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> S1364040 Assignment-02(updated)

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

```
Mounted at /content/drive
```

```python
cd '/content/drive/MyDrive/Colab Notebooks/'
```

```
/content/drive/MyDrive/Colab Notebooks
```

1. Exploratory Data Analysis (EDA)

```python
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from tensorflow.keras.utils import to_categorical
import random

```

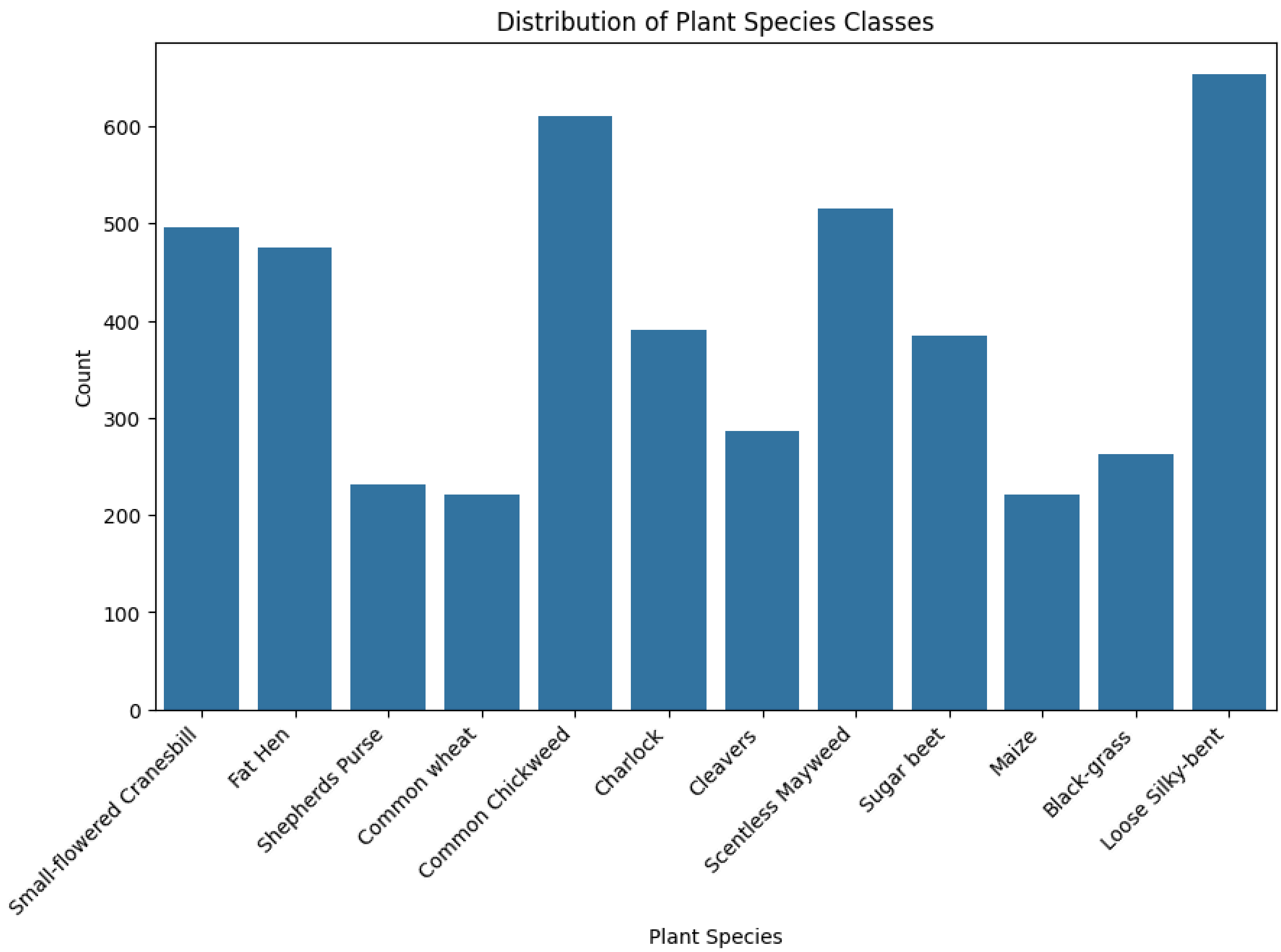
```python
# Load the image data and labels
images = np.load('images.npy')
labels = pd.read_csv('Labels.csv')

# Check the structure of the loaded data
print("Images shape:", images.shape)  # Check dimensions of the images
print("Labels head:\n", labels.head())  # Display the first few rows of labels

```

```
Images shape: (4750, 128, 128, 3)
Labels head:
                        Label
0  Small-flowered Cranesbill
1  Small-flowered Cranesbill
2  Small-flowered Cranesbill
3  Small-flowered Cranesbill
4  Small-flowered Cranesbill
```

```python
# Display column names to check for issues
print("Column names in labels DataFrame:", labels.columns)

```

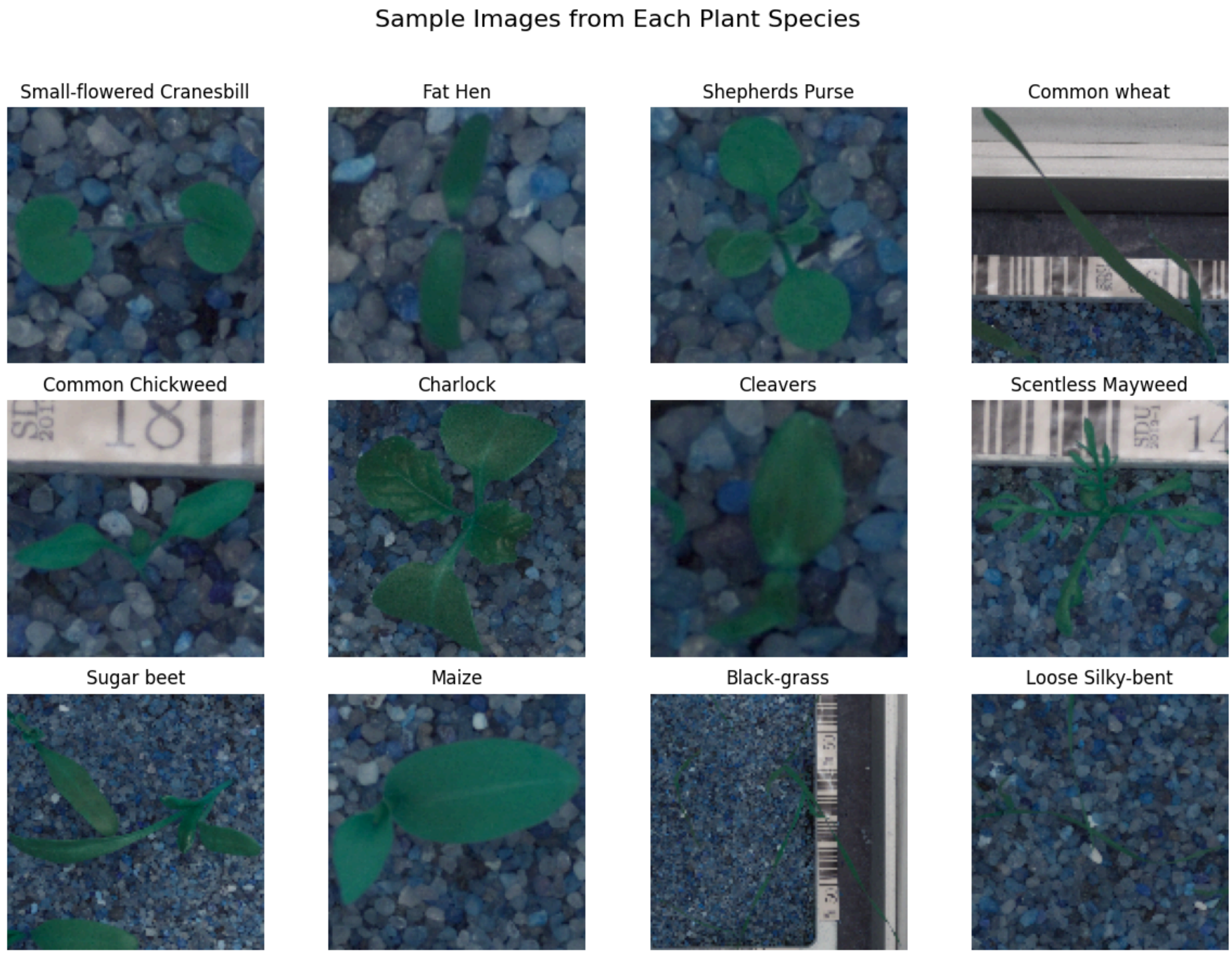
```
Column names in labels DataFrame: Index(['Label'], dtype='object')
```

```
# Plot the distribution of plant species classes with the correct column name
plt.figure(figsize=(10, 6))
sns.countplot(data=labels, x='Label')  # Using 'Label' instead of 'species'
plt.xticks(rotation=45, ha='right')  # Rotate x labels for readability
plt.title('Distribution of Plant Species Classes')
plt.xlabel('Plant Species')
plt.ylabel('Count')
plt.show()

