

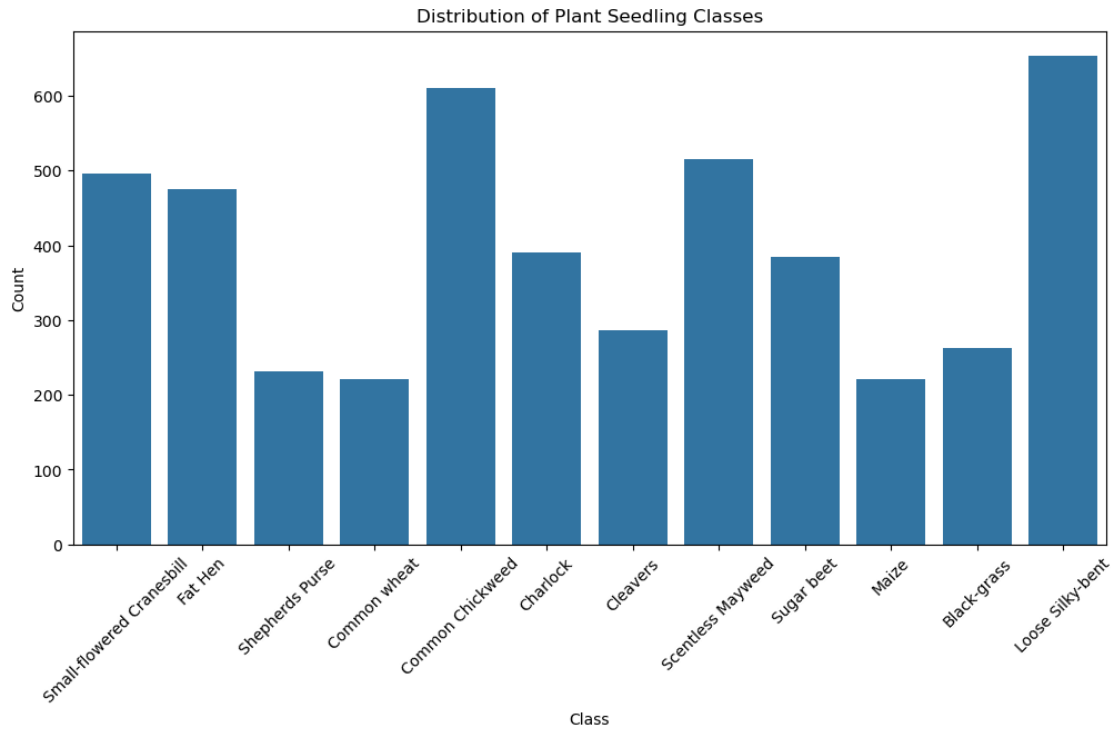
plant_seedling_classification

June 19, 2025

```
[1]: # Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import confusion_matrix, classification_report
import tensorflow as tf
```

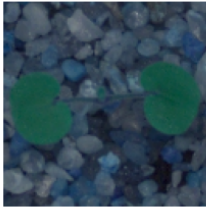
```
[2]: # Load data
images = np.load("images.npy")
labels = pd.read_csv("labels.csv")
class_names = labels['Label'].unique()
```

```
[3]: # Visualize class distribution
plt.figure(figsize=(12, 6))
sns.countplot(x=labels['Label'], order=class_names)
plt.title('Distribution of Plant Seedling Classes')
plt.xlabel('Class')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.savefig('class_distribution.png')
plt.show()
```



```
[4]: # Visualize sample images (all 12 classes)
plt.figure(figsize=(16, 12))
for i, label in enumerate(class_names):
    idx = labels[labels['Label'] == label].index[0]
    plt.subplot(4, 3, i+1)
    plt.imshow(images[idx])
    plt.title(label)
    plt.axis('off')
plt.savefig('sample_images.png')
plt.show()
```

