

PRCP- 1001- RICE LEAF DISEASE DETECTION

DOMAIN ANALYSIS

Domain Background – Agriculture & Crop Disease

Agriculture remains a primary economic sector in many countries, and rice is one of the world's most consumed staple crops. However, rice is particularly susceptible to numerous leaf diseases that reduce yield and quality. Manual diagnosis of these diseases is:

- **Time-consuming**
- **Labor-intensive**
- **Prone to human error**

The integration of **AI-based image recognition**, especially using **Convolutional Neural Networks (CNNs)**, has emerged as a game-changer for crop disease detection. CNNs can automatically extract patterns from leaf images to accurately detect disease types, even under noisy or varied conditions.

Project Objective

The objective of this project is to build a **robust image classification model** using deep learning and transfer learning techniques to classify rice leaf images into three categories:

- **Bacterial Leaf Blight**
- **Brown Spot**
- **Leaf Smut**

This model aims to:

- Achieve high **classification accuracy and generalization**
 - Be scalable for **real-world deployment (e.g., web/mobile apps)**
 - Help **farmers or agronomists** with early, accurate diagnosis
-

Dataset Description

- The dataset consists of rice leaf images categorized into **three classes**:
 - *Bacterial leaf blight*
 - *Brown spot*

- *Leaf smut*
 - Each image is in `.JPG` format and was manually labeled.
 - Data split:
 - 70% Training
 - 15% Validation
 - 15% Testing
-

Problem Framing

- **Task Type:** Multiclass Image Classification
 - **Learning Approach:** Supervised Learning
 - **Input:** Raw image (RGB, 224x224)
 - **Output:** Class label (0, 1, 2)
-

Importance of Automation

- Early disease detection → Reduces economic losses
- Eliminates manual bias in inspection
- Enables **scalable**, **real-time**, and **remote diagnosis** for smart agriculture

PRECHECKS

```
In [1]: import seaborn as sns
import os
import random
from collections import defaultdict
from PIL import Image
import matplotlib.pyplot as plt
import pandas as pd
```

```
In [2]: # Set base folder and expected subfolders
base_folder = "./Data"
expected_classes = ['Leaf smut', 'Brown spot', 'Bacterial leaf blight']

# Validate dataset structure
if not os.path.exists(base_folder):
    raise FileNotFoundError(f"Data folder not found at path: {base_folder}")

missing_classes = [cls for cls in expected_classes if not os.path.isdir(os.path.
if missing_classes:
    raise FileNotFoundError(f"Missing expected class folders: {missing_classes}")
else:
    print(f"Dataset structure is valid in: {base_folder}")

# Get class list dynamically (optional, for flexibility)
classes = sorted([folder for folder in os.listdir(base_folder) if os.path.isdir(

# Count number of images per class
class_counts = defaultdict(int)
```

```

for cls in classes:
    class_dir = os.path.join(base_folder, cls)
    images = [f for f in os.listdir(class_dir) if f.lower().endswith(('.jpg', '.png'))]
    class_counts[cls] = len(images)

print("\nClass Distribution:")
for cls, count in class_counts.items():
    print(f" - {cls}: {count} images")

# Show sample images per class
def show_sample_images(dataset_path, class_names, samples_per_class=2):
    fig, axes = plt.subplots(len(class_names), samples_per_class, figsize=(10, 10))

    for i, cls in enumerate(class_names):
        img_dir = os.path.join(dataset_path, cls)
        image_files = [img for img in os.listdir(img_dir) if img.lower().endswith(('.jpg', '.png'))]

        if len(image_files) < samples_per_class:
            raise ValueError(f"Not enough images in class '{cls}' to sample {samples_per_class} images")

        selected_imgs = random.sample(image_files, samples_per_class)
        for j, img_file in enumerate(selected_imgs):
            img_path = os.path.join(img_dir, img_file)
            img = Image.open(img_path)
            axes[i, j].imshow(img)
            axes[i, j].axis('off')
            axes[i, j].set_title(f"{cls}", fontsize=10)
    plt.tight_layout()
    plt.suptitle("Sample Images per Class", fontsize=16)
    plt.subplots_adjust(top=0.92)
    plt.show()

# Visualize
show_sample_images(base_folder, classes, samples_per_class=2)

```

Dataset structure is valid in: ./Data

Class Distribution:

- Bacterial leaf blight: 40 images
- Brown spot: 40 images
- Leaf smut: 39 images

Sample Images per Class

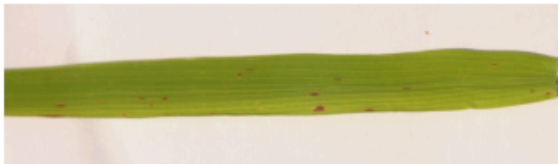
Bacterial leaf blight



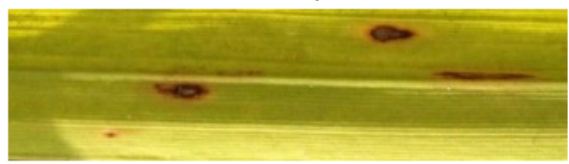
Bacterial leaf blight



Brown spot



Brown spot



Leaf smut



Leaf smut



Import & Organize Data

```
In [3]: # Function to gather image file paths per class
def get_image_data_dict(base_folder, class_names):
    data = []
    for cls in class_names:
        cls_folder = os.path.join(base_folder, cls)
        img_files = [f for f in os.listdir(cls_folder) if f.lower().endswith('.')]
        for img in img_files:
            full_path = os.path.join(cls_folder, img)
            data.append({'image_path': full_path, 'class_label': cls})
    return pd.DataFrame(data)
```

```
# Get DataFrame of all images and Labels
image_df = get_image_data_dict(base_folder, classes)
print(f"Total images collected: {len(image_df)}")
image_df.head()
```

Total images collected: 119

```
Out[3]:
```

	image_path	class_label
0	./Data\Bacterial leaf blight\DSC_0365.JPG	Bacterial leaf blight
1	./Data\Bacterial leaf blight\DSC_0366.jpg	Bacterial leaf blight
2	./Data\Bacterial leaf blight\DSC_0367.JPG	Bacterial leaf blight
3	./Data\Bacterial leaf blight\DSC_0370.jpg	Bacterial leaf blight
4	./Data\Bacterial leaf blight\DSC_0372.JPG	Bacterial leaf blight

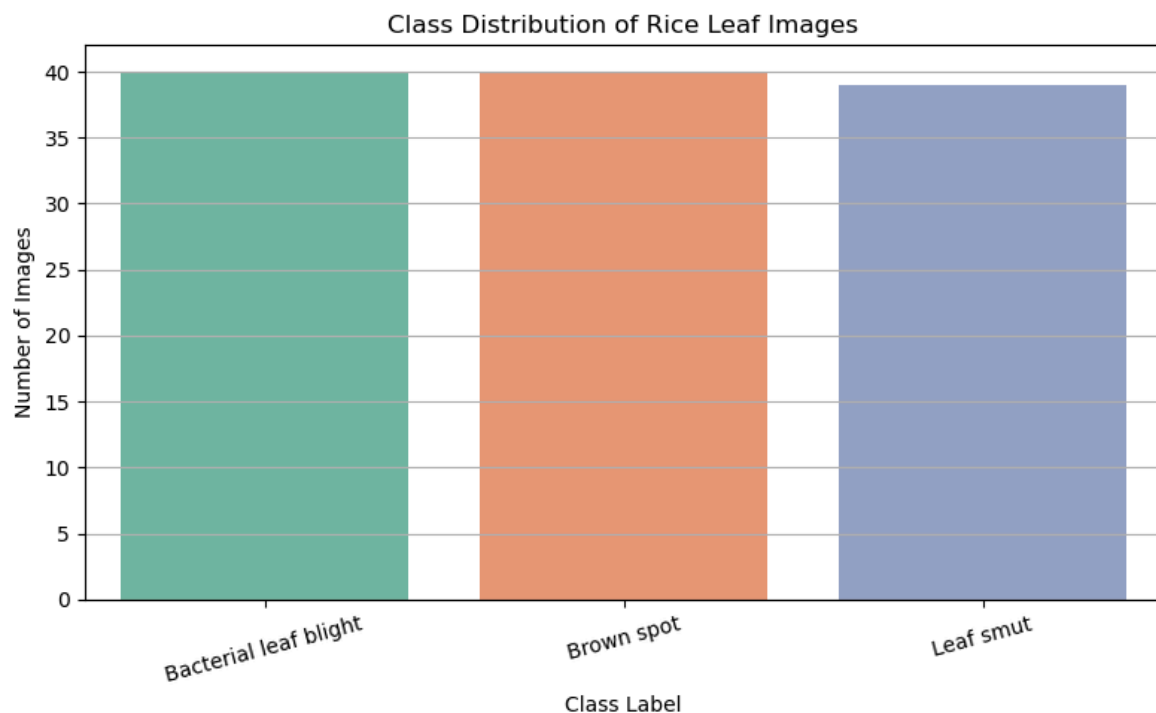
EDA

```
In [4]: # Plot class distribution as a bar plot
plt.figure(figsize=(8, 5))
sns.countplot(data=image_df, x='class_label', order=classes, palette='Set2')
plt.title("Class Distribution of Rice Leaf Images")
plt.xlabel("Class Label")
plt.ylabel("Number of Images")
plt.xticks(rotation=15)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```

C:\Users\prasa\AppData\Local\Temp\ipykernel_14208\32589907.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v 0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

```
sns.countplot(data=image_df, x='class_label', order=classes, palette='Set2')
```