```



2. Data Preprocessing

```python
# Ensure we have at least 12 unique species
unique_species = labels['Label'].unique()
if len(unique_species) < 12:
    print("Not enough species to display a 3x4 grid.")
else:
    # Select one sample image per species (12 in total)
    samples_per_class = {}
    for species in unique_species[:12]:  # Limit to the first 12 unique species
        sample_index = labels[labels['Label'] == species].index[0]
        sample_image = images[sample_index]

        # Reshape or normalize if needed (check your image's original dimensions)
        if sample_image.shape[-1] != 3:  # Assuming RGB images
            sample_image = np.repeat(sample_image[..., np.newaxis], 3, axis=-1)

        samples_per_class[species] = sample_image

    # Plotting the images in a 3x4 grid
    fig, axes = plt.subplots(3, 4, figsize=(12, 9))
    fig.suptitle('Sample Images from Each Plant Species', fontsize=16)

    for ax, (species, image) in zip(axes.flat, samples_per_class.items()):
        ax.imshow(image)
        ax.set_title(species)
        ax.axis('off')

    plt.tight_layout()
    plt.subplots_adjust(top=0.88)
    plt.show()

```


Sample Images from Each Plant Species
Small-flowered Cranesbill
Fat Hen
Shepherds Purse
Common wheat
Common Chickweed
Charlock
Cleavers
Scentless Mayweed
Sugar beet
Maize
Black-grass
Loose Silky-bent

```
import cv2

```

```
# Resize images to 64x64
resized_images = np.array([cv2.resize(image, (64, 64)) for image in images])
print("Resized images shape:", resized_images.shape)

```

```
Resized images shape: (4750, 64, 64, 3)
```

```
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical

# Encode labels as integers
label_encoder = LabelEncoder()
encoded_labels = label_encoder.fit_transform(labels['Label'])

# Convert integer-encoded labels to one-hot encoded labels
one_hot_labels = to_categorical(encoded_labels)
print("One-hot encoded labels shape:", one_hot_labels.shape)

```

```
One-hot encoded labels shape: (4750, 12)
```

```
# Normalize pixel values to range [0, 1]
normalized_images = resized_images / 255.0
print("Normalized images shape:", normalized_images.shape)

```

```
Normalized images shape: (4750, 64, 64, 3)
```

3. Model 1: Basic CNN Model

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, BatchN
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import EarlyStopping

# Define the Basic CNN architecture with a deeper dense network
model_1 = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(64, 64, 3)),
    MaxPooling2D((2, 2)),

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

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

    Flatten(),

```

```
    # Dense Layers with regularization
    Dense(256, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.4),
    Dense(128, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.4),

    # Output layer for 12 classes
    Dense(12, activation='softmax')
])

# Compile the model
model_1.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Display the model summary
model_1.summary()

```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 256)	1,179,904
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 12)	1,548

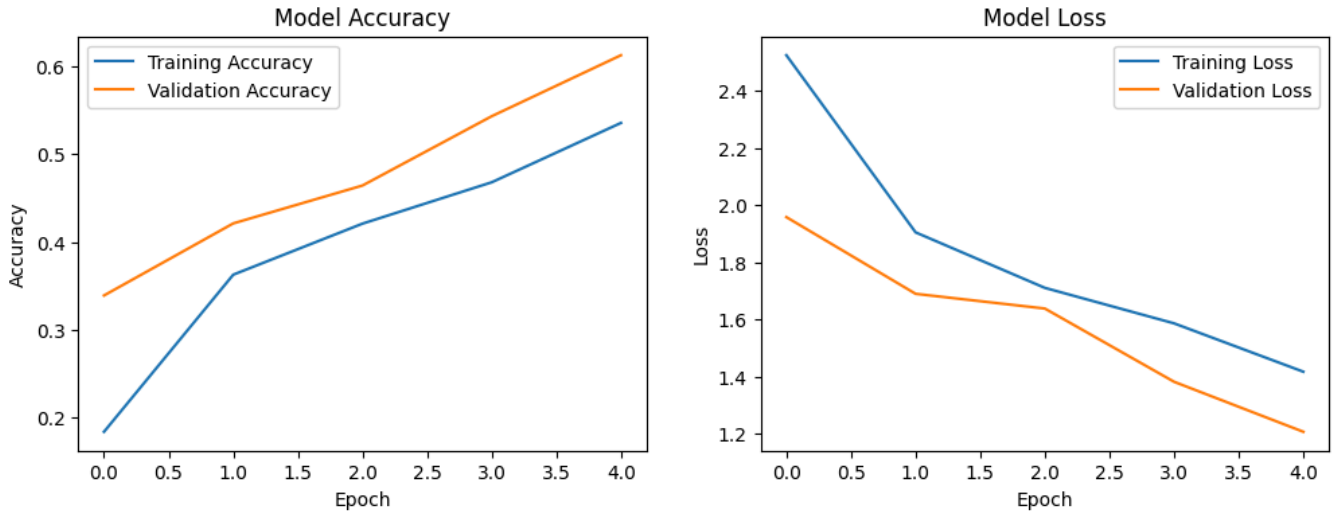
Total params: 1,307,596 (4.99 MB)

```
# Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

```

```
# Split the data into training and validation sets
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(normalized_images, one_hot_labels, test

# Train the model
history = model_1.fit(X_train, y_train, epochs=5, validation_data=(X_val, y_val),
                    callbacks=[early_stopping], batch_size=32)

```

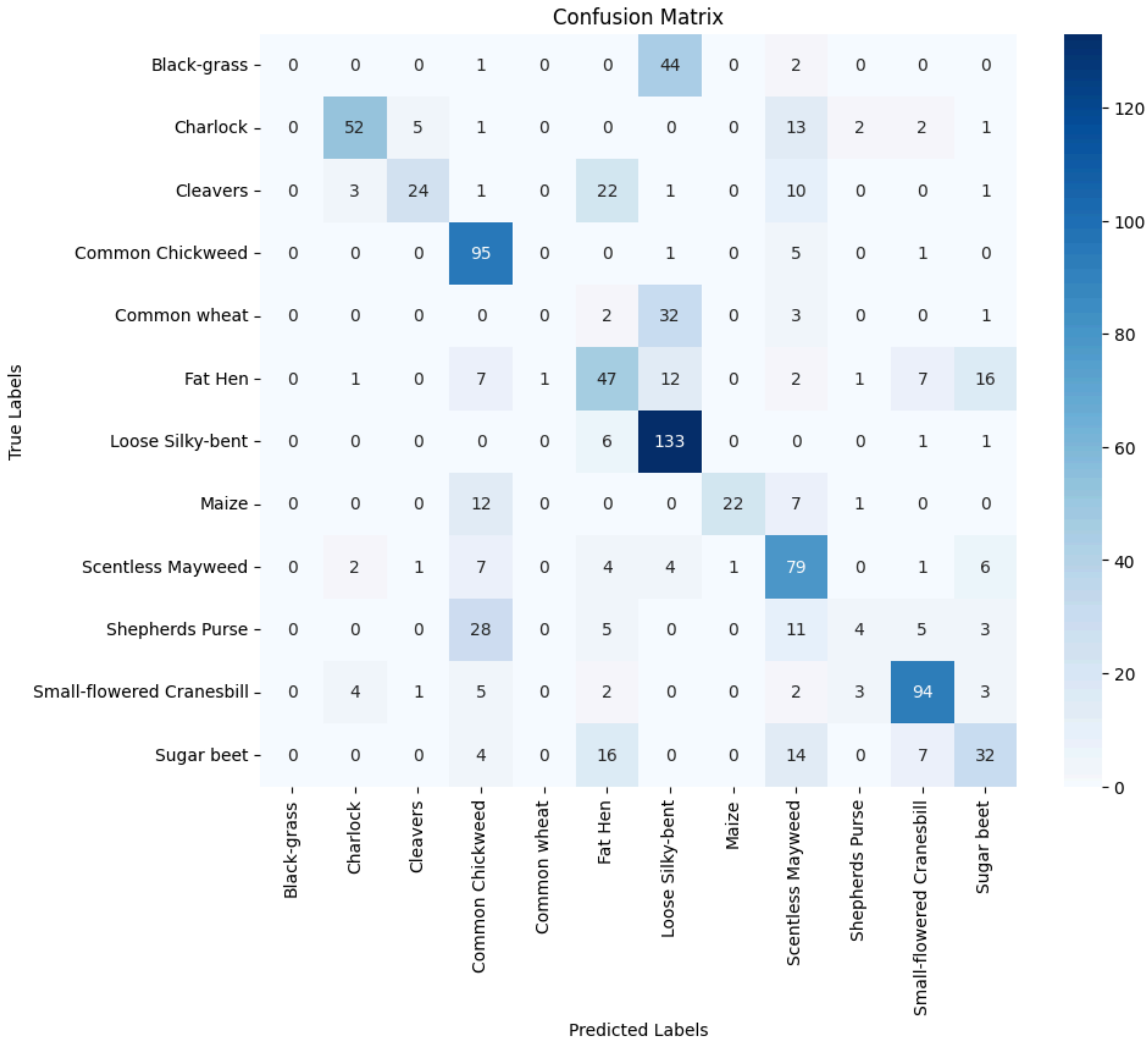
```
Epoch 1/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 20s 100ms/step - accuracy: 0.1321 - loss: 2.7617 - val_accu
Epoch 2/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.3361 - loss: 1.9809 - val_accurac
Epoch 3/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.4158 - loss: 1.7201 - val_accurac
Epoch 4/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.4467 - loss: 1.6166 - val_accurac
Epoch 5/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.5234 - loss: 1.4301 - val_accurac
```