Small-flowered Cranesbill



Fat Hen



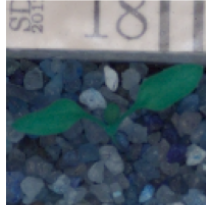
Shepherds Purse



Common wheat



Common Chickweed



Charlock



Cleavers



Scentless Mayweed



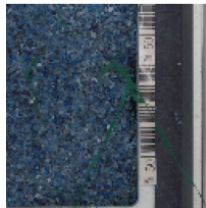
Sugar beet



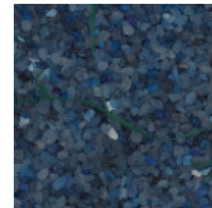
Maize



Black-grass



Loose Silky-bent



```
[5]: # Downsample images to 64x64 and convert to float16
images_resized = tf.image.resize(images, [64, 64]).numpy()
images_resized = images_resized.astype('float16') / 255.0

# Split data
X_train, X_temp, y_train, y_temp = train_test_split(images_resized,
    ↪ labels['Label'], test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5,
    ↪ random_state=42)

# Encode labels
label_encoder = LabelEncoder()
y_train_encoded = to_categorical(label_encoder.fit_transform(y_train))
y_val_encoded = to_categorical(label_encoder.transform(y_val))
y_test_encoded = to_categorical(label_encoder.transform(y_test))
```

```
[6]: # Create tf.data.Dataset
train_dataset = tf.data.Dataset.from_tensor_slices((X_train, y_train_encoded)).
    ↪ batch(32).prefetch(tf.data.AUTOTUNE)
val_dataset = tf.data.Dataset.from_tensor_slices((X_val, y_val_encoded)).
    ↪ batch(32).prefetch(tf.data.AUTOTUNE)
```

```
[7]: # Save datasets
np.save('X_train.npy', X_train)
np.save('y_train_encoded.npy', y_train_encoded)
np.save('X_val.npy', X_val)
np.save('y_val_encoded.npy', y_val_encoded)
np.save('X_test.npy', X_test)
np.save('y_test_encoded.npy', y_test_encoded)
```

```
[8]: # Build and compile model
model = Sequential([
    Input(shape=(64, 64, 3)),
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(12, activation='softmax')
])
model.compile(optimizer='adam', loss='categorical_crossentropy',
    ↪ metrics=['accuracy'])
```

```
[9]: # Generate and save model summary
model.summary()
with open('model_summary.txt', 'w', encoding='utf-8') as f:
    model.summary(print_fn=lambda x: f.write(x + '\n'))
# Take screenshot of model.summary() output from notebook for model_summary.png
```

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, 128)	└
↪ 589,952		
dropout (Dropout)	(None, 128)	└
↪ 0		
dense_1 (Dense)	(None, 12)	└
↪ 1,548		

Total params: 684,748 (2.61 MB)

Trainable params: 684,748 (2.61 MB)

Non-trainable params: 0 (0.00 B)

```
[10]: # Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
    ↪ restore_best_weights=True)

# Train model
history = model.fit(train_dataset,
                    validation_data=val_dataset,
                    epochs=50,
                    callbacks=[early_stopping])
```

Epoch 1/50
104/104 10s 62ms/step -
accuracy: 0.1715 - loss: 2.3981 - val_accuracy: 0.4045 - val_loss: 1.8910

Epoch 2/50
104/104 6s 56ms/step -
accuracy: 0.3416 - loss: 1.8871 - val_accuracy: 0.4607 - val_loss: 1.5709

Epoch 3/50
104/104 6s 57ms/step -
accuracy: 0.4149 - loss: 1.6645 - val_accuracy: 0.5604 - val_loss: 1.2870

Epoch 4/50
104/104 4s 36ms/step -
accuracy: 0.5092 - loss: 1.4077 - val_accuracy: 0.6222 - val_loss: 1.1329

Epoch 5/50
104/104 4s 43ms/step -
accuracy: 0.5647 - loss: 1.2630 - val_accuracy: 0.6728 - val_loss: 0.9734