```
In [5]: # Add image metadata columns
def extract_metadata(df):
    widths = []
    heights = []
    aspect_ratios = []
    file_sizes = []

    for path in df['image_path']:
        img = Image.open(path)
        width, height = img.size
        aspect_ratios.append(round(width / height, 2))
        widths.append(width)
        heights.append(height)
        file_sizes.append(os.path.getsize(path) / 1024) # in KB

    df['width'] = widths
    df['height'] = heights
    df['aspect_ratio'] = aspect_ratios
    df['file_size_kb'] = file_sizes
    return df

image_df = extract_metadata(image_df)
image_df.head()
```

Out[5]:

	image_path	class_label	width	height	aspect_ratio	file_size_kb
0	./Data\Bacterial leaf blight\DSC_0365.JPG	Bacterial leaf blight	3081	897	3.43	456.161133
1	./Data\Bacterial leaf blight\DSC_0366.jpg	Bacterial leaf blight	3081	897	3.43	408.133789
2	./Data\Bacterial leaf blight\DSC_0367.JPG	Bacterial leaf blight	3081	897	3.43	442.016602
3	./Data\Bacterial leaf blight\DSC_0370.jpg	Bacterial leaf blight	3081	897	3.43	418.683594
4	./Data\Bacterial leaf blight\DSC_0372.JPG	Bacterial leaf blight	3081	897	3.43	470.204102

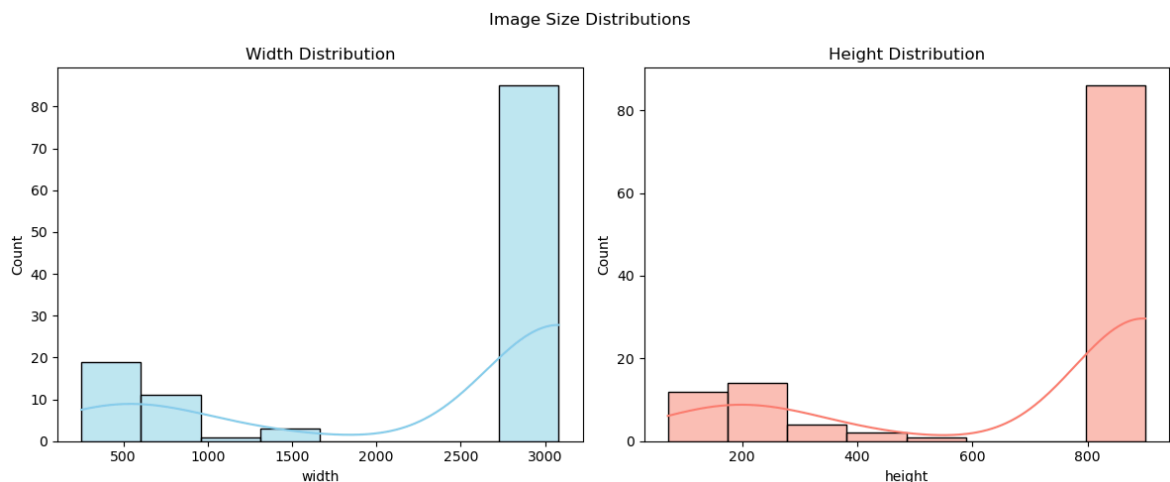
```

In [6]: # Width and Height distribution
fig, ax = plt.subplots(1, 2, figsize=(12, 5))
sns.histplot(image_df['width'], kde=True, ax=ax[0], color='skyblue')
ax[0].set_title("Width Distribution")

sns.histplot(image_df['height'], kde=True, ax=ax[1], color='salmon')
ax[1].set_title("Height Distribution")

plt.suptitle("Image Size Distributions")
plt.tight_layout()
plt.show()

```



```

In [7]: label_counts = image_df['class_label'].value_counts()
label_percentages = (label_counts / len(image_df)) * 100

label_df = pd.DataFrame({
    'Class': label_counts.index,
    'Count': label_counts.values,
    'Percentage': label_percentages.round(2)
})

print("Class Label Summary:\n")
print(label_df)

```

Class Label Summary:

	Class	Count	Percentage
class_label			
Bacterial leaf blight	Bacterial leaf blight	40	33.61
Brown spot	Brown spot	40	33.61
Leaf smut	Leaf smut	39	32.77

Data Preprocessing & Augmentation

```
In [8]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split

# Image shape for all models (we'll use a commonly accepted 224x224x3 for transf
IMG_HEIGHT = 224
IMG_WIDTH = 224
CHANNELS = 3
BATCH_SIZE = 16
SEED = 42
```

```
In [9]: import shutil

def prepare_directory_split(df, base_output_dir, split_ratio=(0.7, 0.15, 0.15)):

    # Remove existing split if any
    if os.path.exists(base_output_dir):
        shutil.rmtree(base_output_dir)

    subsets = ['train', 'val', 'test']
    split_dfs = {}

    # Split the data
    df_train, df_temp = train_test_split(df, test_size=1-split_ratio[0], stratif
    val_ratio_adjusted = split_ratio[1] / (split_ratio[1] + split_ratio[2])
    df_val, df_test = train_test_split(df_temp, test_size=1 - val_ratio_adjusted

    split_dfs['train'] = df_train
    split_dfs['val'] = df_val
    split_dfs['test'] = df_test

    # Copy images to destination folders
    for subset in subsets:
        for cls in df['class_label'].unique():
            dest_dir = os.path.join(base_output_dir, subset, cls)
            os.makedirs(dest_dir, exist_ok=True)

        for _, row in split_dfs[subset].iterrows():
            src = row['image_path']
            dst = os.path.join(base_output_dir, subset, row['class_label'], os.p
            shutil.copy2(src, dst)

    print(f"Dataset split into train/val/test and copied to: {base_output_dir}")

    # Run it
    split_base_dir = './PreparedData'
    prepare_directory_split(image_df, base_output_dir=split_base_dir)
```

Dataset split into train/val/test and copied to: ./PreparedData


```

In [10]: # ImageDataGenerators
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=25,
    width_shift_range=0.2,
    height_shift_range=0.2,
    zoom_range=0.2,
    shear_range=0.15,
    horizontal_flip=True,
    fill_mode='nearest'
)

val_test_datagen = ImageDataGenerator(rescale=1./255)

# Flow from directory
train_generator = train_datagen.flow_from_directory(
    directory=os.path.join(split_base_dir, 'train'),
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    shuffle=True,
    seed=SEED
)

val_generator = val_test_datagen.flow_from_directory(
    directory=os.path.join(split_base_dir, 'val'),
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    shuffle=False,
    seed=SEED
)

test_generator = val_test_datagen.flow_from_directory(
    directory=os.path.join(split_base_dir, 'test'),
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    shuffle=False,
    seed=SEED
)

# Label Mapping
class_indices = train_generator.class_indices
print("Class to Index Mapping:", class_indices)

```

Found 83 images belonging to 3 classes.

Found 18 images belonging to 3 classes.

Found 18 images belonging to 3 classes.

Class to Index Mapping: {'Bacterial leaf blight': 0, 'Brown spot': 1, 'Leaf smut': 2}

Dataset Splitting & Pipeline Preparation

```

In [11]: # Print the number of images in each set
print(f"Training samples: {train_generator.samples}")
print(f"Validation samples: {val_generator.samples}")
print(f"Testing samples: {test_generator.samples}")

```

```

# Print class index mapping
print("Class Index Mapping (from train_generator):")
for class_name, index in class_indices.items():
    print(f" - {class_name}: {index}")

# Inspect batch shape
x_batch, y_batch = next(train_generator)
print(f"\nOne training batch - X shape: {x_batch.shape}, Y shape: {y_batch.shape}

```

Training samples: 83

Validation samples: 18

Testing samples: 18

Class Index Mapping (from train_generator):

- Bacterial leaf blight: 0
- Brown spot: 1
- Leaf smut: 2

One training batch - X shape: (16, 224, 224, 3), Y shape: (16, 3)

```

In [12]: import tensorflow as tf

AUTOTUNE = tf.data.AUTOTUNE

# Wrap generator into tf.data.Dataset
def generator_to_dataset(generator):
    ds = tf.data.Dataset.from_generator(
        lambda: generator,
        output_types=(tf.float32, tf.float32),
        output_shapes=(None, IMG_HEIGHT, IMG_WIDTH, CHANNELS), [None, len(class
    )
    return ds.unbatch().batch(BATCH_SIZE).prefetch(AUTOTUNE)

# Convert train, val, test
train_ds = generator_to_dataset(train_generator)
val_ds = generator_to_dataset(val_generator)
test_ds = generator_to_dataset(test_generator)

# Peek a batch from train_ds
for images, labels in train_ds.take(1):
    print(f"tf.data Train batch - Images shape: {images.shape}, Labels shape: {l

```

WARNING:tensorflow:From C:\Users\prasa\AppData\Local\Temp\ipykernel_14208\2953255845.py:7: calling DatasetV2.from_generator (from tensorflow.python.data.ops.datas et_ops) with output_types is deprecated and will be removed in a future version. Instructions for updating:

Use output_signature instead

WARNING:tensorflow:From C:\Users\prasa\AppData\Local\Temp\ipykernel_14208\2953255845.py:7: calling DatasetV2.from_generator (from tensorflow.python.data.ops.datas et_ops) with output_shapes is deprecated and will be removed in a future version. Instructions for updating:

Use output_signature instead

tf.data Train batch - Images shape: (16, 224, 224, 3), Labels shape: (16, 3)

Model Design & Baseline Training

```

In [13]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropou
from tensorflow.keras.optimizers import Adam

```

```
def create_custom_cnn(input_shape=(224, 224, 3), num_classes=3):
    model = Sequential([
        Input(shape=input_shape),

        Conv2D(32, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D(2, 2),

        Conv2D(64, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D(2, 2),

        Conv2D(128, (3, 3), activation='relu', padding='same'),
        BatchNormalization(),
        MaxPooling2D(2, 2),

        Flatten(),

        Dense(128, activation='relu'),
        Dropout(0.4),
        Dense(num_classes, activation='softmax')
    ])

    model.compile(
        loss='categorical_crossentropy',
        optimizer=Adam(learning_rate=0.001),
        metrics=['accuracy']
    )
    return model

# Build model
custom_cnn = create_custom_cnn()
custom_cnn.summary()
```

Model: "sequential"

Layer (type)	Output Shape	
conv2d (Conv2D)	(None, 224, 224, 32)	
batch_normalization (BatchNormalization)	(None, 224, 224, 32)	
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	
conv2d_1 (Conv2D)	(None, 112, 112, 64)	
batch_normalization_1 (BatchNormalization)	(None, 112, 112, 64)	
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 64)	
conv2d_2 (Conv2D)	(None, 56, 56, 128)	
batch_normalization_2 (BatchNormalization)	(None, 56, 56, 128)	
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 128)	
flatten (Flatten)	(None, 100352)	
dense (Dense)	(None, 128)	
dropout (Dropout)	(None, 128)	
dense_1 (Dense)	(None, 3)	



Total params: 12,939,715 (49.36 MB)

Trainable params: 12,939,267 (49.36 MB)

Non-trainable params: 448 (1.75 KB)

```
In [14]: from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Directory to save the best model
model_dir = "./models"
os.makedirs(model_dir, exist_ok=True)

checkpoint_path = os.path.join(model_dir, "custom_cnn_best.h5")

callbacks = [
    EarlyStopping(monitor='val_loss', patience=8, restore_best_weights=True, verbose=1),
    ModelCheckpoint(filepath=checkpoint_path, monitor='val_loss', save_best_only=True, verbose=1)
]
```

```
In [15]: history = custom_cnn.fit(
    train_generator,
    epochs=50,
    validation_data=val_generator,
    callbacks=callbacks,
    verbose=1
)
```

```
C:\Users\prasa\anaconda3\Lib\site-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 include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignored.
```