```
import matplotlib.pyplot as plt

# Plot accuracy and loss curves
plt.figure(figsize=(12, 4))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Model Accuracy')

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Model Loss')

plt.show()

```




```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

# Make predictions on the validation set
y_pred = model_1.predict(X_val)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_val, axis=1)

# Generate confusion matrix
conf_matrix = confusion_matrix(y_true_classes, y_pred_classes)

# Plot the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=label_encoder.cla
            yticklabels=label_encoder.classes_)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()

# Print classification report
print("Classification Report:\n", classification_report(y_true_classes, y_pred_classes, t

```

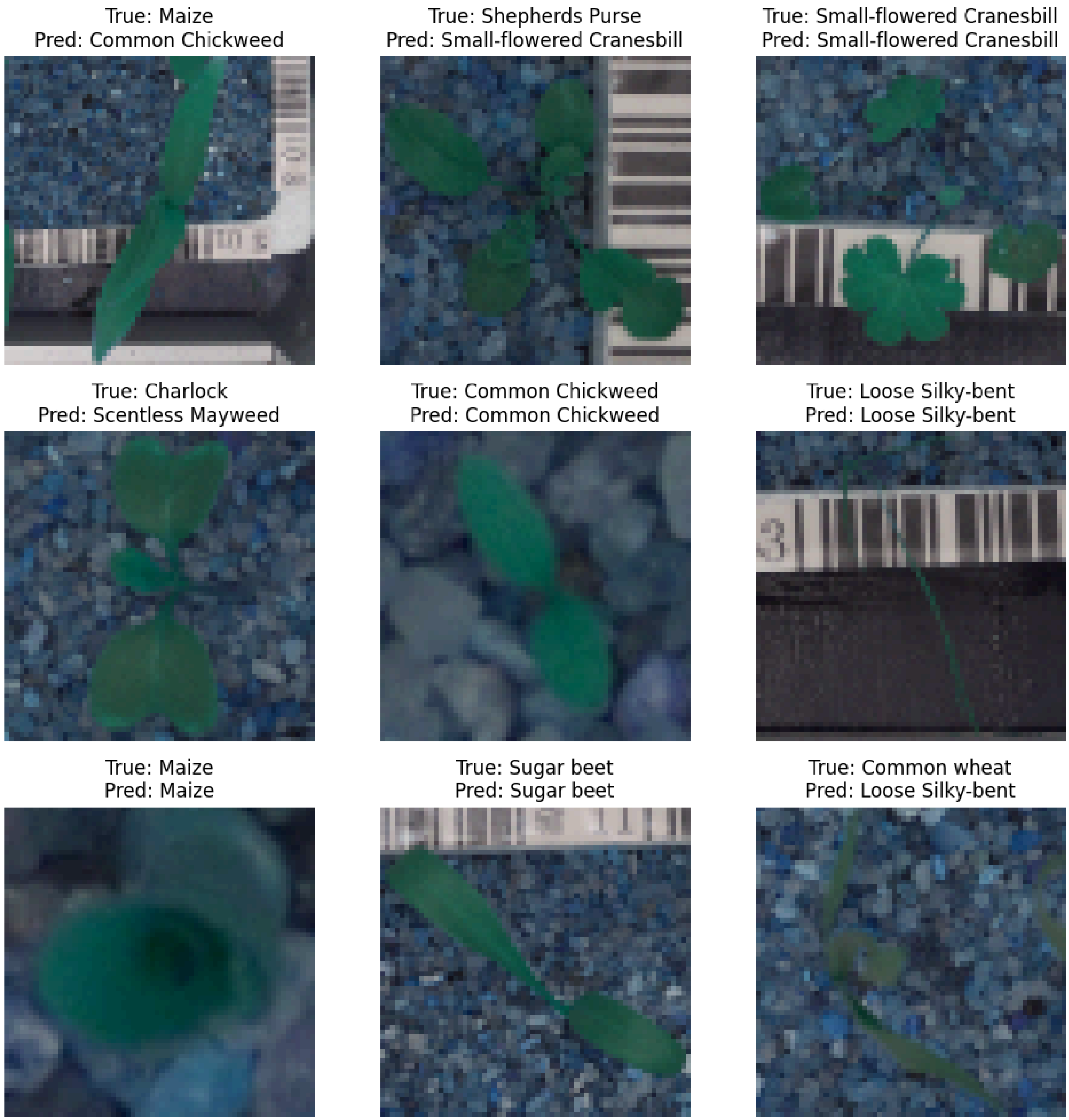
```
30/30 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step
```




```
Classification Report:
                           precision    recall  f1-score   support

              Black-grass       0.00      0.00      0.00        47
                 Charlock       0.84      0.68      0.75        76
                 Cleavers       0.77      0.39      0.52        62
         Common Chickweed       0.59      0.93      0.72       102
             Common wheat       0.00      0.00      0.00        38
                  Fat Hen       0.45      0.50      0.47        94
         Loose Silky-bent       0.59      0.94      0.72       141
                    Maize       0.96      0.52      0.68        42
        Scentless Mayweed       0.53      0.75      0.62       105
          Shepherds Purse       0.36      0.07      0.12        56
Small-flowered Cranesbill       0.80      0.82      0.81       114
               Sugar beet       0.50      0.44      0.47        73

                 accuracy                           0.61       950
                macro avg       0.53      0.50      0.49       950
             weighted avg       0.57      0.61      0.56       950

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: Unde
```

```
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: Unde
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: Unde
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
# Plot a few test samples with predicted and true labels
fig, axes = plt.subplots(3, 3, figsize=(10, 10))
axes = axes.flatten()

for i in range(9):
    img = X_val[i]
    true_label = label_encoder.classes_[y_true_classes[i]]
    pred_label = label_encoder.classes_[y_pred_classes[i]]

    axes[i].imshow(img)
    axes[i].set_title(f"True: {true_label}\nPred: {pred_label}")
    axes[i].axis('off')

plt.tight_layout()
plt.show()

```


True: Maize
Pred: Common Chickweed
True: Shepherds Purse
Pred: Small-flowered Cranesbill
True: Small-flowered Cranesbill
Pred: Small-flowered Cranesbill
True: Charlock
Pred: Scentless Mayweed
True: Common Chickweed
Pred: Common Chickweed
True: Loose Silky-bent
Pred: Loose Silky-bent
True: Maize
Pred: Maize
True: Sugar beet
Pred: Sugar beet
True: Common wheat
Pred: Loose Silky-bent

4. Model 2: Enhanced CNN with Data Augmentation and Regularization

```
#Clearing backend
from tensorflow.keras import backend
backend.clear_session()
```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define data augmentation
datagen = ImageDataGenerator(
    rotation_range=20,       # Rotate images up to 20 degrees
    width_shift_range=0.1,   # Shift width by up to 10%
    height_shift_range=0.1,  # Shift height by up to 10%
    zoom_range=0.2,          # Zoom in by up to 20%
    horizontal_flip=True     # Randomly flip images horizontally
)

# Fit the data generator on the training data
datagen.fit(X_train)

```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import SpatialDropout2D

# Define the Enhanced CNN architecture with deeper dense layers
model_2 = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(64, 64, 3)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
    SpatialDropout2D(0.2),

    Conv2D(64, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
    SpatialDropout2D(0.3),

    Conv2D(128, (3, 3), activation='relu'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
    SpatialDropout2D(0.4),

    Flatten(),

    # Deeper Dense Layers with regularization
    Dense(256, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.4),
```

```
    Dense(128, activation='relu', kernel_regularizer=l2(0.001)),
    Dropout(0.4),