Epoch 6/50
104/104 5s 43ms/step -
accuracy: 0.5971 - loss: 1.1590 - val_accuracy: 0.6138 - val_loss: 1.0688

Epoch 7/50
104/104 4s 40ms/step -
accuracy: 0.6269 - loss: 1.0837 - val_accuracy: 0.7219 - val_loss: 0.8485

Epoch 8/50
104/104 4s 41ms/step -
accuracy: 0.6734 - loss: 0.9561 - val_accuracy: 0.7121 - val_loss: 0.8630

Epoch 9/50
104/104 4s 40ms/step -
accuracy: 0.6806 - loss: 0.9075 - val_accuracy: 0.7093 - val_loss: 0.8273

Epoch 10/50
104/104 4s 41ms/step -
accuracy: 0.6944 - loss: 0.8575 - val_accuracy: 0.7528 - val_loss: 0.7717

Epoch 11/50
104/104 4s 39ms/step -
accuracy: 0.7197 - loss: 0.7873 - val_accuracy: 0.7683 - val_loss: 0.7025

Epoch 12/50
104/104 4s 41ms/step -
accuracy: 0.7440 - loss: 0.7620 - val_accuracy: 0.7879 - val_loss: 0.6723

Epoch 13/50
104/104 4s 39ms/step -
accuracy: 0.7488 - loss: 0.7090 - val_accuracy: 0.7500 - val_loss: 0.7408

Epoch 14/50
104/104 4s 39ms/step -
accuracy: 0.7327 - loss: 0.7320 - val_accuracy: 0.7725 - val_loss: 0.7177

Epoch 15/50
104/104 4s 41ms/step -
accuracy: 0.7710 - loss: 0.6406 - val_accuracy: 0.8020 - val_loss: 0.6541

Epoch 16/50
104/104 4s 41ms/step -
accuracy: 0.7674 - loss: 0.6492 - val_accuracy: 0.7851 - val_loss: 0.6632

```

Epoch 17/50
104/104          4s 42ms/step -
accuracy: 0.7811 - loss: 0.6002 - val_accuracy: 0.8048 - val_loss: 0.6182
Epoch 18/50
104/104          4s 40ms/step -
accuracy: 0.7922 - loss: 0.5729 - val_accuracy: 0.7879 - val_loss: 0.6368
Epoch 19/50
104/104          4s 41ms/step -
accuracy: 0.7936 - loss: 0.5414 - val_accuracy: 0.7907 - val_loss: 0.6646
Epoch 20/50
104/104          4s 39ms/step -
accuracy: 0.8121 - loss: 0.5264 - val_accuracy: 0.7879 - val_loss: 0.6229
Epoch 21/50
104/104          4s 38ms/step -
accuracy: 0.8036 - loss: 0.5284 - val_accuracy: 0.7992 - val_loss: 0.6287
Epoch 22/50
104/104          4s 38ms/step -
accuracy: 0.8273 - loss: 0.4792 - val_accuracy: 0.7935 - val_loss: 0.6676

```

```

[11]: # Evaluate model
      test_loss, test_accuracy = model.evaluate(X_test, y_test_encoded)
      print(f"Test accuracy: {test_accuracy}")

```

```

23/23          0s 12ms/step -
accuracy: 0.7959 - loss: 0.6575
Test accuracy: 0.7868162989616394