```
self._warn_if_super_not_called()
```

Epoch 1/50

6/6  0s 2s/step - accuracy: 0.3771 - loss: 15.5135

Epoch 1: val_loss improved from inf to 2.58673, saving model to ./models\custom_cnn_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
```

6/6  22s 3s/step - accuracy: 0.3800 - loss: 15.9880 - val_accuracy: 0.3333 - val_loss: 2.5867

Epoch 2/50

6/6  0s 2s/step - accuracy: 0.4784 - loss: 12.8661

Epoch 2: val_loss improved from 2.58673 to 1.57032, saving model to ./models\custom_cnn_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
```

```

6/6 ----- 12s 2s/step - accuracy: 0.4824 - loss: 12.7205 - val_acc
uracy: 0.3333 - val_loss: 1.5703
Epoch 3/50
6/6 ----- 0s 2s/step - accuracy: 0.6461 - loss: 11.1781
Epoch 3: val_loss did not improve from 1.57032
6/6 ----- 11s 2s/step - accuracy: 0.6347 - loss: 11.6860 - val_acc
uracy: 0.3333 - val_loss: 6.8183
Epoch 4/50
6/6 ----- 0s 2s/step - accuracy: 0.6420 - loss: 9.8574
Epoch 4: val_loss did not improve from 1.57032
6/6 ----- 13s 2s/step - accuracy: 0.6398 - loss: 9.8543 - val_accu
racy: 0.5556 - val_loss: 2.1443
Epoch 5/50
6/6 ----- 0s 2s/step - accuracy: 0.5170 - loss: 9.9060
Epoch 5: val_loss did not improve from 1.57032
6/6 ----- 13s 2s/step - accuracy: 0.5189 - loss: 9.6618 - val_accu
racy: 0.3889 - val_loss: 4.5320
Epoch 6/50
6/6 ----- 0s 2s/step - accuracy: 0.6415 - loss: 5.7784
Epoch 6: val_loss did not improve from 1.57032
6/6 ----- 13s 2s/step - accuracy: 0.6428 - loss: 5.6994 - val_accu
racy: 0.3889 - val_loss: 7.9477
Epoch 7/50
6/6 ----- 0s 2s/step - accuracy: 0.6196 - loss: 2.6125
Epoch 7: val_loss did not improve from 1.57032
6/6 ----- 13s 2s/step - accuracy: 0.6206 - loss: 2.6342 - val_accu
racy: 0.4444 - val_loss: 9.7817
Epoch 8/50
6/6 ----- 0s 2s/step - accuracy: 0.6363 - loss: 2.9531
Epoch 8: val_loss did not improve from 1.57032
6/6 ----- 13s 2s/step - accuracy: 0.6315 - loss: 3.0453 - val_accu
racy: 0.5000 - val_loss: 12.0271
Epoch 9/50
6/6 ----- 0s 2s/step - accuracy: 0.5188 - loss: 2.5073
Epoch 9: val_loss did not improve from 1.57032
6/6 ----- 12s 2s/step - accuracy: 0.5136 - loss: 2.5016 - val_accu
racy: 0.4444 - val_loss: 14.7567
Epoch 10/50
6/6 ----- 0s 1s/step - accuracy: 0.5866 - loss: 1.1736
Epoch 10: val_loss did not improve from 1.57032
6/6 ----- 18s 2s/step - accuracy: 0.5906 - loss: 1.1567 - val_accu
racy: 0.4444 - val_loss: 17.1211
Epoch 10: early stopping
Restoring model weights from the end of the best epoch: 2.

```

```

In [16]: def plot_training_history(history):
    acc = history.history['accuracy']
    val_acc = history.history['val_accuracy']
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(1, len(acc) + 1)

    plt.figure(figsize=(14, 5))

    plt.subplot(1, 2, 1)
    plt.plot(epochs, acc, 'b-', label='Training Accuracy')
    plt.plot(epochs, val_acc, 'g-', label='Validation Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')

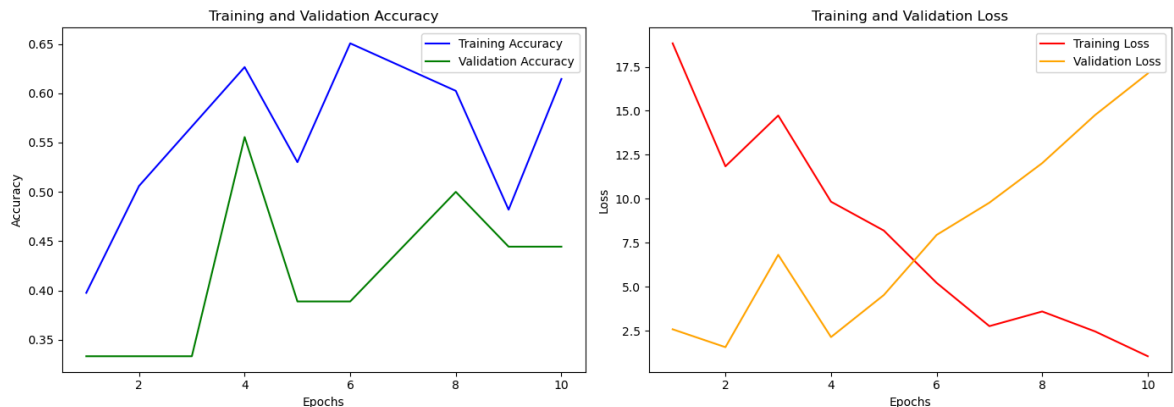
```

```
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(epochs, loss, 'r-', label='Training Loss')
plt.plot(epochs, val_loss, 'orange', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()

plot_training_history(history)
```



Model Evaluation

```
In [17]: # Evaluate on test set
test_loss, test_acc = custom_cnn.evaluate(test_generator, verbose=1)
print(f"\nFinal Test Accuracy: {test_acc:.4f}")
print(f"Final Test Loss: {test_loss:.4f}")
```

2/2 ————— 1s 65ms/step - accuracy: 0.3472 - loss: 1.7625

Final Test Accuracy: 0.3333

Final Test Loss: 1.8451

```
In [18]: from sklearn.metrics import classification_report, confusion_matrix, ConfusionMa
import numpy as np

# Get true labels and predictions
y_true = test_generator.classes
y_pred_probs = custom_cnn.predict(test_generator)
y_pred = np.argmax(y_pred_probs, axis=1)

# Label mapping
target_names = list(test_generator.class_indices.keys())

# Classification report
print("\nClassification Report:")
print(classification_report(y_true, y_pred, target_names=target_names, digits=4))

# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=target_names)
```

```
plt.figure(figsize=(6, 5))
disp.plot(cmap=plt.cm.Blues, values_format='d')
plt.title("Confusion Matrix - Test Set")
plt.tight_layout()
plt.show()
```

2/2 ————— 2s 400ms/step

Classification Report:

	precision	recall	f1-score	support
Bacterial leaf blight	0.0000	0.0000	0.0000	6
Brown spot	0.3333	1.0000	0.5000	6
Leaf smut	0.0000	0.0000	0.0000	6
accuracy			0.3333	18
macro avg	0.1111	0.3333	0.1667	18
weighted avg	0.1111	0.3333	0.1667	18

C:\Users\prasa\anaconda3\Lib\site-packages\sklearn\metrics_classification.py:1706: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])

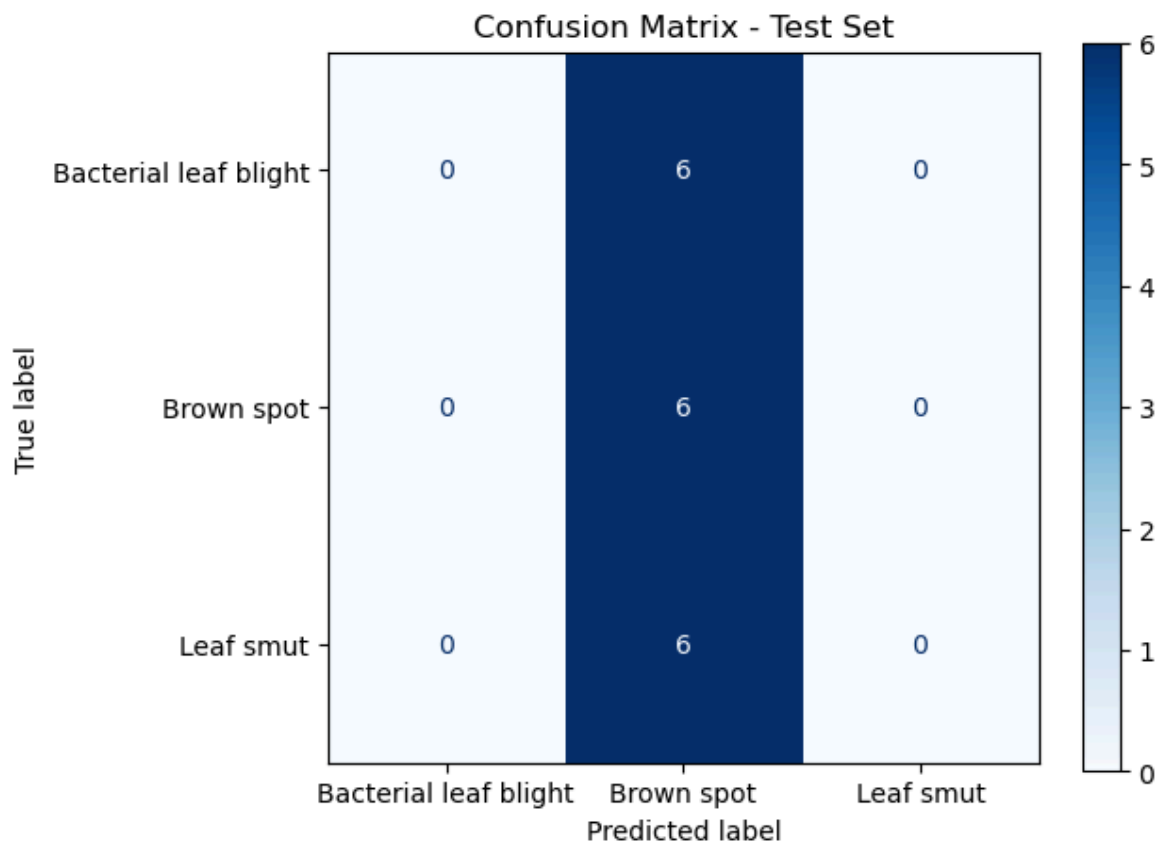
C:\Users\prasa\anaconda3\Lib\site-packages\sklearn\metrics_classification.py:1706: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])

C:\Users\prasa\anaconda3\Lib\site-packages\sklearn\metrics_classification.py:1706: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])

<Figure size 600x500 with 0 Axes>