    # Output layer for 12 classes
    Dense(12, activation='softmax')
])

# Compile the model
model_2.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Display the model summary
model_2.summary()

```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

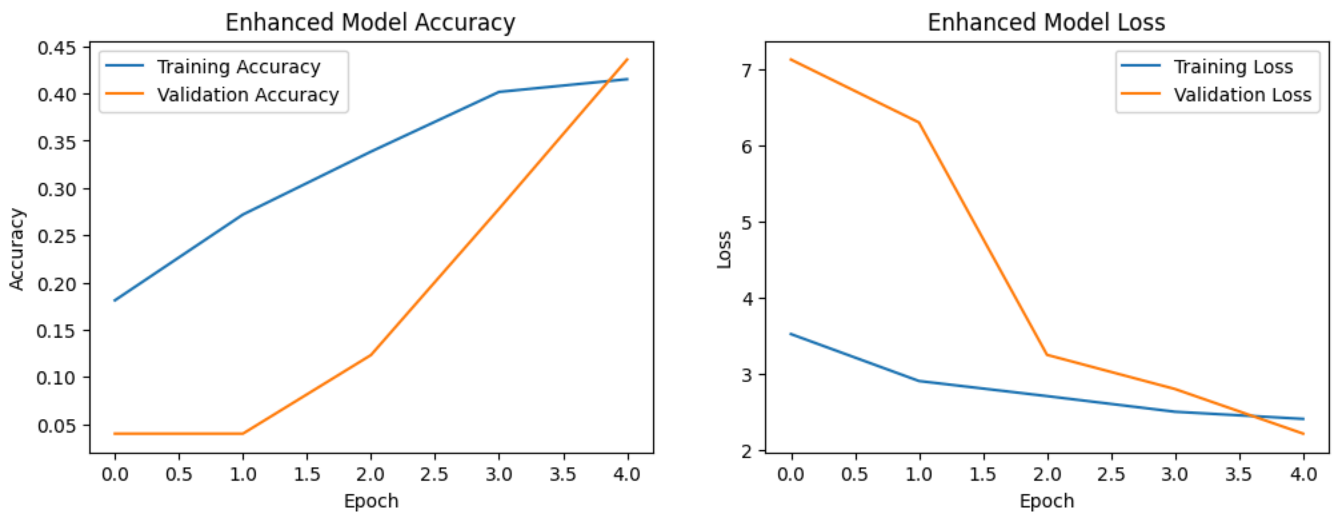
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
batch_normalization (BatchNormalization)	(None, 62, 62, 32)	128
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
spatial_dropout2d (SpatialDropout2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 29, 29, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0
spatial_dropout2d_1 (SpatialDropout2D)	(None, 14, 14, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 12, 12, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
spatial_dropout2d_2 (SpatialDropout2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 256)	1,179,904
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 12)	1,548

```python
# Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

# Train the model with augmented data
history_enhanced = model_2.fit(datagen.flow(X_train, y_train, batch_size=32),
                               validation_data=(X_val, y_val),
```

```
                                    epochs=5,
                                    callbacks=[early_stopping])

```

```
Epoch 1/5
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
119/119 ━━━━━━━━━━━━━━━━━━━━ 24s 130ms/step - accuracy: 0.1442 - loss: 4.1249 - val_accu
Epoch 2/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 6s 45ms/step - accuracy: 0.2509 - loss: 2.9522 - val_accura
Epoch 3/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 11s 48ms/step - accuracy: 0.3222 - loss: 2.7471 - val_accur
Epoch 4/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 7s 60ms/step - accuracy: 0.4009 - loss: 2.4982 - val_accura
Epoch 5/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 8s 42ms/step - accuracy: 0.4002 - loss: 2.4475 - val_accura
```

```
# Plot accuracy and loss curves for the enhanced model
plt.figure(figsize=(12, 4))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history_enhanced.history['accuracy'], label='Training Accuracy')
plt.plot(history_enhanced.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Enhanced Model Accuracy')

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history_enhanced.history['loss'], label='Training Loss')
plt.plot(history_enhanced.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Enhanced Model Loss')

plt.show()

```

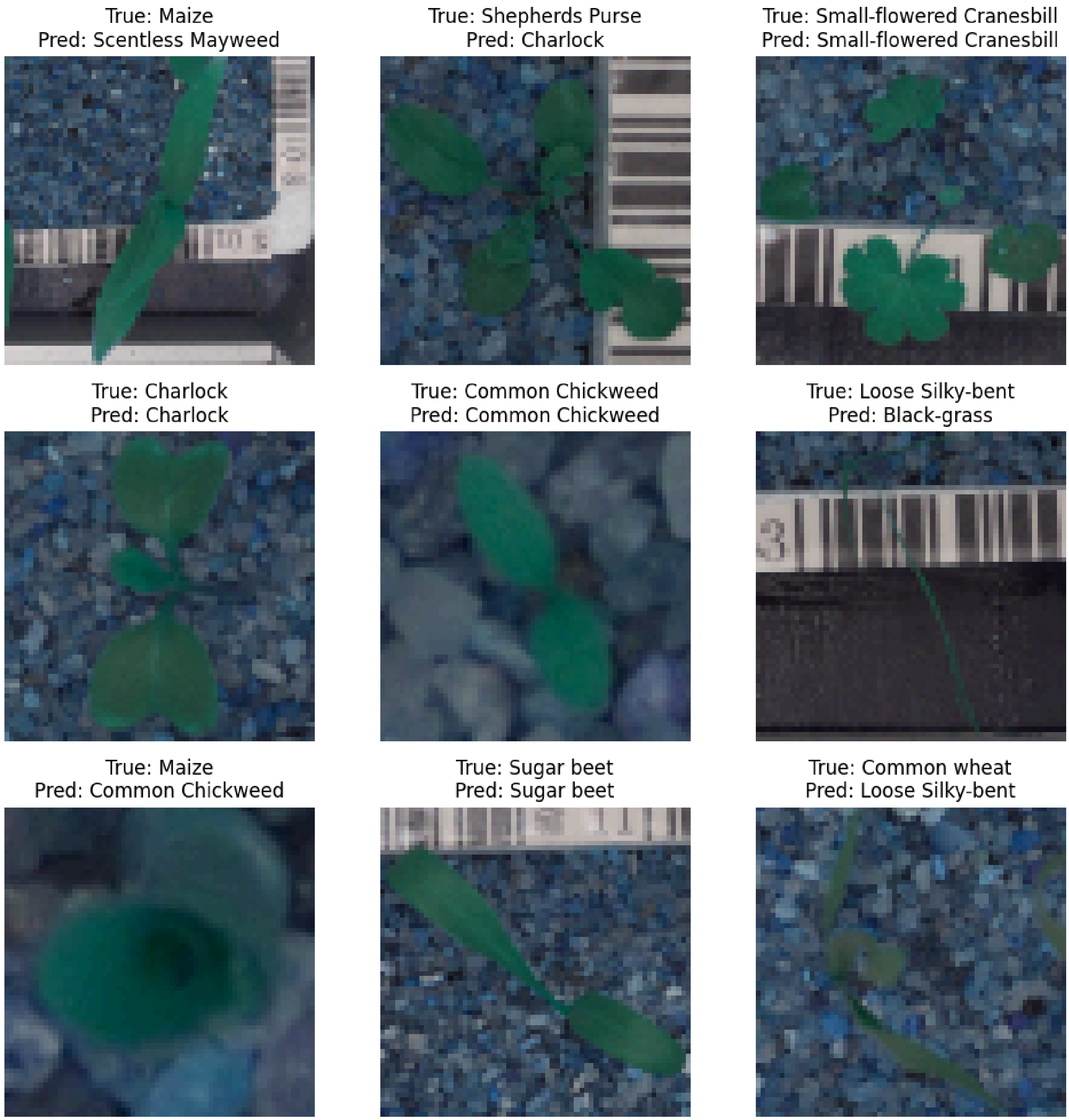



```
# Make predictions on the validation set
y_pred_enhanced = model_2.predict(X_val)
y_pred_classes_enhanced = np.argmax(y_pred_enhanced, axis=1)
y_true_classes_enhanced = np.argmax(y_val, axis=1)

# Generate confusion matrix
conf_matrix_enhanced = confusion_matrix(y_true_classes_enhanced, y_pred_classes_enhanced)

# Plot the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix_enhanced, annot=True, fmt='d', cmap='Blues',
            xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Enhanced Model Confusion Matrix')
plt.show()

# Print classification report
print("Enhanced Model Classification Report:\n",
      classification_report(y_true_classes_enhanced, y_pred_classes_enhanced, target_name
```

```
30/30 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step
```


```
Enhanced Model Classification Report:
                           precision    recall  f1-score   support

              Black-grass       0.26      0.38      0.31        47
                 Charlock       0.35      0.88      0.50        76
                 Cleavers       0.39      0.73      0.51        62
         Common Chickweed       0.68      0.35      0.46       102
             Common wheat       0.18      0.34      0.23        38
                  Fat Hen       0.32      0.07      0.12        94
         Loose Silky-bent       0.57      0.74      0.64       141
                    Maize       0.00      0.00      0.00        42
        Scentless Mayweed       0.25      0.31      0.28       105
          Shepherds Purse       0.75      0.05      0.10        56
Small-flowered Cranesbill       0.83      0.56      0.67       114
               Sugar beet       0.92      0.33      0.48        73

                 accuracy                           0.44       950
                macro avg       0.46      0.40      0.36       950
             weighted avg       0.50      0.44      0.41       950
```

```python
# Plot a few test samples with predicted and true labels
fig, axes = plt.subplots(3, 3, figsize=(10, 10))
axes = axes.flatten()

for i in range(9):
    img = X_val[i]
    true_label = label_encoder.classes_[y_true_classes_enhanced[i]]
    pred_label = label_encoder.classes_[y_pred_classes_enhanced[i]]

    axes[i].imshow(img)
    axes[i].set_title(f"True: {true_label}\nPred: {pred_label}")
    axes[i].axis('off')