```

```

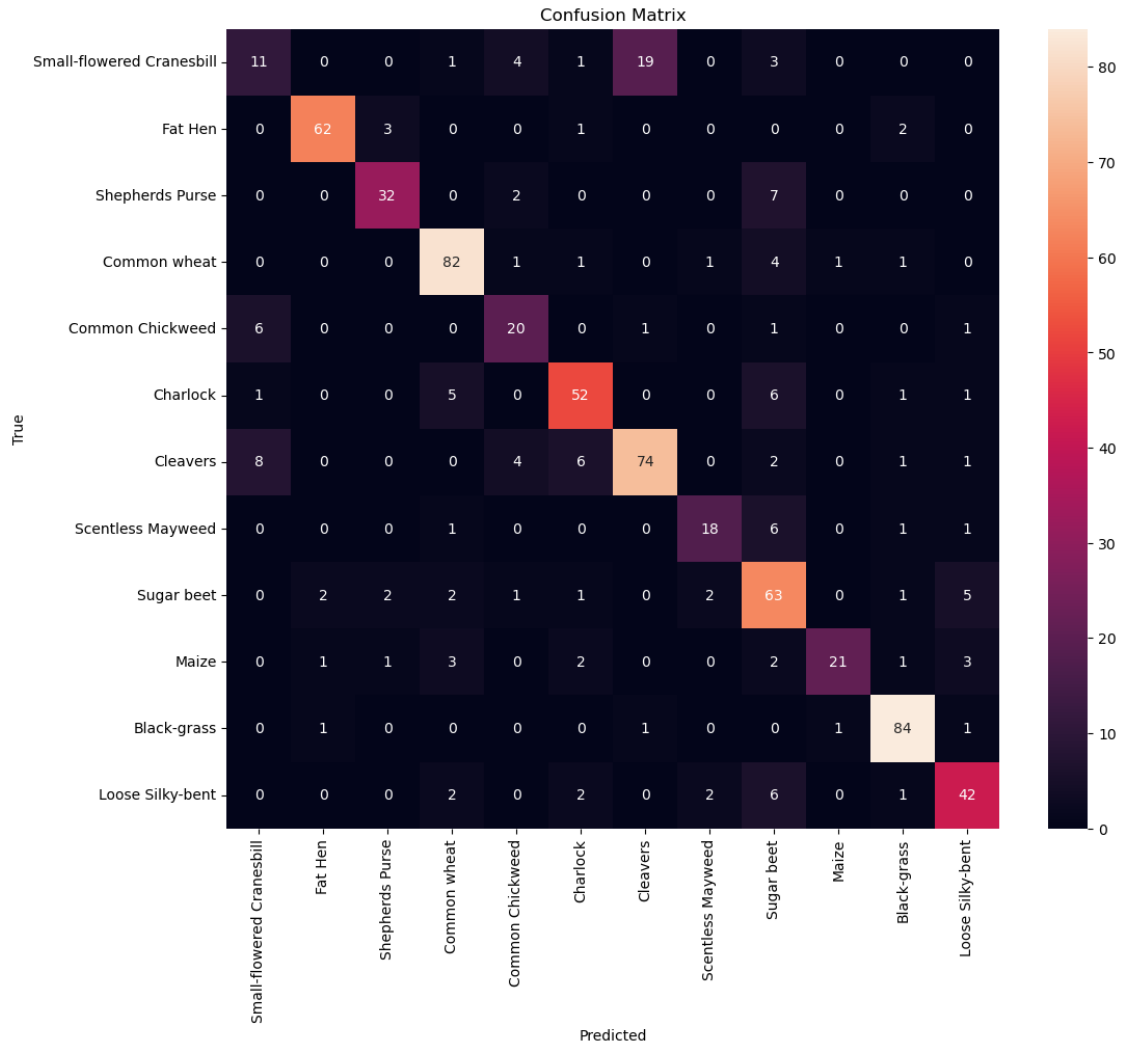
[12]: # Generate and save confusion matrix
      y_pred = model.predict(X_test)
      y_pred_classes = np.argmax(y_pred, axis=1)
      y_true_classes = np.argmax(y_test_encoded, axis=1)
      cm = confusion_matrix(y_true_classes, y_pred_classes)
      plt.figure(figsize=(12, 10))
      sns.heatmap(cm, annot=True, fmt='d', xticklabels=class_names,
                  yticklabels=class_names)
      plt.title('Confusion Matrix')
      plt.xlabel('Predicted')
      plt.ylabel('True')
      plt.savefig('confusion_matrix.png')
      plt.show()