```
In [19]: # Get filepaths and class info
test_filepaths = test_generator.filepaths
misclassified_indices = np.where(y_true != y_pred)[0]

print(f"Total Misclassified Images: {len(misclassified_indices)}")

# Show a few misclassified images
def show_misclassified_images(indices, n=6):
    n = min(n, len(indices))
    if n == 0:
        print("No misclassified images!")
        return

    sample_indices = np.random.choice(indices, n, replace=False)
    plt.figure(figsize=(15, 5))

    for i, idx in enumerate(sample_indices):
        img_path = test_filepaths[idx]
        img = Image.open(img_path)

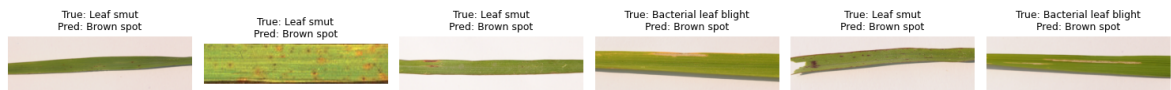
        true_label = target_names[y_true[idx]]
        predicted_label = target_names[y_pred[idx]]

        plt.subplot(1, n, i+1)
        plt.imshow(img)
        plt.axis('off')
        plt.title(f"True: {true_label}\nPred: {predicted_label}", fontsize=9)

    plt.tight_layout()
    plt.show()

show_misclassified_images(misclassified_indices, n=6)
```

Total Misclassified Images: 12



```
In [20]: # Store evaluation results for comparison
baseline_results = {
    "Model": "Custom CNN",
    "Test Accuracy": round(test_acc, 4),
    "Test Loss": round(test_loss, 4),
    "Precision": None, # To be updated from report
    "Recall": None,
    "F1-Score": None
}

from sklearn.metrics import precision_score, recall_score, f1_score

baseline_results["Precision"] = round(precision_score(y_true, y_pred, average='macro'), 4)
baseline_results["Recall"] = round(recall_score(y_true, y_pred, average='macro'), 4)
baseline_results["F1-Score"] = round(f1_score(y_true, y_pred, average='macro'), 4)

print("Baseline CNN Evaluation Summary:")
for k, v in baseline_results.items():
    print(f" - {k}: {v}")
```

Baseline CNN Evaluation Summary:

- Model: Custom CNN
- Test Accuracy: 0.3333
- Test Loss: 1.8451
- Precision: 0.1111
- Recall: 0.3333
- F1-Score: 0.1667

C:\Users\prasa\anaconda3\Lib\site-packages\sklearn\metrics_classification.py:170: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])

Transfer Learning with Pretrained CNNs

```
In [21]: from tensorflow.keras.applications import VGG16, ResNet50, MobileNetV2, EfficientNetB0
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
from tensorflow.keras.optimizers import Adam

def build_transfer_model(base_model_class, input_shape=(224, 224, 3), num_classes=1000):
    base_model = base_model_class(include_top=False, weights='imagenet', input_shape=input_shape)

    if freeze_all:
        for layer in base_model.layers:
            layer.trainable = False

    x = base_model.output
    x = GlobalAveragePooling2D()(x)
    x = Dense(128, activation='relu')(x)
    x = Dropout(0.4)(x)
    outputs = Dense(num_classes, activation='softmax')(x)

    model = Model(inputs=base_model.input, outputs=outputs, name=base_model.name)
    model.compile(optimizer=Adam(learning_rate=0.0003),
```

```

        loss='categorical_crossentropy',
        metrics=['accuracy'])
    return model

```

```

In [22]: # Callback reuse
checkpoint_dir = "./models"
os.makedirs(checkpoint_dir, exist_ok=True)

def train_and_evaluate_model(model, model_key):
    print(f"\nTraining model: {model.name}")

    checkpoint_path = os.path.join(checkpoint_dir, f"{model_key}_best.h5")
    callbacks = [
        EarlyStopping(monitor='val_loss', patience=8, restore_best_weights=True,
            ModelCheckpoint(filepath=checkpoint_path, monitor='val_loss', save_best_
        ]

    history = model.fit(
        train_generator,
        epochs=30,
        validation_data=val_generator,
        callbacks=callbacks,
        verbose=1
    )

    test_loss, test_acc = model.evaluate(test_generator, verbose=0)
    y_true = test_generator.classes
    y_pred = np.argmax(model.predict(test_generator), axis=1)

    metrics = {
        "Model": model.name,
        "Test Accuracy": round(test_acc, 4),
        "Test Loss": round(test_loss, 4),
        "Precision": round(precision_score(y_true, y_pred, average='macro'), 4),
        "Recall": round(recall_score(y_true, y_pred, average='macro'), 4),
        "F1-Score": round(f1_score(y_true, y_pred, average='macro'), 4)
    }

    return history, metrics

```

```

In [23]: vgg_model = build_transfer_model(VGG16, model_name="VGG16", freeze_all=True)
vgg_history, vgg_metrics = train_and_evaluate_model(vgg_model, "vgg16")

```

Training model: VGG16

Epoch 1/30

6/6 ————— 0s 4s/step - accuracy: 0.3397 - loss: 1.1976

Epoch 1: val_loss improved from inf to 1.16163, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 37s 5s/step - accuracy: 0.3377 - loss: 1.2000 - val_accuracy: 0.3333 - val_loss: 1.1616

Epoch 2/30

6/6 ————— 0s 5s/step - accuracy: 0.3569 - loss: 1.1371

Epoch 2: val_loss improved from 1.16163 to 1.13559, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 6s/step - accuracy: 0.3610 - loss: 1.1419 - val_accuracy: 0.2222 - val_loss: 1.1356

Epoch 3/30

6/6 ————— 0s 4s/step - accuracy: 0.3576 - loss: 1.1729

Epoch 3: val_loss improved from 1.13559 to 1.12529, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 5s/step - accuracy: 0.3547 - loss: 1.1718 - val_accuracy: 0.2222 - val_loss: 1.1253

Epoch 4/30

6/6 ————— 0s 4s/step - accuracy: 0.3113 - loss: 1.1821

Epoch 4: val_loss improved from 1.12529 to 1.11587, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 6s/step - accuracy: 0.3099 - loss: 1.1863 - val_accuracy: 0.2222 - val_loss: 1.1159

Epoch 5/30

6/6 ————— 0s 4s/step - accuracy: 0.4217 - loss: 1.1223

Epoch 5: val_loss improved from 1.11587 to 1.09484, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 5s/step - accuracy: 0.4217 - loss: 1.1239 - val_accuracy: 0.3333 - val_loss: 1.0948

Epoch 6/30

6/6 ————— 0s 4s/step - accuracy: 0.2560 - loss: 1.2345

Epoch 6: val_loss improved from 1.09484 to 1.08583, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 6s/step - accuracy: 0.2693 - loss: 1.2207 - val_accuracy: 0.5000 - val_loss: 1.0858

Epoch 7/30

6/6 ————— 0s 4s/step - accuracy: 0.6087 - loss: 1.0016

Epoch 7: val_loss did not improve from 1.08583

6/6 ————— 29s 5s/step - accuracy: 0.5923 - loss: 1.0150 - val_accuracy: 0.4444 - val_loss: 1.0889

Epoch 8/30

6/6 ————— 0s 4s/step - accuracy: 0.3911 - loss: 1.1413

Epoch 8: val_loss improved from 1.08583 to 1.06548, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 5s/step - accuracy: 0.3955 - loss: 1.1367 - val_accuracy: 0.5000 - val_loss: 1.0655

Epoch 9/30

6/6 ————— 0s 4s/step - accuracy: 0.5334 - loss: 0.9624

Epoch 9: val_loss improved from 1.06548 to 1.04944, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 40s 6s/step - accuracy: 0.5261 - loss: 0.9720 - val_accuracy: 0.4444 - val_loss: 1.0494

Epoch 10/30

6/6 ————— 0s 4s/step - accuracy: 0.4059 - loss: 1.0791

Epoch 10: val_loss improved from 1.04944 to 1.03621, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 42s 5s/step - accuracy: 0.4081 - loss: 1.0778 - val_accuracy: 0.4444 - val_loss: 1.0362

Epoch 11/30

6/6 ————— 0s 4s/step - accuracy: 0.3797 - loss: 1.0575

Epoch 11: val_loss improved from 1.03621 to 1.02607, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 5s/step - accuracy: 0.3857 - loss: 1.0550 - val_accuracy: 0.3889 - val_loss: 1.0261

Epoch 12/30

6/6 ————— 0s 4s/step - accuracy: 0.4777 - loss: 1.0183

Epoch 12: val_loss improved from 1.02607 to 1.01427, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 5s/step - accuracy: 0.4749 - loss: 1.0229 - val_accuracy: 0.3889 - val_loss: 1.0143

Epoch 13/30

6/6 ————— 0s 4s/step - accuracy: 0.4878 - loss: 1.0443

Epoch 13: val_loss improved from 1.01427 to 1.00042, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 5s/step - accuracy: 0.4852 - loss: 1.0439 - val_accuracy: 0.6667 - val_loss: 1.0004

Epoch 14/30

6/6 ————— 0s 4s/step - accuracy: 0.5296 - loss: 0.9910

Epoch 14: val_loss improved from 1.00042 to 0.99061, saving model to ./models\vgg16_best.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.save_model(model, 'my_model.keras')`.

6/6 ————— 42s 5s/step - accuracy: 0.5245 - loss: 0.9916 - val_accuracy: 0.6111 - val_loss: 0.9906

Epoch 15/30

6/6 ————— 0s 4s/step - accuracy: 0.4022 - loss: 1.0515

Epoch 15: val_loss improved from 0.99061 to 0.97876, saving model to ./models\vgg16_best.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 5s/step - accuracy: 0.4067 - loss: 1.0470 - val_accuracy: 0.6111 - val_loss: 0.9788

Epoch 16/30

6/6 ————— 0s 4s/step - accuracy: 0.4028 - loss: 1.0429

Epoch 16: val_loss improved from 0.97876 to 0.96881, saving model to ./models\vgg16_best.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 5s/step - accuracy: 0.4055 - loss: 1.0439 - val_accuracy: 0.6667 - val_loss: 0.9688

Epoch 17/30

6/6 ————— 0s 4s/step - accuracy: 0.5663 - loss: 0.9781

Epoch 17: val_loss improved from 0.96881 to 0.95922, saving model to ./models\vgg16_best.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 5s/step - accuracy: 0.5629 - loss: 0.9763 - val_accuracy: 0.6111 - val_loss: 0.9592

Epoch 18/30

6/6 ————— 0s 4s/step - accuracy: 0.6214 - loss: 0.8994

Epoch 18: val_loss improved from 0.95922 to 0.95668, saving model to ./models\vgg16_best.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 5s/step - accuracy: 0.6118 - loss: 0.9087 - val_accuracy: 0.7222 - val_loss: 0.9567

Epoch 19/30

6/6 ————— 0s 4s/step - accuracy: 0.3795 - loss: 1.0199

Epoch 19: val_loss improved from 0.95668 to 0.94412, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 41s 5s/step - accuracy: 0.3872 - loss: 1.0146 - val_accuracy: 0.6111 - val_loss: 0.9441

Epoch 20/30

6/6 ————— 0s 4s/step - accuracy: 0.4880 - loss: 0.9815

Epoch 20: val_loss improved from 0.94412 to 0.93136, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 40s 5s/step - accuracy: 0.4940 - loss: 0.9800 - val_accuracy: 0.6111 - val_loss: 0.9314

Epoch 21/30

6/6 ————— 0s 4s/step - accuracy: 0.5949 - loss: 0.9029

Epoch 21: val_loss improved from 0.93136 to 0.92487, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 28s 5s/step - accuracy: 0.5891 - loss: 0.9079 - val_accuracy: 0.6667 - val_loss: 0.9249

Epoch 22/30

6/6 ————— 0s 4s/step - accuracy: 0.5365 - loss: 0.9368

Epoch 22: val_loss improved from 0.92487 to 0.92365, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 42s 5s/step - accuracy: 0.5391 - loss: 0.9375 - val_accuracy: 0.7222 - val_loss: 0.9237

Epoch 23/30

6/6 ————— 0s 4s/step - accuracy: 0.5944 - loss: 0.8605

Epoch 23: val_loss improved from 0.92365 to 0.91808, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 39s 5s/step - accuracy: 0.6059 - loss: 0.8567 - val_accuracy: 0.7222 - val_loss: 0.9181

Epoch 24/30

6/6 ————— 0s 4s/step - accuracy: 0.6653 - loss: 0.8910

Epoch 24: val_loss improved from 0.91808 to 0.89683, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 42s 5s/step - accuracy: 0.6598 - loss: 0.8962 - val_accuracy: 0.7222 - val_loss: 0.8968

Epoch 25/30

6/6 ————— 0s 4s/step - accuracy: 0.5828 - loss: 0.8766

Epoch 25: val_loss improved from 0.89683 to 0.88815, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 28s 5s/step - accuracy: 0.5821 - loss: 0.8836 - val_accuracy: 0.7222 - val_loss: 0.8882

Epoch 26/30

6/6 ————— 0s 4s/step - accuracy: 0.5961 - loss: 0.8717

Epoch 26: val_loss improved from 0.88815 to 0.87739, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 29s 5s/step - accuracy: 0.5970 - loss: 0.8756 - val_accuracy: 0.7222 - val_loss: 0.8774

Epoch 27/30

6/6 ————— 0s 4s/step - accuracy: 0.5214 - loss: 0.9078

Epoch 27: val_loss did not improve from 0.87739

6/6 ————— 41s 5s/step - accuracy: 0.5278 - loss: 0.9030 - val_accuracy: 0.6667 - val_loss: 0.8804

Epoch 28/30

6/6 ————— 0s 5s/step - accuracy: 0.7422 - loss: 0.9357

Epoch 28: val_loss did not improve from 0.87739

6/6 ————— 30s 6s/step - accuracy: 0.7343 - loss: 0.9300 - val_accuracy: 0.6667 - val_loss: 0.8811

Epoch 29/30

6/6 ————— 0s 4s/step - accuracy: 0.6296 - loss: 0.8434

Epoch 29: val_loss improved from 0.87739 to 0.85954, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 40s 5s/step - accuracy: 0.6309 - loss: 0.8448 - val_accuracy: 0.6111 - val_loss: 0.8595

Epoch 30/30

6/6 ————— 0s 4s/step - accuracy: 0.5800 - loss: 0.9400

Epoch 30: val_loss improved from 0.85954 to 0.84590, saving model to ./models\vgg16_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 40s 6s/step - accuracy: 0.5746 - loss: 0.9387 - val_accuracy: 0.6667 - val_loss: 0.8459

Restoring model weights from the end of the best epoch: 30.

2/2 ————— 7s 958ms/step