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


True: Maize
Pred: Scentless Mayweed
True: Shepherds Purse
Pred: Charlock
True: Small-flowered Cranesbill
Pred: Small-flowered Cranesbill
True: Charlock
Pred: Charlock
True: Common Chickweed
Pred: Common Chickweed
True: Loose Silky-bent
Pred: Black-grass
True: Maize
Pred: Common Chickweed
True: Sugar beet
Pred: Sugar beet
True: Common wheat
Pred: Loose Silky-bent

5. Model 3: Transfer Learning with Pre-trained Models

```
!pip install keras
!pip install keras-tuner
from tensorflow.keras.applications import VGG16, ResNet50
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout, BatchNormaliz
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from keras_tuner import HyperModel, RandomSearch # This import should now work
from tensorflow.keras.regularizers import l2
```

```
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (3.4.1)
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-packages (from
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from ke
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages (from ker
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages (from ke
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages (from ker
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages (from k
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-packages (fro
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (fro
Requirement already satisfied: typing-extensions>=4.5.0 in /usr/local/lib/python3.10/dis
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-packages (fr
Collecting keras-tuner
  Downloading keras_tuner-1.4.7-py3-none-any.whl.metadata (5.4 kB)
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Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.7 kt-legacy-1.0.5
```

```python
class TransferLearningHyperModel(HyperModel):
    def __init__(self, base_model):
        self.base_model = base_model

    def build(self, hp):
        self.base_model.trainable = False

        # Add layers to the base model
        x = self.base_model.output
        x = GlobalAveragePooling2D()(x)

        # Add dense layers with regularization
        for i in range(hp.Int('num_dense_layers', 2, 3)):
            units = hp.Int(f'units_{i}', min_value=64, max_value=256, step=32)
            x = Dense(units, activation='relu', kernel_regularizer=l2(0.001))(x)
            x = BatchNormalization()(x)
            x = Dropout(hp.Float('dropout_rate', 0.3, 0.5))(x)

        # Final output layer
        output = Dense(12, activation='softmax')(x)
        model = Model(inputs=self.base_model.input, outputs=output)

        # Compile model
        learning_rate = hp.Choice('learning_rate', [1e-4, 1e-3, 5e-4])
        model.compile(optimizer=Adam(learning_rate=learning_rate),
                      loss='categorical_crossentropy',
                      metrics=['accuracy'])
        return model

```

```python
# VGG16 Transfer Learning with Tuner
vgg16_base = VGG16(weights='imagenet', include_top=False, input_shape=(64, 64, 3))
vgg16_hypermodel = TransferLearningHyperModel(vgg16_base)

vgg16_tuner = RandomSearch(
    vgg16_hypermodel,
    objective='val_accuracy',
    max_trials=5,
    executions_per_trial=2,
    directory='vgg16_tuner',
    project_name='vgg16_tuning'
)

vgg16_tuner.search(X_train, y_train, epochs=5, validation_data=(X_val, y_val))
best_vgg16_model = vgg16_tuner.get_best_models(num_models=1)[0]

# ResNet50 Transfer Learning with Tuner
resnet50_base = ResNet50(weights='imagenet', include_top=False, input_shape=(64, 64, 3))
```

```
resnet50_hypermodel = TransferLearningHyperModel(resnet50_base)

resnet50_tuner = RandomSearch(
    resnet50_hypermodel,
    objective='val_accuracy',
    max_trials=5,
    executions_per_trial=2,
    directory='resnet50_tuner',
    project_name='resnet50_tuning'
)

resnet50_tuner.search(X_train, y_train, epochs=5, validation_data=(X_val, y_val))
best_resnet50_model = resnet50_tuner.get_best_models(num_models=1)[0]

```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Reloading Tuner from vgg16_tuner/vgg16_tuning/tuner0.json
/usr/local/lib/python3.10/dist-packages/keras/src/saving/saving_lib.py:576: UserWarning:
  saveable.load_own_variables(weights_store.get(inner_path))
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resne
94765736/94765736 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
Reloading Tuner from resnet50_tuner/resnet50_tuning/tuner0.json
```

```
# For the VGG16 transfer learning model
best_vgg16_model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 64, 64, 3)	0
block1_conv1 (Conv2D)	(None, 64, 64, 64)	1,792
block1_conv2 (Conv2D)	(None, 64, 64, 64)	36,928
block1_pool (MaxPooling2D)	(None, 32, 32, 64)	0
block2_conv1 (Conv2D)	(None, 32, 32, 128)	73,856
block2_conv2 (Conv2D)	(None, 32, 32, 128)	147,584
block2_pool (MaxPooling2D)	(None, 16, 16, 128)	0
block3_conv1 (Conv2D)	(None, 16, 16, 256)	295,168
block3_conv2 (Conv2D)	(None, 16, 16, 256)	590,080
block3_conv3 (Conv2D)	(None, 16, 16, 256)	590,080
block3_pool (MaxPooling2D)	(None, 8, 8, 256)	0
block4_conv1 (Conv2D)	(None, 8, 8, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 8, 8, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 8, 8, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 4, 4, 512)	0
block5_conv1 (Conv2D)	(None, 4, 4, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 4, 4, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 4, 4, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 2, 2, 512)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense (Dense)	(None, 256)	131,328
batch_normalization (BatchNormalization)	(None, 256)	1,024
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 256)	65,792
batch_normalization_1 (BatchNormalization)	(None, 256)	1,024

dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 12)	3,084

```
# For the ResNet50 transfer learning model
best_resnet50_model.summary()

```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 64, 64, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 70, 70, 3)	0	input_layer[0][(
conv1_conv (Conv2D)	(None, 32, 32, 64)	9,472	conv1_pad[0][0]
conv1_bn (BatchNormalization)	(None, 32, 32, 64)	256	conv1_conv[0][0
conv1_relu (Activation)	(None, 32, 32, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, 34, 34, 64)	0	conv1_relu[0][0
pool1_pool (MaxPooling2D)	(None, 16, 16, 64)	0	pool1_pad[0][0]
conv2_block1_1_conv (Conv2D)	(None, 16, 16, 64)	4,160	pool1_pool[0][0
conv2_block1_1_bn (BatchNormalization)	(None, 16, 16, 64)	256	conv2_block1_1_c
conv2_block1_1_relu (Activation)	(None, 16, 16, 64)	0	conv2_block1_1_b
conv2_block1_2_conv (Conv2D)	(None, 16, 16, 64)	36,928	conv2_block1_1_r
conv2_block1_2_bn (BatchNormalization)	(None, 16, 16, 64)	256	conv2_block1_2_c
conv2_block1_2_relu (Activation)	(None, 16, 16, 64)	0	conv2_block1_2_b
conv2_block1_0_conv (Conv2D)	(None, 16, 16, 256)	16,640	pool1_pool[0][0
conv2_block1_3_conv (Conv2D)	(None, 16, 16, 256)	16,640	conv2_block1_2_r
conv2_block1_0_bn (BatchNormalization)	(None, 16, 16, 256)	1,024	conv2_block1_0_c
conv2_block1_3_bn (BatchNormalization)	(None, 16, 16, 256)	1,024	conv2_block1_3_c
conv2_block1_add (Add)	(None, 16, 16, 256)	0	conv2_block1_0_b conv2_block1_3_b
conv2_block1_out (Activation)	(None, 16, 16, 256)	0	conv2_block1_ad(
conv2_block2_1_conv (Conv2D)	(None, 16, 16, 64)	16,448	conv2_block1_out

conv2_block2_1_bn (BatchNormalization)	(None, 16, 16, 64)	256	conv2_block2_1_c
conv2_block2_1_relu (Activation)	(None, 16, 16, 64)	0	conv2_block2_1_b
conv2_block2_2_conv (Conv2D)	(None, 16, 16, 64)	36,928	conv2_block2_1_r
conv2_block2_2_bn (BatchNormalization)	(None, 16, 16, 64)	256	conv2_block2_2_c
conv2_block2_2_relu (Activation)	(None, 16, 16, 64)	0	conv2_block2_2_b
conv2_block2_3_conv (Conv2D)	(None, 16, 16, 256)	16,640	conv2_block2_2_r
conv2_block2_3_bn (BatchNormalization)	(None, 16, 16, 256)	1,024	conv2_block2_3_c
conv2_block2_add (Add)	(None, 16, 16, 256)	0	conv2_block1_out conv2_block2_3_b
conv2_block2_out (Activation)	(None, 16, 16, 256)	0	conv2_block2_add
conv2_block3_1_conv (Conv2D)	(None, 16, 16, 64)	16,448	conv2_block2_out
conv2_block3_1_bn (BatchNormalization)	(None, 16, 16, 64)	256	conv2_block3_1_c
conv2_block3_1_relu (Activation)	(None, 16, 16, 64)	0	conv2_block3_1_b
conv2_block3_2_conv (Conv2D)	(None, 16, 16, 64)	36,928	conv2_block3_1_r
conv2_block3_2_bn (BatchNormalization)	(None, 16, 16, 64)	256	conv2_block3_2_c
conv2_block3_2_relu (Activation)	(None, 16, 16, 64)	0	conv2_block3_2_b
conv2_block3_3_conv (Conv2D)	(None, 16, 16, 256)	16,640	conv2_block3_2_r
conv2_block3_3_bn (BatchNormalization)	(None, 16, 16, 256)	1,024	conv2_block3_3_c
conv2_block3_add (Add)	(None, 16, 16, 256)	0	conv2_block2_out conv2_block3_b
conv2_block3_out (Activation)	(None, 16, 16, 256)	0	conv2_block3_add

