the transfer learning model
predictions_transfer = model_transfer.predict(test_generator)
y_pred_transfer = np.argmax(predictions_transfer, axis=1)

# Print classification report for transfer learning model
print(classification_report(y_true, y_pred_transfer, target_names=test_generator.class_indices
```

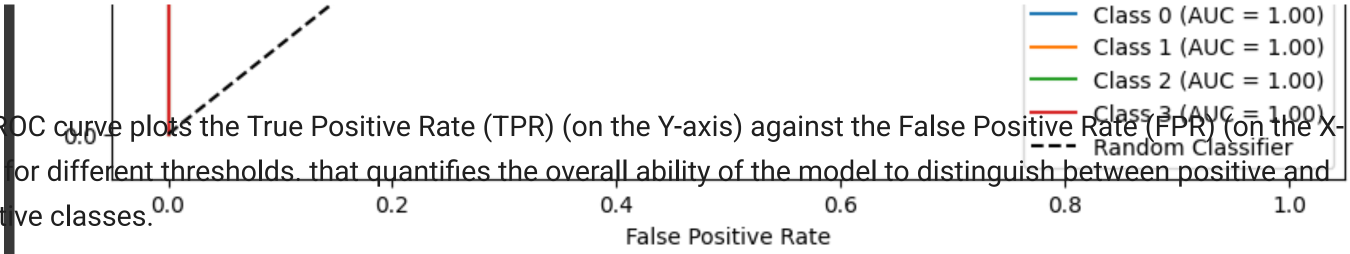
```
49/49 ━━━━━━━━━━━━━━━━━━━━ 10s 184ms/step
                          precision    recall  f1-score   support

       Apple___Apple_scab       0.99      0.87      0.92       403
        Apple___Black_rot       0.97      0.99      0.98       397
 Apple___Cedar_apple_rust       0.93      0.99      0.96       352
          Apple___healthy       0.94      0.99      0.96       401

                 accuracy                           0.96      1553
                macro avg       0.96      0.96      0.96      1553
             weighted avg       0.96      0.96      0.96      1553
```

ROC curve (Receiver Operating Characteristic curve)

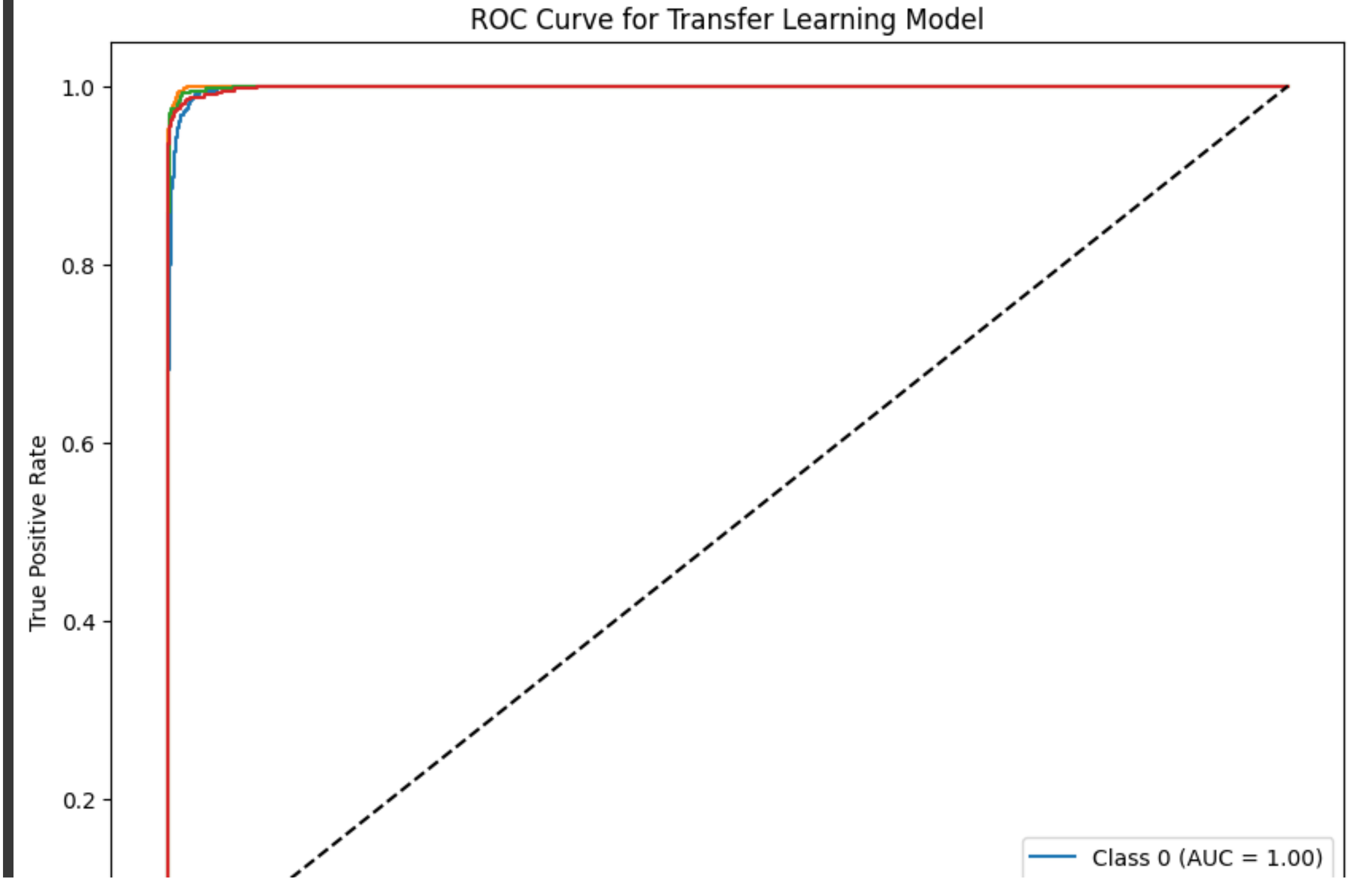
```
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize

# Binarize the true labels (multi-class one-hot encoding)
y_true_binarized = label_binarize(y_true, classes=[0, 1, 2, 3])

# Function to plot the ROC curve for each class
def plot_roc_curve(y_true, y_pred_prob, model_name):
    n_classes = y_true.shape[1]  # Number of classes
    fpr, tpr, auc_scores = {}, {}, {}

    # Plot ROC curve for each class
    plt.figure(figsize=(10, 8))

    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_true[:, i], y_pred_prob[:, i])  # Get FPR, TPR for cla
        auc_scores[i] = auc(fpr[i], tpr[i])  # Calculate AUC for each class
        plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {auc_scores[i]:.2f})')

    # Plot a random classifier (diagonal line)
    plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')

    plt.title(f'ROC Curve for {model_name}')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.legend(loc='best')
    plt.show()

# Get predicted probabilities for each model (probabilities for each class)
y_pred_baseline_prob = model.predict(test_generator)
y_pred_deeper_prob = model_deeper.predict(test_generator)
y_pred_transfer_prob = model_transfer.predict(test_generator)

# Plot ROC curve for each model
plot_roc_curve(y_true_binarized, y_pred_baseline_prob, 'Baseline Model')
plot_roc_curve(y_true_binarized, y_pred_deeper_prob, 'Deeper Model')
plot_roc_curve(y_true_binarized, y_pred_transfer_prob, 'Transfer Learning Model')
```



```
49/49 ━━━━━━━━━━━━━━━━━━━━ 6s 126ms/step
49/49 ━━━━━━━━━━━━━━━━━━━━ 8s 146ms/step
49/49 ━━━━━━━━━━━━━━━━━━━━ 9s 173ms/step
```



The ROC curve plots the True Positive Rate (TPR) (on the Y-axis) against the False Positive Rate (FPR) (on the X-axis) for different thresholds. that quantifies the overall ability of the model to distinguish between positive and negative classes.


ROC Curve for Transfer Learning Model
True Positive Rate
Class 0 (AUC = 1.00)