```
In [24]: resnet_model = build_transfer_model(ResNet50, model_name="ResNet50", freeze_all=
         resnet_history, resnet_metrics = train_and_evaluate_model(resnet_model, "resnet5
```



Training model: ResNet50

Epoch 1/30

6/6  0s 1s/step - accuracy: 0.3506 - loss: 1.4561

Epoch 1: val_loss improved from inf to 1.10560, saving model to ./models\resnet50_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6  36s 3s/step - accuracy: 0.3505 - loss: 1.4471 - val_accuracy: 0.3333 - val_loss: 1.1056

Epoch 2/30

6/6  0s 1s/step - accuracy: 0.3512 - loss: 1.2300

Epoch 2: val_loss did not improve from 1.10560


6/6  11s 2s/step - accuracy: 0.3509 - loss: 1.2315 - val_accuracy: 0.3333 - val_loss: 1.1332

Epoch 3/30

6/6  0s 1s/step - accuracy: 0.2101 - loss: 1.2702

Epoch 3: val_loss improved from 1.10560 to 1.10360, saving model to ./models\resnet50_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6  21s 2s/step - accuracy: 0.2145 - loss: 1.2668 - val_accuracy: 0.3333 - val_loss: 1.1036

Epoch 4/30

6/6  0s 2s/step - accuracy: 0.3756 - loss: 1.1592

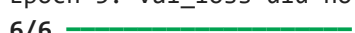
Epoch 4: val_loss did not improve from 1.10360

6/6  12s 2s/step - accuracy: 0.3736 - loss: 1.1672 - val_accuracy: 0.3333 - val_loss: 1.1196

Epoch 5/30

6/6  0s 1s/step - accuracy: 0.3531 - loss: 1.2184

Epoch 5: val_loss did not improve from 1.10360


6/6  19s 2s/step - accuracy: 0.3457 - loss: 1.2204 - val_accuracy: 0.3333 - val_loss: 1.1130

Epoch 6/30

6/6  0s 1s/step - accuracy: 0.1854 - loss: 1.2924

Epoch 6: val_loss improved from 1.10360 to 1.10175, saving model to ./models\resnet50_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6  13s 2s/step - accuracy: 0.1864 - loss: 1.2865 - val_accuracy: 0.3333 - val_loss: 1.1017

Epoch 7/30

6/6  0s 1s/step - accuracy: 0.4309 - loss: 1.1036

Epoch 7: val_loss did not improve from 1.10175

6/6  11s 2s/step - accuracy: 0.4210 - loss: 1.1164 - val_accuracy: 0.3333 - val_loss: 1.1165

Epoch 8/30

6/6  0s 2s/step - accuracy: 0.3400 - loss: 1.0902

Epoch 8: val_loss improved from 1.10175 to 1.10092, saving model to ./models\resnet50_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 13s 2s/step - accuracy: 0.3413 - loss: 1.0968 - val_accuracy: 0.3333 - val_loss: 1.1009
Epoch 9/30
6/6 ————— 0s 1s/step - accuracy: 0.3033 - loss: 1.1605
Epoch 9: val_loss did not improve from 1.10092
6/6 ————— 11s 2s/step - accuracy: 0.3047 - loss: 1.1639 - val_accuracy: 0.3333 - val_loss: 1.1108
Epoch 10/30
6/6 ————— 0s 2s/step - accuracy: 0.4968 - loss: 1.0566
Epoch 10: val_loss did not improve from 1.10092
6/6 ————— 12s 2s/step - accuracy: 0.4775 - loss: 1.0673 - val_accuracy: 0.3333 - val_loss: 1.1320
Epoch 11/30
6/6 ————— 0s 2s/step - accuracy: 0.3126 - loss: 1.1661
Epoch 11: val_loss did not improve from 1.10092
6/6 ————— 12s 2s/step - accuracy: 0.3109 - loss: 1.1729 - val_accuracy: 0.3333 - val_loss: 1.1148
Epoch 12/30
6/6 ————— 0s 2s/step - accuracy: 0.3137 - loss: 1.2634
Epoch 12: val_loss improved from 1.10092 to 1.09136, saving model to ./models\resnet50_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