```

```

23/23          0s 13ms/step

```

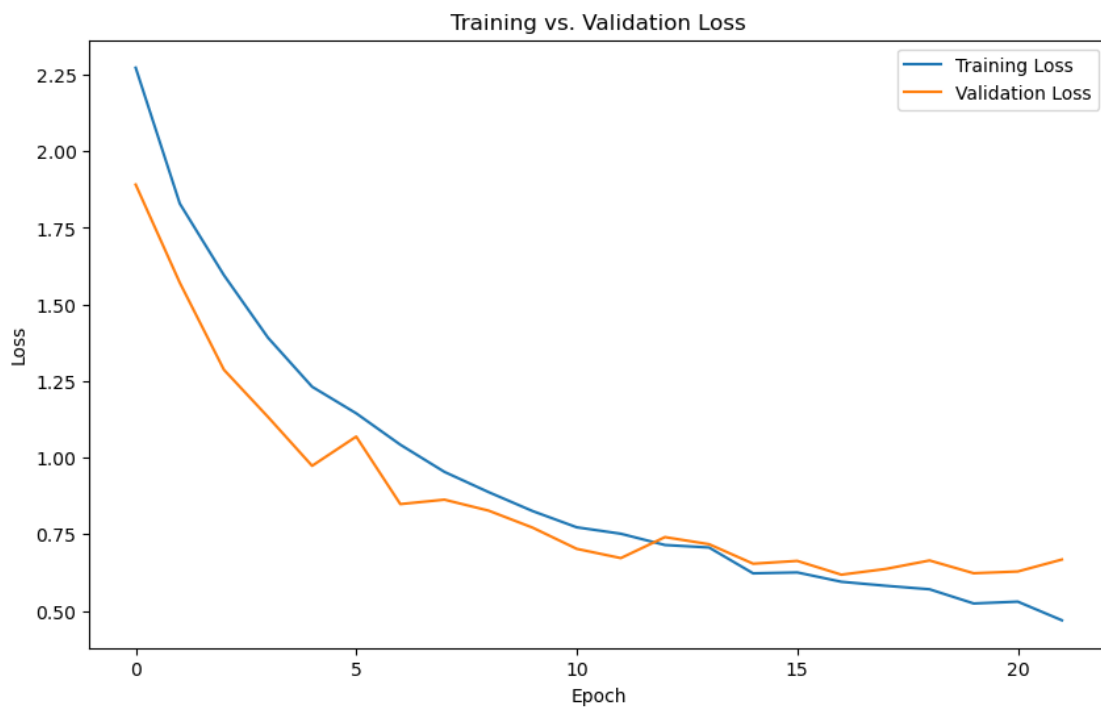


```
[13]: # Generate and save classification report
report = classification_report(y_true_classes, y_pred_classes,
    ↪target_names=class_names)
with open('classification_report.txt', 'w', encoding='utf-8') as f:
    f.write(report)
print(report) # Screenshot this output for classification_report.png
```

	precision	recall	f1-score	support
Small-flowered Cranesbill	0.42	0.28	0.34	39
Fat Hen	0.94	0.91	0.93	68
Shepherds Purse	0.84	0.78	0.81	41
Common wheat	0.85	0.90	0.88	91
Common Chickweed	0.62	0.69	0.66	29
Charlock	0.79	0.79	0.79	66

Cleavers	0.78	0.77	0.77	96
Scentless Mayweed	0.78	0.67	0.72	27
Sugar beet	0.63	0.80	0.70	79
Maize	0.91	0.62	0.74	34
Black-grass	0.90	0.95	0.93	88
Loose Silky-bent	0.76	0.76	0.76	55
accuracy			0.79	713
macro avg	0.77	0.74	0.75	713
weighted avg	0.79	0.79	0.78	713

```
[14]: # Generate and save loss plot
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training vs. Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.savefig('loss_plot.png')
plt.show()
```



```
[15]: # Save model  
model.save('plant_seedling_cnn.keras')
```