conv3_block1_1_conv (Conv2D)	(None, 8, 8, 128)	32,896	conv2_block3_out
conv3_block1_1_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block1_1_c
conv3_block1_1_relu (Activation)	(None, 8, 8, 128)	0	conv3_block1_1_b
conv3_block1_2_conv (Conv2D)	(None, 8, 8, 128)	147,584	conv3_block1_1_r
conv3_block1_2_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block1_2_c
conv3_block1_2_relu (Activation)	(None, 8, 8, 128)	0	conv3_block1_2_b
conv3_block1_0_conv (Conv2D)	(None, 8, 8, 512)	131,584	conv2_block3_out
conv3_block1_3_conv (Conv2D)	(None, 8, 8, 512)	66,048	conv3_block1_2_r
conv3_block1_0_bn (BatchNormalization)	(None, 8, 8, 512)	2,048	conv3_block1_0_c
conv3_block1_3_bn (BatchNormalization)	(None, 8, 8, 512)	2,048	conv3_block1_3_c
conv3_block1_add (Add)	(None, 8, 8, 512)	0	conv3_block1_0_b conv3_block1_3_b
conv3_block1_out (Activation)	(None, 8, 8, 512)	0	conv3_block1_add
conv3_block2_1_conv (Conv2D)	(None, 8, 8, 128)	65,664	conv3_block1_out
conv3_block2_1_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block2_1_c
conv3_block2_1_relu (Activation)	(None, 8, 8, 128)	0	conv3_block2_1_b
conv3_block2_2_conv (Conv2D)	(None, 8, 8, 128)	147,584	conv3_block2_1_r
conv3_block2_2_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block2_2_c
conv3_block2_2_relu (Activation)	(None, 8, 8, 128)	0	conv3_block2_2_b
conv3_block2_3_conv (Conv2D)	(None, 8, 8, 512)	66,048	conv3_block2_2_r
conv3_block2_3_bn	(None, 8, 8, 512)	2,048	conv3_block2_3_c

conv3_block2_3_bn (BatchNormalization)	(None, 8, 8, 512)	2,048	conv3_block2_3_
conv3_block2_add (Add)	(None, 8, 8, 512)	0	conv3_block1_out conv3_block2_3_b
conv3_block2_out (Activation)	(None, 8, 8, 512)	0	conv3_block2_add
conv3_block3_1_conv (Conv2D)	(None, 8, 8, 128)	65,664	conv3_block2_out
conv3_block3_1_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block3_1_c
conv3_block3_1_relu (Activation)	(None, 8, 8, 128)	0	conv3_block3_1_b
conv3_block3_2_conv (Conv2D)	(None, 8, 8, 128)	147,584	conv3_block3_1_r
conv3_block3_2_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block3_2_c
conv3_block3_2_relu (Activation)	(None, 8, 8, 128)	0	conv3_block3_2_b
conv3_block3_3_conv (Conv2D)	(None, 8, 8, 512)	66,048	conv3_block3_2_r
conv3_block3_3_bn (BatchNormalization)	(None, 8, 8, 512)	2,048	conv3_block3_3_c
conv3_block3_add (Add)	(None, 8, 8, 512)	0	conv3_block2_out conv3_block3_3_b
conv3_block3_out (Activation)	(None, 8, 8, 512)	0	conv3_block3_add
conv3_block4_1_conv (Conv2D)	(None, 8, 8, 128)	65,664	conv3_block3_out
conv3_block4_1_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block4_1_c
conv3_block4_1_relu (Activation)	(None, 8, 8, 128)	0	conv3_block4_1_b
conv3_block4_2_conv (Conv2D)	(None, 8, 8, 128)	147,584	conv3_block4_1_r
conv3_block4_2_bn (BatchNormalization)	(None, 8, 8, 128)	512	conv3_block4_2_c
conv3_block4_2_relu (Activation)	(None, 8, 8, 128)	0	conv3_block4_2_b
conv3_block4_3_conv (Conv2D)	(None, 8, 8, 512)	66,048	conv3_block4_2_r

(Conv2D)			
conv3_block4_3_bn (BatchNormalization)	(None, 8, 8, 512)	2,048	conv3_block4_3_c
conv3_block4_add (Add)	(None, 8, 8, 512)	0	conv3_block3_out conv3_block4_3_b
conv3_block4_out (Activation)	(None, 8, 8, 512)	0	conv3_block4_add
conv4_block1_1_conv (Conv2D)	(None, 4, 4, 256)	131,328	conv3_block4_out
conv4_block1_1_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block1_1_c
conv4_block1_1_relu (Activation)	(None, 4, 4, 256)	0	conv4_block1_1_b
conv4_block1_2_conv (Conv2D)	(None, 4, 4, 256)	590,080	conv4_block1_1_r
conv4_block1_2_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block1_2_c
conv4_block1_2_relu (Activation)	(None, 4, 4, 256)	0	conv4_block1_2_b
conv4_block1_0_conv (Conv2D)	(None, 4, 4, 1024)	525,312	conv3_block4_out
conv4_block1_3_conv (Conv2D)	(None, 4, 4, 1024)	263,168	conv4_block1_2_r
conv4_block1_0_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block1_0_c
conv4_block1_3_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block1_3_c
conv4_block1_add (Add)	(None, 4, 4, 1024)	0	conv4_block1_0_b conv4_block1_3_b
conv4_block1_out (Activation)	(None, 4, 4, 1024)	0	conv4_block1_add
conv4_block2_1_conv (Conv2D)	(None, 4, 4, 256)	262,400	conv4_block1_out
conv4_block2_1_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block2_1_c
conv4_block2_1_relu (Activation)	(None, 4, 4, 256)	0	conv4_block2_1_b
conv4_block2_2_conv (Conv2D)	(None, 4, 4, 256)	590,080	conv4_block2_1_r

conv4_block2_2_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block2_2_c
conv4_block2_2_relu (Activation)	(None, 4, 4, 256)	0	conv4_block2_2_b
conv4_block2_3_conv (Conv2D)	(None, 4, 4, 1024)	263,168	conv4_block2_2_r
conv4_block2_3_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block2_3_c
conv4_block2_add (Add)	(None, 4, 4, 1024)	0	conv4_block1_out conv4_block2_3_b
conv4_block2_out (Activation)	(None, 4, 4, 1024)	0	conv4_block2_add
conv4_block3_1_conv (Conv2D)	(None, 4, 4, 256)	262,400	conv4_block2_out
conv4_block3_1_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block3_1_c
conv4_block3_1_relu (Activation)	(None, 4, 4, 256)	0	conv4_block3_1_b
conv4_block3_2_conv (Conv2D)	(None, 4, 4, 256)	590,080	conv4_block3_1_r
conv4_block3_2_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block3_2_c
conv4_block3_2_relu (Activation)	(None, 4, 4, 256)	0	conv4_block3_2_b
conv4_block3_3_conv (Conv2D)	(None, 4, 4, 1024)	263,168	conv4_block3_2_r
conv4_block3_3_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block3_3_c
conv4_block3_add (Add)	(None, 4, 4, 1024)	0	conv4_block2_out conv4_block3_3_b
conv4_block3_out (Activation)	(None, 4, 4, 1024)	0	conv4_block3_add
conv4_block4_1_conv (Conv2D)	(None, 4, 4, 256)	262,400	conv4_block3_out
conv4_block4_1_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block4_1_c
conv4_block4_1_relu (Activation)	(None, 4, 4, 256)	0	conv4_block4_1_b