```

6/6 ----- 13s 2s/step - accuracy: 0.3137 - loss: 1.2571 - val_accu
racy: 0.3333 - val_loss: 1.0914
Epoch 13/30
6/6 ----- 0s 2s/step - accuracy: 0.3008 - loss: 1.1607
Epoch 13: val_loss did not improve from 1.09136
6/6 ----- 12s 2s/step - accuracy: 0.2922 - loss: 1.1626 - val_accu
racy: 0.3333 - val_loss: 1.1203
Epoch 14/30
6/6 ----- 0s 2s/step - accuracy: 0.2055 - loss: 1.2071
Epoch 14: val_loss did not improve from 1.09136
6/6 ----- 12s 2s/step - accuracy: 0.2089 - loss: 1.2067 - val_accu
racy: 0.3889 - val_loss: 1.1083
Epoch 15/30
6/6 ----- 0s 2s/step - accuracy: 0.2929 - loss: 1.1787
Epoch 15: val_loss did not improve from 1.09136
6/6 ----- 13s 2s/step - accuracy: 0.2975 - loss: 1.1761 - val_accu
racy: 0.3333 - val_loss: 1.1005
Epoch 16/30
6/6 ----- 0s 1s/step - accuracy: 0.3375 - loss: 1.1251
Epoch 16: val_loss did not improve from 1.09136
6/6 ----- 10s 2s/step - accuracy: 0.3409 - loss: 1.1195 - val_accu
racy: 0.3333 - val_loss: 1.0950
Epoch 17/30
6/6 ----- 0s 2s/step - accuracy: 0.2339 - loss: 1.1749
Epoch 17: val_loss did not improve from 1.09136
6/6 ----- 13s 2s/step - accuracy: 0.2366 - loss: 1.1745 - val_accu
racy: 0.3333 - val_loss: 1.0960
Epoch 18/30
6/6 ----- 0s 1s/step - accuracy: 0.3457 - loss: 1.1085
Epoch 18: val_loss did not improve from 1.09136
6/6 ----- 19s 2s/step - accuracy: 0.3445 - loss: 1.1076 - val_accu
racy: 0.3333 - val_loss: 1.0938
Epoch 19/30
6/6 ----- 0s 2s/step - accuracy: 0.3698 - loss: 1.1340
Epoch 19: val_loss did not improve from 1.09136
6/6 ----- 23s 2s/step - accuracy: 0.3721 - loss: 1.1299 - val_accu
racy: 0.3333 - val_loss: 1.0967
Epoch 20/30
6/6 ----- 0s 2s/step - accuracy: 0.2951 - loss: 1.1168
Epoch 20: val_loss did not improve from 1.09136
6/6 ----- 14s 2s/step - accuracy: 0.3029 - loss: 1.1166 - val_accu
racy: 0.3333 - val_loss: 1.0980
Epoch 20: early stopping
Restoring model weights from the end of the best epoch: 12.
WARNING:tensorflow:5 out of the last 5 calls to <function TensorFlowTrainer.make_
predict_function.<locals>.one_step_on_data_distributed at 0x0000021B1750F7E0> tri
ggered tf.function retracing. Tracing is expensive and the excessive number of tr
acings could be due to (1) creating @tf.function repeatedly in a loop, (2) passin
g tensors with different shapes, (3) passing Python objects instead of tensors. F
or (1), please define your @tf.function outside of the loop. For (2), @tf.function
n has reduce_retracing=True option that can avoid unnecessary retracing. For (3),
please refer to https://www.tensorflow.org/guide/function#controlling_retracing a
nd https://www.tensorflow.org/api_docs/python/tf/function for more details.

```

WARNING:tensorflow:5 out of the last 5 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x0000021B1750F7E0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

1/2 ————— 5s 6s/step
WARNING:tensorflow:6 out of the last 6 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x0000021B1750F7E0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

WARNING:tensorflow:6 out of the last 6 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x0000021B1750F7E0> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

2/2 ————— 9s 4s/step

C:\Users\prasa\anaconda3\Lib\site-packages\sklearn\metrics_classification.py:1706: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])

In [25]: mobilenet_model = build_transfer_model(MobileNetV2, model_name="MobileNetV2", fr
mobilenet_history, mobilenet_metrics = train_and_evaluate_model(mobilenet_model,

Training model: MobileNetV2

Epoch 1/30

6/6 ————— 0s 2s/step - accuracy: 0.3126 - loss: 1.9129

Epoch 1: val_loss improved from inf to 0.93508, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 31s 4s/step - accuracy: 0.3110 - loss: 1.8797 - val_accuracy: 0.5000 - val_loss: 0.9351

Epoch 2/30

6/6 ————— 0s 1s/step - accuracy: 0.4962 - loss: 1.2409

Epoch 2: val_loss improved from 0.93508 to 0.70978, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.5010 - loss: 1.2287 - val_accuracy: 0.7222 - val_loss: 0.7098

Epoch 3/30

6/6 ————— 0s 1s/step - accuracy: 0.5908 - loss: 0.8352

Epoch 3: val_loss improved from 0.70978 to 0.58653, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.5856 - loss: 0.8403 - val_accuracy: 0.8333 - val_loss: 0.5865

Epoch 4/30

6/6 ————— 0s 1s/step - accuracy: 0.5910 - loss: 0.8562

Epoch 4: val_loss improved from 0.58653 to 0.54097, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 9s 2s/step - accuracy: 0.5927 - loss: 0.8507 - val_accuracy: 0.8333 - val_loss: 0.5410

Epoch 5/30

6/6 ————— 0s 1s/step - accuracy: 0.8500 - loss: 0.4787

Epoch 5: val_loss improved from 0.54097 to 0.47856, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.8405 - loss: 0.4921 - val_accuracy: 0.8333 - val_loss: 0.4786

Epoch 6/30

6/6 ————— 0s 1s/step - accuracy: 0.7521 - loss: 0.5011

Epoch 6: val_loss improved from 0.47856 to 0.41814, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.7531 - loss: 0.5104 - val_accuracy: 0.9444 - val_loss: 0.4181

Epoch 7/30

6/6 ————— 0s 1s/step - accuracy: 0.7364 - loss: 0.5829

Epoch 7: val_loss improved from 0.41814 to 0.39338, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 12s 2s/step - accuracy: 0.7414 - loss: 0.5719 - val_accuracy: 0.9444 - val_loss: 0.3934

Epoch 8/30

6/6 ————— 0s 1s/step - accuracy: 0.8197 - loss: 0.5591

Epoch 8: val_loss improved from 0.39338 to 0.33451, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.8196 - loss: 0.5568 - val_accuracy: 0.9444 - val_loss: 0.3345

Epoch 9/30

6/6 ————— 0s 1s/step - accuracy: 0.9082 - loss: 0.3903

Epoch 9: val_loss improved from 0.33451 to 0.30060, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.9059 - loss: 0.3919 - val_accuracy: 0.9444 - val_loss: 0.3006

Epoch 10/30

6/6 ————— 0s 1s/step - accuracy: 0.7975 - loss: 0.4823

Epoch 10: val_loss improved from 0.30060 to 0.29142, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.8041 - loss: 0.4716 - val_accuracy: 0.9444 - val_loss: 0.2914

Epoch 11/30

6/6 ————— 0s 1s/step - accuracy: 0.9039 - loss: 0.3131

Epoch 11: val_loss improved from 0.29142 to 0.26105, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

6/6 ————— 10s 2s/step - accuracy: 0.9021 - loss: 0.3141 - val_accuracy: 0.9444 - val_loss: 0.2611

Epoch 12/30

6/6 ————— 0s 1s/step - accuracy: 0.8260 - loss: 0.3685

Epoch 12: val_loss improved from 0.26105 to 0.23133, saving model to ./models\mobilenetv2_best.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

```

6/6 ————— 9s 2s/step - accuracy: 0.8319 - loss: 0.3697 - val_accu
acy: 0.9444 - val_loss: 0.2313
Epoch 13/30
6/6 ————— 0s 1s/step - accuracy: 0.8432 - loss: 0.4004
Epoch 13: val_loss did not improve from 0.23133
6/6 ————— 11s 2s/step - accuracy: 0.8433 - loss: 0.3974 - val_accu
racy: 0.9444 - val_loss: 0.2394
Epoch 14/30
6/6 ————— 0s 1s/step - accuracy: 0.8553 - loss: 0.3200
Epoch 14: val_loss did not improve from 0.23133
6/6 ————— 9s 2s/step - accuracy: 0.8605 - loss: 0.3159 - val_accu
acy: 0.9444 - val_loss: 0.2530
Epoch 15/30
6/6 ————— 0s 1s/step - accuracy: 0.9161 - loss: 0.2907
Epoch 15: val_loss did not improve from 0.23133
6/6 ————— 7s 1s/step - accuracy: 0.9143 - loss: 0.2916 - val_accu
acy: 0.9444 - val_loss: 0.2547
Epoch 16/30
6/6 ————— 0s 1s/step - accuracy: 0.9375 - loss: 0.2126
Epoch 16: val_loss improved from 0.23133 to 0.18769, saving model to ./models\mob
ilenetv2_best.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `ker
as.saving.save_model(model)`. This file format is considered legacy. We recommend
using instead the native Keras format, e.g. `model.save('my_model.keras')` or `ke
ras.saving.save_model(model, 'my_model.keras')`.
6/6 ————— 8s 1s/step - accuracy: 0.9344 - loss: 0.2170 - val_accu
acy: 0.9444 - val_loss: 0.1877
Epoch 17/30
6/6 ————— 0s 1s/step - accuracy: 0.9498 - loss: 0.2270
Epoch 17: val_loss improved from 0.18769 to 0.16736, saving model to ./models\mob
ilenetv2_best.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `ker
as.saving.save_model(model)`. This file format is considered legacy. We recommend
using instead the native Keras format, e.g. `model.save('my_model.keras')` or `ke
ras.saving.save_model(model, 'my_model.keras')`.
6/6 ————— 9s 2s/step - accuracy: 0.9466 - loss: 0.2309 - val_accu
acy: 0.9444 - val_loss: 0.1674
Epoch 18/30
6/6 ————— 0s 1s/step - accuracy: 0.9401 - loss: 0.2089
Epoch 18: val_loss improved from 0.16736 to 0.16571, saving model to ./models\mob
ilenetv2_best.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `ker
as.saving.save_model(model)`. This file format is considered legacy. We recommend
using instead the native Keras format, e.g. `model.save('my_model.keras')` or `ke
ras.saving.save_model(model, 'my_model.keras')`.

```



```

6/6 ----- 11s 2s/step - accuracy: 0.9401 - loss: 0.2095 - val_accu
racy: 0.9444 - val_loss: 0.1657
Epoch 19/30
6/6 ----- 0s 1s/step - accuracy: 0.9413 - loss: 0.1844
Epoch 19: val_loss did not improve from 0.16571
6/6 ----- 19s 2s/step - accuracy: 0.9411 - loss: 0.1859 - val_accu
racy: 0.9444 - val_loss: 0.1844
Epoch 20/30
6/6 ----- 0s 1s/step - accuracy: 0.9008 - loss: 0.2268
Epoch 20: val_loss did not improve from 0.16571
6/6 ----- 9s 2s/step - accuracy: 0.8994 - loss: 0.2295 - val_accu
racy: 0.9444 - val_loss: 0.1881
Epoch 21/30
6/6 ----- 0s 1s/step - accuracy: 0.9732 - loss: 0.1108
Epoch 21: val_loss did not improve from 0.16571
6/6 ----- 8s 1s/step - accuracy: 0.9702 - loss: 0.1181 - val_accu
racy: 0.9444 - val_loss: 0.1876
Epoch 22/30
6/6 ----- 0s 1s/step - accuracy: 0.9597 - loss: 0.2046
Epoch 22: val_loss did not improve from 0.16571
6/6 ----- 10s 2s/step - accuracy: 0.9568 - loss: 0.2022 - val_accu
racy: 0.9444 - val_loss: 0.1823
Epoch 23/30
6/6 ----- 0s 1s/step - accuracy: 0.9021 - loss: 0.2427
Epoch 23: val_loss did not improve from 0.16571
6/6 ----- 10s 2s/step - accuracy: 0.9075 - loss: 0.2356 - val_accu
racy: 0.9444 - val_loss: 0.2035
Epoch 24/30
6/6 ----- 0s 1s/step - accuracy: 0.8645 - loss: 0.4553
Epoch 24: val_loss did not improve from 0.16571
6/6 ----- 9s 2s/step - accuracy: 0.8736 - loss: 0.4241 - val_accu
racy: 0.9444 - val_loss: 0.1885
Epoch 25/30
6/6 ----- 0s 1s/step - accuracy: 0.9053 - loss: 0.2217
Epoch 25: val_loss did not improve from 0.16571
6/6 ----- 9s 2s/step - accuracy: 0.9068 - loss: 0.2166 - val_accu
racy: 0.9444 - val_loss: 0.1743
Epoch 26/30
6/6 ----- 0s 1s/step - accuracy: 0.9496 - loss: 0.1757
Epoch 26: val_loss did not improve from 0.16571
6/6 ----- 9s 2s/step - accuracy: 0.9517 - loss: 0.1722 - val_accu
racy: 0.9444 - val_loss: 0.1874
Epoch 26: early stopping
Restoring model weights from the end of the best epoch: 18.
2/2 ----- 8s 3s/step

```

```

In [26]: efficientnet_model = build_transfer_model(EfficientNetB0, model_name="EfficientN
efficientnet_history, efficientnet_metrics = train_and_evaluate_model(efficientn

```

Training model: EfficientNetB0

Epoch 1/30

```

6/6 ----- 0s 2s/step - accuracy: 0.4800 - loss: 1.0616

```

Epoch 1: val_loss improved from inf to 1.09952, saving model to ./models\efficientnetb0_best.h5

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.save_model(model, 'my_model.keras')`.