conv4_block4_2_conv (Conv2D)	(None, 4, 4, 256)	590,080	conv4_block4_1_r
conv4_block4_2_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block4_2_c
conv4_block4_2_relu (Activation)	(None, 4, 4, 256)	0	conv4_block4_2_b
conv4_block4_3_conv (Conv2D)	(None, 4, 4, 1024)	263,168	conv4_block4_2_r
conv4_block4_3_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block4_3_c
conv4_block4_add (Add)	(None, 4, 4, 1024)	0	conv4_block3_out conv4_block4_3_b
conv4_block4_out (Activation)	(None, 4, 4, 1024)	0	conv4_block4_ad
conv4_block5_1_conv (Conv2D)	(None, 4, 4, 256)	262,400	conv4_block4_out
conv4_block5_1_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block5_1_c
conv4_block5_1_relu (Activation)	(None, 4, 4, 256)	0	conv4_block5_1_b
conv4_block5_2_conv (Conv2D)	(None, 4, 4, 256)	590,080	conv4_block5_1_r
conv4_block5_2_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block5_2_c
conv4_block5_2_relu (Activation)	(None, 4, 4, 256)	0	conv4_block5_2_b
conv4_block5_3_conv (Conv2D)	(None, 4, 4, 1024)	263,168	conv4_block5_2_r
conv4_block5_3_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block5_3_c
conv4_block5_add (Add)	(None, 4, 4, 1024)	0	conv4_block4_out conv4_block5_3_b
conv4_block5_out (Activation)	(None, 4, 4, 1024)	0	conv4_block5_ad
conv4_block6_1_conv (Conv2D)	(None, 4, 4, 256)	262,400	conv4_block5_out
conv4_block6_1_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block6_1_c
conv4_block6_1_relu	(None, 4, 4, 256)	0	conv4_block6_1_b

conv4_block6_1_relu (Activation)	(None, 4, 4, 256)	0	conv4_block6_1_b
conv4_block6_2_conv (Conv2D)	(None, 4, 4, 256)	590,080	conv4_block6_1_r
conv4_block6_2_bn (BatchNormalization)	(None, 4, 4, 256)	1,024	conv4_block6_2_c
conv4_block6_2_relu (Activation)	(None, 4, 4, 256)	0	conv4_block6_2_b
conv4_block6_3_conv (Conv2D)	(None, 4, 4, 1024)	263,168	conv4_block6_2_r
conv4_block6_3_bn (BatchNormalization)	(None, 4, 4, 1024)	4,096	conv4_block6_3_c
conv4_block6_add (Add)	(None, 4, 4, 1024)	0	conv4_block5_out conv4_block6_3_b
conv4_block6_out (Activation)	(None, 4, 4, 1024)	0	conv4_block6_add
conv5_block1_1_conv (Conv2D)	(None, 2, 2, 512)	524,800	conv4_block6_out
conv5_block1_1_bn (BatchNormalization)	(None, 2, 2, 512)	2,048	conv5_block1_1_c
conv5_block1_1_relu (Activation)	(None, 2, 2, 512)	0	conv5_block1_1_b
conv5_block1_2_conv (Conv2D)	(None, 2, 2, 512)	2,359,808	conv5_block1_1_r
conv5_block1_2_bn (BatchNormalization)	(None, 2, 2, 512)	2,048	conv5_block1_2_c
conv5_block1_2_relu (Activation)	(None, 2, 2, 512)	0	conv5_block1_2_b
conv5_block1_0_conv (Conv2D)	(None, 2, 2, 2048)	2,099,200	conv4_block6_out
conv5_block1_3_conv (Conv2D)	(None, 2, 2, 2048)	1,050,624	conv5_block1_2_r
conv5_block1_0_bn (BatchNormalization)	(None, 2, 2, 2048)	8,192	conv5_block1_0_c
conv5_block1_3_bn (BatchNormalization)	(None, 2, 2, 2048)	8,192	conv5_block1_3_c
conv5_block1_add (Add)	(None, 2, 2, 2048)	0	conv5_block1_0_b conv5_block1_3_b
conv5_block1_out	(None, 2, 2, 2048)	0	conv5_block1_add

(Activation)			
conv5_block2_1_conv (Conv2D)	(None, 2, 2, 512)	1,049,088	conv5_block1_out
conv5_block2_1_bn (BatchNormalization)	(None, 2, 2, 512)	2,048	conv5_block2_1_c
conv5_block2_1_relu (Activation)	(None, 2, 2, 512)	0	conv5_block2_1_b
conv5_block2_2_conv (Conv2D)	(None, 2, 2, 512)	2,359,808	conv5_block2_1_r
conv5_block2_2_bn (BatchNormalization)	(None, 2, 2, 512)	2,048	conv5_block2_2_c
conv5_block2_2_relu (Activation)	(None, 2, 2, 512)	0	conv5_block2_2_b
conv5_block2_3_conv (Conv2D)	(None, 2, 2, 2048)	1,050,624	conv5_block2_2_r
conv5_block2_3_bn (BatchNormalization)	(None, 2, 2, 2048)	8,192	conv5_block2_3_c
conv5_block2_add (Add)	(None, 2, 2, 2048)	0	conv5_block1_out conv5_block2_3_b
conv5_block2_out (Activation)	(None, 2, 2, 2048)	0	conv5_block2_add
conv5_block3_1_conv (Conv2D)	(None, 2, 2, 512)	1,049,088	conv5_block2_out
conv5_block3_1_bn (BatchNormalization)	(None, 2, 2, 512)	2,048	conv5_block3_1_c
conv5_block3_1_relu (Activation)	(None, 2, 2, 512)	0	conv5_block3_1_b
conv5_block3_2_conv (Conv2D)	(None, 2, 2, 512)	2,359,808	conv5_block3_1_r
conv5_block3_2_bn (BatchNormalization)	(None, 2, 2, 512)	2,048	conv5_block3_2_c
conv5_block3_2_relu (Activation)	(None, 2, 2, 512)	0	conv5_block3_2_b
conv5_block3_3_conv (Conv2D)	(None, 2, 2, 2048)	1,050,624	conv5_block3_2_r

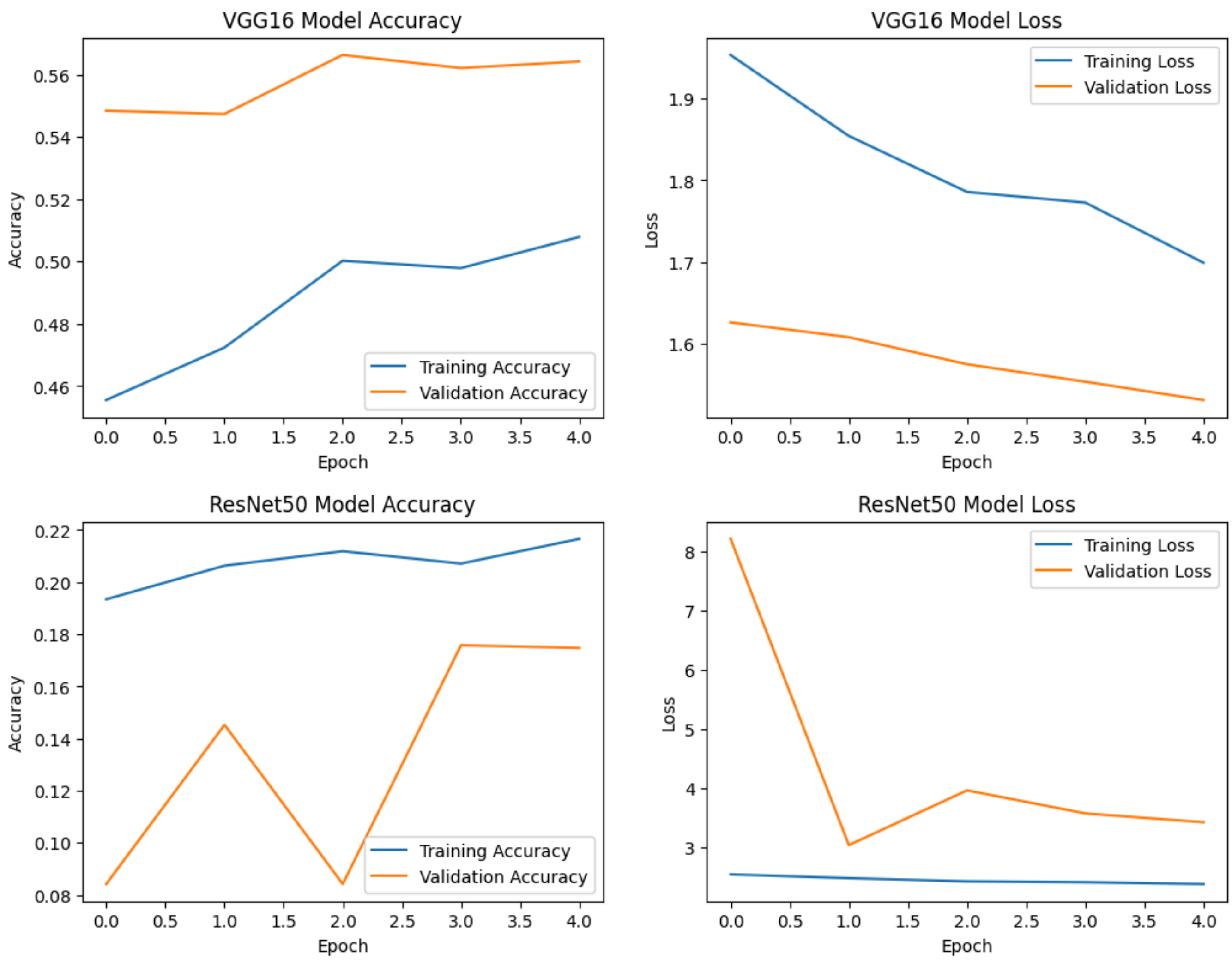
```
with open('model_summary.txt', 'w') as f:
    best_vgg16_model.summary(print_fn=lambda x: f.write(x + '\n'))