```

6/6 ————— 50s 4s/step - accuracy: 0.4631 - loss: 1.0682 - val_accu
racy: 0.3333 - val_loss: 1.0995
Epoch 2/30
6/6 ————— 0s 1s/step - accuracy: 0.2343 - loss: 1.1631
Epoch 2: val_loss improved from 1.09952 to 1.09893, saving model to ./models\effi
cientnetb0_best.h5
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `ker
as.saving.save_model(model)`. This file format is considered legacy. We recommend
using instead the native Keras format, e.g. `model.save('my_model.keras')` or `ke
ras.saving.save_model(model, 'my_model.keras')`.
6/6 ————— 9s 2s/step - accuracy: 0.2335 - loss: 1.1662 - val_accu
racy: 0.3333 - val_loss: 1.0989
Epoch 3/30
6/6 ————— 0s 1s/step - accuracy: 0.2902 - loss: 1.1174
Epoch 3: val_loss did not improve from 1.09893
6/6 ————— 10s 2s/step - accuracy: 0.2969 - loss: 1.1169 - val_accu
racy: 0.3333 - val_loss: 1.1011
Epoch 4/30
6/6 ————— 0s 1s/step - accuracy: 0.3968 - loss: 1.1398
Epoch 4: val_loss did not improve from 1.09893
6/6 ————— 10s 2s/step - accuracy: 0.3918 - loss: 1.1390 - val_accu
racy: 0.3333 - val_loss: 1.1091
Epoch 5/30
6/6 ————— 0s 1s/step - accuracy: 0.4039 - loss: 1.1122
Epoch 5: val_loss did not improve from 1.09893
6/6 ————— 10s 2s/step - accuracy: 0.4082 - loss: 1.1120 - val_accu
racy: 0.3333 - val_loss: 1.1017
Epoch 6/30
6/6 ————— 0s 1s/step - accuracy: 0.3324 - loss: 1.1199
Epoch 6: val_loss did not improve from 1.09893
6/6 ————— 9s 2s/step - accuracy: 0.3296 - loss: 1.1210 - val_accu
racy: 0.3333 - val_loss: 1.1009
Epoch 7/30
6/6 ————— 0s 2s/step - accuracy: 0.4042 - loss: 1.1123
Epoch 7: val_loss did not improve from 1.09893
6/6 ————— 10s 2s/step - accuracy: 0.3946 - loss: 1.1131 - val_accu
racy: 0.3333 - val_loss: 1.1040
Epoch 8/30
6/6 ————— 0s 1s/step - accuracy: 0.3377 - loss: 1.1311
Epoch 8: val_loss did not improve from 1.09893
6/6 ————— 10s 2s/step - accuracy: 0.3446 - loss: 1.1282 - val_accu
racy: 0.3333 - val_loss: 1.1043
Epoch 9/30
6/6 ————— 0s 2s/step - accuracy: 0.3724 - loss: 1.1040
Epoch 9: val_loss did not improve from 1.09893
6/6 ————— 11s 2s/step - accuracy: 0.3691 - loss: 1.1041 - val_accu
racy: 0.3333 - val_loss: 1.1031
Epoch 10/30
6/6 ————— 0s 2s/step - accuracy: 0.2909 - loss: 1.1550
Epoch 10: val_loss did not improve from 1.09893
6/6 ————— 11s 2s/step - accuracy: 0.2993 - loss: 1.1517 - val_accu
racy: 0.3333 - val_loss: 1.1049
Epoch 10: early stopping
Restoring model weights from the end of the best epoch: 2.
2/2 ————— 15s 7s/step

```

```
C:\Users\prasa\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:170
6: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
```

```
In [27]: # Compile all results
all_model_results = [
    baseline_results,
    vgg_metrics,
    resnet_metrics,
    mobilenet_metrics,
    efficientnet_metrics
]

results_df = pd.DataFrame(all_model_results)
results_df = results_df.sort_values(by='F1-Score', ascending=False).reset_index()

print("\nFinal Model Comparison:")
results_df
```

Final Model Comparison:

```
Out[27]:
```

	Model	Test Accuracy	Test Loss	Precision	Recall	F1-Score
0	MobileNetV2	0.7222	0.5524	0.7349	0.7222	0.7253
1	VGG16	0.6111	0.9233	0.5972	0.6111	0.5937
2	Custom CNN	0.3333	1.8451	0.1111	0.3333	0.1667
3	ResNet50	0.3333	1.0949	0.1111	0.3333	0.1667
4	EfficientNetB0	0.3333	1.0994	0.1111	0.3333	0.1667

Fine-Tune the Best Model

```
In [28]: # Pick the best performing model by F1-Score
best_model_name = results_df.iloc[0]['Model']
print(f"Best model selected for fine-tuning: {best_model_name}")
```

Best model selected for fine-tuning: MobileNetV2

```
In [29]: # Mapping model names to builder functions
model_map = {
    "VGG16": VGG16,
    "ResNet50": ResNet50,
    "MobileNetV2": MobileNetV2,
    "EfficientNetB0": EfficientNetB0
}

def load_best_model_for_finetuning(name, checkpoint_dir="./models", input_shape=
model_path = os.path.join(checkpoint_dir, f"{name.lower()}_best.h5")
base_class = model_map[name]

# Rebuild and Load weights
model = build_transfer_model(base_class, input_shape=input_shape, num_classes=
model.load_weights(model_path)

# Unfreeze only the top N layers
```

```

trainable = False
unfreeze_from = int(len(model.layers) * 0.7) # Top 30% Layers
for i, layer in enumerate(model.layers):
    if i >= unfreeze_from:
        trainable = True
        layer.trainable = trainable

print(f"Unfroze top {100 - int(unfreeze_from/len(model.layers)*100)}% layers

# Compile again with a lower learning rate
model.compile(
    optimizer=Adam(learning_rate=1e-5),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
return model

# Load and prepare for fine-tuning
finetune_model = load_best_model_for_finetuning(best_model_name)

```

Unfroze top 31% layers of MobileNetV2

```

In [30]: # Merge train and val generators (simulate new training set)
combined_dir = "./PreparedData/combined"
if os.path.exists(combined_dir):
    shutil.rmtree(combined_dir)

for subset in ['train', 'val']:
    src_path = os.path.join(split_base_dir, subset)
    for cls in os.listdir(src_path):
        src_cls_path = os.path.join(src_path, cls)
        dst_cls_path = os.path.join(combined_dir, cls)
        os.makedirs(dst_cls_path, exist_ok=True)
        for file in os.listdir(src_cls_path):
            shutil.copy2(os.path.join(src_cls_path, file), dst_cls_path)

# New generator with augmentation
combined_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    zoom_range=0.2,
    shear_range=0.15,
    horizontal_flip=True,
    fill_mode='nearest'
)

combined_generator = combined_datagen.flow_from_directory(
    combined_dir,
    target_size=(224, 224),
    batch_size=BATCH_SIZE,
    class_mode='categorical',
    shuffle=True
)

# Retrain with callbacks
fine_tune_callbacks = [
    EarlyStopping(monitor='loss', patience=5, restore_best_weights=True),
    ModelCheckpoint(f"./models/{best_model_name.lower()}_finetuned.h5", save_best

```

```

]

# Fine-tune
finetune_history = finetune_model.fit(
    combined_generator,
    epochs=20,
    verbose=1,
    callbacks=fine_tune_callbacks
)

```

Found 101 images belonging to 3 classes.

C:\Users\prasa\anaconda3\Lib\site-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 include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignored.

```
self.warn_if_super_not_called()
```

Epoch 1/20

7/7 ————— 0s 2s/step - accuracy: 0.6752 - loss: 0.6932

Epoch 1: loss improved from inf to 0.75975, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 45s 2s/step - accuracy: 0.6725 - loss: 0.7015

Epoch 2/20

7/7 ————— 0s 1s/step - accuracy: 0.6026 - loss: 0.7851

Epoch 2: loss improved from 0.75975 to 0.74046, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 17s 1s/step - accuracy: 0.6040 - loss: 0.7796

Epoch 3/20

7/7 ————— 0s 2s/step - accuracy: 0.7730 - loss: 0.6320

Epoch 3: loss improved from 0.74046 to 0.66499, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 12s 2s/step - accuracy: 0.7704 - loss: 0.6361

Epoch 4/20

7/7 ————— 0s 2s/step - accuracy: 0.7878 - loss: 0.5236

Epoch 4: loss improved from 0.66499 to 0.56815, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 13s 2s/step - accuracy: 0.7871 - loss: 0.5292

Epoch 5/20

7/7 ————— 0s 1s/step - accuracy: 0.6865 - loss: 0.5892

Epoch 5: loss improved from 0.56815 to 0.55540, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 11s 2s/step - accuracy: 0.6935 - loss: 0.5850

Epoch 6/20

7/7 ————— 0s 1s/step - accuracy: 0.8315 - loss: 0.4622

Epoch 6: loss improved from 0.55540 to 0.51681, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 19s 1s/step - accuracy: 0.8303 - loss: 0.4690

Epoch 7/20

7/7 ————— 0s 2s/step - accuracy: 0.8570 - loss: 0.4076

Epoch 7: loss improved from 0.51681 to 0.44891, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 11s 2s/step - accuracy: 0.8539 - loss: 0.4127

Epoch 8/20

7/7 ————— 0s 1s/step - accuracy: 0.8048 - loss: 0.4592

Epoch 8: loss improved from 0.44891 to 0.43309, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 11s 2s/step - accuracy: 0.8081 - loss: 0.4559

Epoch 9/20

7/7 ————— 0s 1s/step - accuracy: 0.8308 - loss: 0.4450

Epoch 9: loss did not improve from 0.43309

7/7 ————— 10s 1s/step - accuracy: 0.8309 - loss: 0.4456

Epoch 10/20

7/7 ————— 0s 1s/step - accuracy: 0.8622 - loss: 0.4813

Epoch 10: loss did not improve from 0.43309

7/7 ————— 10s 1s/step - accuracy: 0.8596 - loss: 0.4844

Epoch 11/20

7/7 ————— 0s 2s/step - accuracy: 0.8603 - loss: 0.4211

Epoch 11: loss improved from 0.43309 to 0.39498, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

7/7 ————— 11s 2s/step - accuracy: 0.8605 - loss: 0.4178

Epoch 12/20

7/7 ————— 0s 1s/step - accuracy: 0.9191 - loss: 0.2872

Epoch 12: loss improved from 0.39498 to 0.28250, saving model to ./models/mobilenetv2_finetuned.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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