```

```
# Train the best VGG16 model
history_vgg16 = best_vgg16_model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    validation_data=(X_val, y_val),
    epochs=5,
    callbacks=[early_stopping]
)

# Train the best ResNet50 model
history_resnet50 = best_resnet50_model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    validation_data=(X_val, y_val),
    epochs=5,
    callbacks=[early_stopping]
)

```

```
Epoch 1/5
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adap
  self._warn_if_super_not_called()
119/119 ━━━━━━━━━━━━━━━━━━━━ 33s 183ms/step - accuracy: 0.4654 - loss: 1.9510 - val_accu
Epoch 2/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 18s 51ms/step - accuracy: 0.4613 - loss: 1.8782 - val_accur
Epoch 3/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 8s 66ms/step - accuracy: 0.5049 - loss: 1.7891 - val_accura
Epoch 4/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 9s 52ms/step - accuracy: 0.4990 - loss: 1.7889 - val_accura
Epoch 5/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 8s 65ms/step - accuracy: 0.4981 - loss: 1.7152 - val_accura
Epoch 1/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 35s 172ms/step - accuracy: 0.1882 - loss: 2.5381 - val_accu
Epoch 2/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 8s 66ms/step - accuracy: 0.2030 - loss: 2.4945 - val_accura
Epoch 3/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.2178 - loss: 2.4226 - val_accur
Epoch 4/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 9s 53ms/step - accuracy: 0.2065 - loss: 2.4228 - val_accura
Epoch 5/5
119/119 ━━━━━━━━━━━━━━━━━━━━ 10s 53ms/step - accuracy: 0.2145 - loss: 2.3693 - val_accur
```

```
# Plot accuracy and loss curves for both models
def plot_history(history, model_name):
    plt.figure(figsize=(12, 4))

```

```
    # Accuracy plot
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.title(f'{model_name} Model Accuracy')

    # Loss plot
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Training Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.title(f'{model_name} Model Loss')

    plt.show()

plot_history(history_vgg16, "VGG16")
plot_history(history_resnet50, "ResNet50")
```

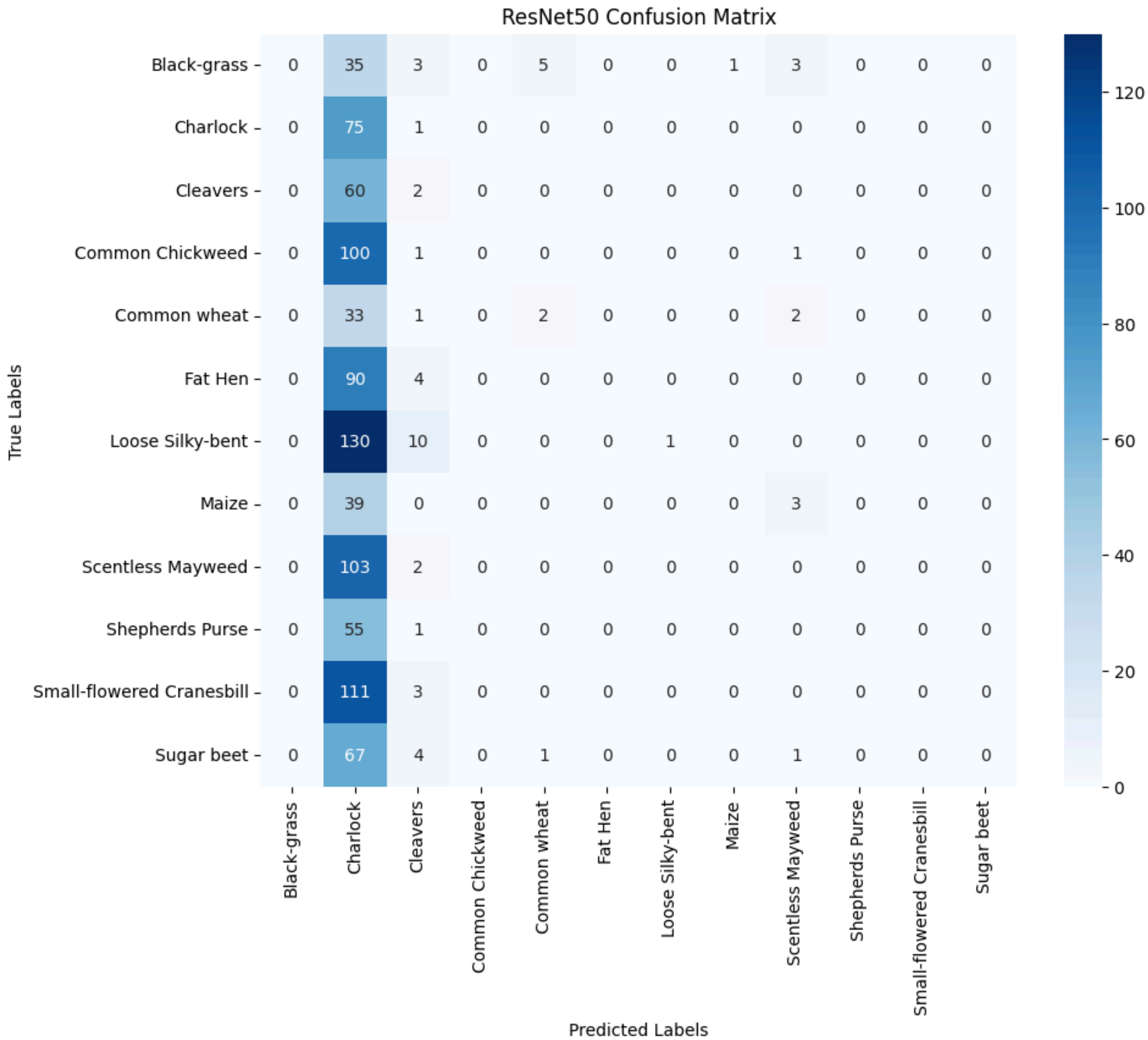



```
from sklearn.metrics import confusion_matrix, classification_report

def evaluate_model(model, X_val, y_val, model_name):
    # Make predictions
    y_pred = model.predict(X_val)
    y_pred_classes = np.argmax(y_pred, axis=1)
    y_true_classes = np.argmax(y_val, axis=1)

```

```
    # Generate confusion matrix
    conf_matrix = confusion_matrix(y_true_classes, y_pred_classes)

    # Plot confusion matrix
    plt.figure(figsize=(10, 8))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
                xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title(f'{model_name} Confusion Matrix')
    plt.show()

    # Print classification report
    print(f"{model_name} Classification Report:\n",
          classification_report(y_true_classes, y_pred_classes, target_names=label_encode

# Evaluate both models
evaluate_model(best_vgg16_model, X_val, y_val, "VGG16")
evaluate_model(best_resnet50_model, X_val, y_val, "ResNet50") # Use the tuned ResNet50 mo
```

```
30/30 ━━━━━━━━━━━━━━━━━━━━ 1s 30ms/step
```


```
VGG16 Classification Report:
                           precision    recall  f1-score   support

              Black-grass       0.32      0.38      0.35        47
                 Charlock       0.43      0.80      0.56        76
                 Cleavers       0.53      0.68      0.60        62
         Common Chickweed       0.65      0.62      0.63       102
             Common wheat       0.65      0.34      0.45        38
                  Fat Hen       0.52      0.45      0.48        94
         Loose Silky-bent       0.68      0.74      0.71       141
                    Maize       0.95      0.43      0.59        42
        Scentless Mayweed       0.59      0.47      0.52       105
           Shepherds Purse       0.53      0.16      0.25        56
Small-flowered Cranesbill       0.73      0.61      0.66       114
               Sugar beet       0.44      0.66      0.53        73

                 accuracy                           0.56       950
                macro avg       0.58      0.53      0.53       950
             weighted avg       0.59      0.56      0.56       950

30/30 ━━━━━━━━━━━━━━━━━━━━ 7s 118ms/step
```




```
ResNet50 Classification Report:
                           precision    recall  f1-score   support

              Black-grass       0.00      0.00      0.00        47
                 Charlock       0.08      0.99      0.15        76
                 Cleavers       0.06      0.03      0.04        62
         Common Chickweed       0.00      0.00      0.00       102
             Common wheat       0.25      0.05      0.09        38
                  Fat Hen       0.00      0.00      0.00        94
         Loose Silky-bent       1.00      0.01      0.01       141
                    Maize       0.00      0.00      0.00        42
        Scentless Mayweed       0.00      0.00      0.00       105
          Shepherds Purse       0.00      0.00      0.00        56
Small-flowered Cranesbill       0.00      0.00      0.00       114
               Sugar beet       0.00      0.00      0.00        73

                 accuracy                           0.08       950
                macro avg       0.12      0.09      0.02       950
             weighted avg       0.17      0.08      0.02       950

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: Unde
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```