```

7/7 ----- 20s 2s/step - accuracy: 0.9181 - loss: 0.2866
Epoch 13/20
7/7 ----- 0s 1s/step - accuracy: 0.8889 - loss: 0.3587
Epoch 13: loss did not improve from 0.28250
7/7 ----- 8s 1s/step - accuracy: 0.8867 - loss: 0.3642
Epoch 14/20
7/7 ----- 0s 1s/step - accuracy: 0.8538 - loss: 0.3517
Epoch 14: loss did not improve from 0.28250
7/7 ----- 8s 1s/step - accuracy: 0.8510 - loss: 0.3525
Epoch 15/20
7/7 ----- 0s 1s/step - accuracy: 0.8474 - loss: 0.3268
Epoch 15: loss did not improve from 0.28250
7/7 ----- 10s 1s/step - accuracy: 0.8492 - loss: 0.3279
Epoch 16/20
7/7 ----- 0s 1s/step - accuracy: 0.9653 - loss: 0.2705
Epoch 16: loss did not improve from 0.28250
7/7 ----- 9s 1s/step - accuracy: 0.9610 - loss: 0.2757
Epoch 17/20
7/7 ----- 0s 1s/step - accuracy: 0.8656 - loss: 0.3146
Epoch 17: loss did not improve from 0.28250
7/7 ----- 9s 1s/step - accuracy: 0.8675 - loss: 0.3126

```

```

In [31]: # Evaluate
test_loss, test_acc = finetune_model.evaluate(test_generator)
y_pred_ft = np.argmax(finetune_model.predict(test_generator), axis=1)
y_true = test_generator.classes

finetuned_metrics = {
    "Model": f"{best_model_name} + Fine-Tuned",
    "Test Accuracy": round(test_acc, 4),
    "Test Loss": round(test_loss, 4),
    "Precision": round(precision_score(y_true, y_pred_ft, average='macro'), 4),
    "Recall": round(recall_score(y_true, y_pred_ft, average='macro'), 4),
    "F1-Score": round(f1_score(y_true, y_pred_ft, average='macro'), 4)
}

# Add to results
results_df = pd.concat([results_df, pd.DataFrame([finetuned_metrics])], ignore_index=True)
results_df = results_df.sort_values(by="F1-Score", ascending=False).reset_index()

print("\nFinal Comparison Including Fine-Tuned Model:")
results_df

```

```

2/2 ----- 4s 91ms/step - accuracy: 0.8472 - loss: 0.5194
2/2 ----- 7s 3s/step

```

Final Comparison Including Fine-Tuned Model:

Out[31]:

	Model	Test Accuracy	Test Loss	Precision	Recall	F1-Score
0	MobileNetV2 + Fine-Tuned	0.8333	0.5635	0.8500	0.8333	0.8312
1	MobileNetV2	0.7222	0.5524	0.7349	0.7222	0.7253
2	VGG16	0.6111	0.9233	0.5972	0.6111	0.5937
3	Custom CNN	0.3333	1.8451	0.1111	0.3333	0.1667
4	ResNet50	0.3333	1.0949	0.1111	0.3333	0.1667
5	EfficientNetB0	0.3333	1.0994	0.1111	0.3333	0.1667

Save, Export, and Prepare Model for Deployment

```
In [32]: final_model_path = f"./models/{best_model_name.lower()}_finetuned_final.h5"
         finetune_model.save(final_model_path)
         print(f"Model saved as: {final_model_path}")
```

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.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

Model saved as: ./models/mobilenetv2_finetuned_final.h5

```
In [33]: import os

         saved_model_dir = f"./saved_models/{best_model_name.lower()}_finetuned"
         os.makedirs(os.path.dirname(saved_model_dir), exist_ok=True)
         finetune_model.export(saved_model_dir)
         print(f"Model successfully exported in TensorFlow SavedModel format to: {saved_m
```

INFO:tensorflow:Assets written to: ./saved_models/mobilenetv2_finetuned/assets

INFO:tensorflow:Assets written to: ./saved_models/mobilenetv2_finetuned/assets

Saved artifact at './saved_models/mobilenetv2_finetuned'. The following endpoints are available:

* Endpoint 'serve'

args_0 (POSITIONAL_ONLY): TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name='keras_tensor_616')

Output Type:

TensorSpec(shape=(None, 3), dtype=tf.float32, name=None)

Captures:

2318331413904: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331412944: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331418320: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331413712: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331414288: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331418512: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331412560: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331416400: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331412752: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331413520: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331414672: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331416976: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331416016: TensorSpec(shape=(), dtype=tf.resource, name=None)
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2318331417552: TensorSpec(shape=(), dtype=tf.resource, name=None)
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2318331417360: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331416208: TensorSpec(shape=(), dtype=tf.resource, name=None)
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2318331417936: TensorSpec(shape=(), dtype=tf.resource, name=None)
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2318331419472: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331419664: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331419856: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331416592: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331421008: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331420432: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331420624: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331420816: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331417744: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331421968: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331421392: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331421584: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331421776: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331419280: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331422928: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331422352: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331422544: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331422736: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331420240: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331423888: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331423312: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331423504: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331423696: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331421200: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331424848: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331424272: TensorSpec(shape=(), dtype=tf.resource, name=None)

2318331424464: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331424656: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331422160: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331425808: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331425232: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331424080: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331425616: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331423120: TensorSpec(shape=(), dtype=tf.resource, name=None)
2316306218064: TensorSpec(shape=(), dtype=tf.resource, name=None)
2318331426192: TensorSpec(shape=(), dtype=tf.resource, name=None)
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Model successfully exported in TensorFlow SavedModel format to: ./saved_models/mobilenetv2_finetuned

```

```

In [34]: import json

label_map_path = f"./models/{best_model_name.lower()}_label_map.json"
with open(label_map_path, "w") as f:
    json.dump(class_indices, f)

print(f"Class label map saved to: {label_map_path}")

```

Class label map saved to: ./models/mobilenetv2_label_map.json

```

In [35]: from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import numpy as np

# Load model and Label map
model = load_model(final_model_path)
with open(label_map_path, "r") as f:
    label_map = json.load(f)
inv_label_map = {v: k for k, v in label_map.items()}

def predict_image(img_path):
    img = image.load_img(img_path, target_size=(224, 224))
    img_tensor = image.img_to_array(img)
    img_tensor = np.expand_dims(img_tensor, axis=0) / 255.0

```

```
prediction = model.predict(img_tensor)
pred_index = np.argmax(prediction)
confidence = np.max(prediction)

print(f"Image: {os.path.basename(img_path)}")
print(f"Predicted: {inv_label_map[pred_index]} with confidence {confidence:.1}
```

WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.

```
In [36]: predict_image(r"C:\Users\prasa\Downloads\Prasad\Capston\Rice Leaf\PreparedData\t
1/1 4s 4s/step
Image: DSC_0394.jpg
Predicted: Bacterial leaf blight with confidence 0.64
```

FINAL MODEL COMPARISON REPORT & CONCLUSION

FINAL MODEL COMPARISON REPORT AND CONCLUSION

1. Models Evaluated

A wide range of deep learning models were trained and evaluated to determine the most effective approach for rice leaf disease classification:

Model Name	Architecture	Trainable Layers	Strategy
Custom CNN	Manually built	All layers	Baseline CNN
VGG16	Transfer Learning	Head only	Frozen base layers
ResNet50	Transfer Learning	Head only	Frozen base layers
MobileNetV2	Transfer Learning	Head only	Frozen base layers
EfficientNetB0	Transfer Learning	Head only	Frozen base layers
MobileNetV2 (Fine-Tuned)	Transfer Learning	Top 30% unfrozen	Final selected model

2. Evaluation Metrics Used

Each model was evaluated using the following metrics:

- Test Accuracy
- Test Loss
- Precision (Macro-Averaged)
- Recall (Macro-Averaged)
- F1-Score (Macro-Averaged)

These metrics ensure fair evaluation across all disease classes.

3. Performance Summary

Model	Test Accuracy	Test Loss	Precision	Recall	F1-Score
MobileNetV2 (Fine-Tuned)	0.8333	0.5635	0.8500	0.8333	0.8312
MobileNetV2	0.7222	0.5524	0.7349	0.7222	0.7253
VGG16	0.6111	0.9233	0.5972	0.6111	0.5937
Custom CNN	0.3333	1.8451	0.1111	0.3333	0.1667
ResNet50	0.3333	1.0949	0.1111	0.3333	0.1667
EfficientNetB0	0.3333	1.0994	0.1111	0.3333	0.1667

4. Best Performing Model

The **fine-tuned MobileNetV2** model demonstrated the highest performance, achieving **83.33% accuracy** and an **F1-score of 0.8312**. Its combination of accuracy, generalization, and inference efficiency makes it ideal for production-level deployment in resource-constrained environments like mobile devices.

5. Key Insights

- Transfer learning drastically improved performance over the custom CNN baseline, reaffirming the effectiveness of pretrained feature extractors.
- Fine-tuning the MobileNetV2 model led to significant gains in F1-score and generalization ability.
- MobileNetV2 showed strong standalone performance and became even more effective after fine-tuning.
- Lightweight models like MobileNetV2 are especially suitable for edge or mobile deployment without compromising accuracy.

6. Limitations

- The dataset was relatively small, limiting the model’s ability to generalize in uncontrolled conditions.
- Some visual similarity between diseases (e.g., Brown Spot vs. Leaf Smut) may still lead to misclassification.
- The test set consisted of relatively clean images; further testing on field images is needed.

7. Future Scope

- Augment the dataset with field images captured under different lighting, angles, and environmental conditions.
 - Add Grad-CAM visualizations to analyze model decision regions for better explainability.
 - Convert the model to TFLite or ONNX for edge deployment on smartphones or drones.
 - Build a complete mobile/web-based user interface using Streamlit, Flask, or Android frameworks.
 - Explore attention-based architectures like Vision Transformers (ViT) or ConvNeXt for improved robustness.
-

8. Final Conclusion

This project demonstrated the successful application of deep learning, specifically **transfer learning and fine-tuning**, for accurate rice leaf disease classification. Among the models tested, **MobileNetV2 (fine-tuned)** emerged as the top performer, combining high accuracy with efficiency. The final pipeline is production-ready, scalable, and provides a strong foundation for deployment in smart agriculture systems to assist farmers with early and automated disease diagnosis.

In []: