```
!pip install torch torchvision matplotlib seaborn scikit-learn kaggle
```

```
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (2.5.1+cu121)
Requirement already satisfied: torchvision in /usr/local/lib/python3.10/dist-packages (0.20.1+cu121)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.8.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.13.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.5.2)
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages (1.6.17)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch) (3.16.1)
Requirement already satisfied: typing-extensions>=4.8.0 in /usr/local/lib/python3.10/dist-packages (from torch) (4.12.2)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch) (3.1.4)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch) (2024.10.0)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.10/dist-packages (from torch) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy==1.13.1->torch) (1.3.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from torchvision) (1.26.4)
Requirement already satisfied: pillow!=8.3.*,>=5.3.0 in /usr/local/lib/python3.10/dist-packages (from torchvision) (11.0.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-packages (from seaborn) (2.2.2)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi>=2023.7.22 in /usr/local/lib/python3.10/dist-packages (from kaggle) (2024.8.30)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from kaggle) (2.32.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from kaggle) (4.66.6)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-packages (from kaggle) (8.0.4)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (from kaggle) (2.2.3)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages (from kaggle) (6.2.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn) (2024.2)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-packages (from bleach->kaggle) (0.5.1)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch) (3.0.2)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.4.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.10)
```

```
# Import necessary libraries
import os
import torch
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from torchvision import models, datasets, transforms
from torch.utils.data import DataLoader, random_split
from sklearn.metrics import classification_report, confusion_matrix
```

```
# Check if GPU is available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")
```

```
Using device: cuda
```

```
# Kaggle API setup for dataset download
!mkdir -p ~/.kaggle
!echo '{"username":"maheralqarra","key":"4552955eece9b6be27da4db74b1430f1"}' > ~/.kaggle/kaggle.json
!chmod 600 ~/.kaggle/kaggle.json
!kaggle datasets download -d vbookshelf/v2-plant-seedlings-dataset -p ./data
```

```
Dataset URL: https://www.kaggle.com/datasets/vbookshelf/v2-plant-seedlings-dataset
License(s): CC-BY-SA-4.0
Downloading v2-plant-seedlings-dataset.zip to ./data
100% 3.18G/3.19G [00:38<00:00, 89.2MB/s]
100% 3.19G/3.19G [00:38<00:00, 89.5MB/s]
```

```
# Unzip the downloaded file
import zipfile
with zipfile.ZipFile('./data/v2-plant-seedlings-dataset.zip', 'r') as zip_ref:
    zip_ref.extractall('./data')
```

```
# Organize the dataset structure
import shutil

dataset_path = './data/plant-seedlings-dataset'
os.makedirs(dataset_path, exist_ok=True)

for folder in os.listdir('./data'):
    folder_path = os.path.join('./data', folder)
    if os.path.isdir(folder_path) and folder not in ['plant-seedlings-dataset']:
        shutil.move(folder_path, dataset_path)
```

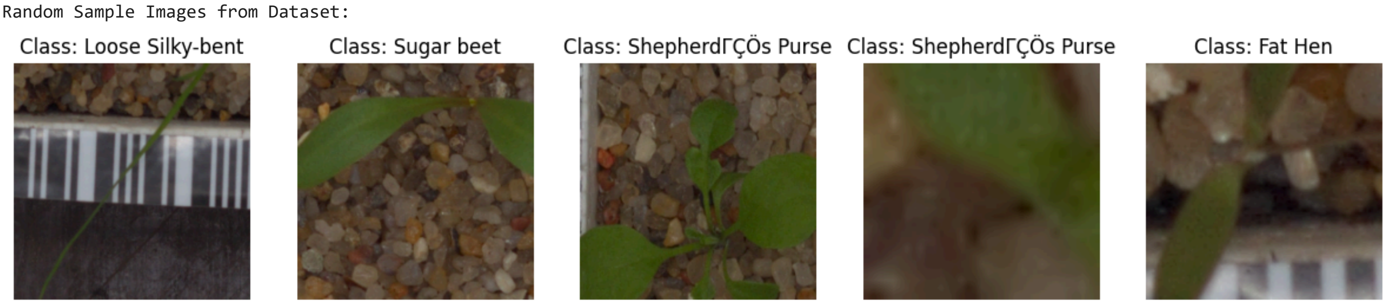
```
# Remove the "nonsegmentedv2" class
def remove_unwanted_class(dataset_path, unwanted_class):
    folder_to_remove = os.path.join(dataset_path, unwanted_class)
    if os.path.exists(folder_to_remove):
        shutil.rmtree(folder_to_remove)

remove_unwanted_class(dataset_path, 'nonsegmentedv2')
```

```
# Data Preprocessing
transform = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor()
])
```

```
# Load the dataset
dataset = datasets.ImageFolder(root=dataset_path, transform=transform)
```

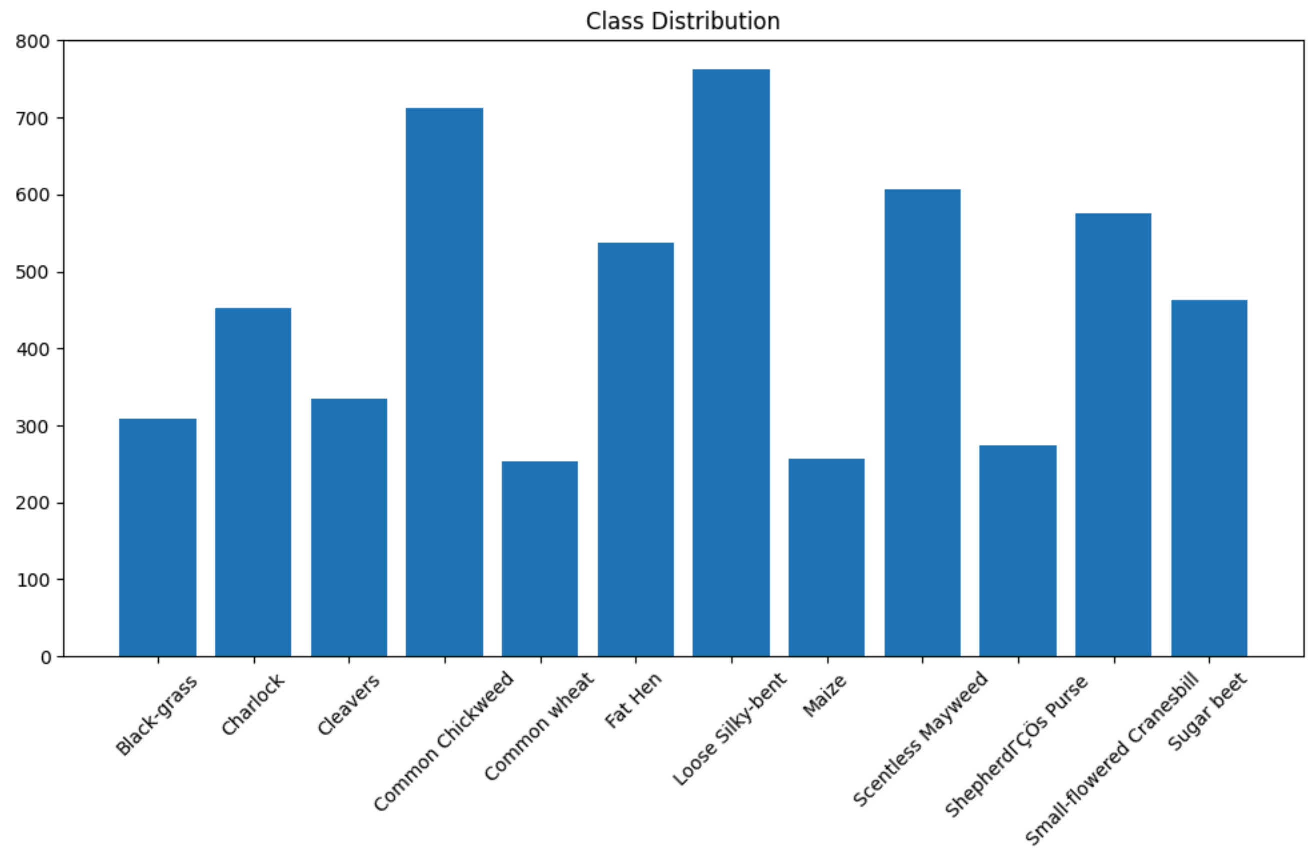
```
# Function to show random images from the dataset
def show_random_images(dataset, num_images=5):
    fig, axes = plt.subplots(1, num_images, figsize=(15, 5))
    for i in range(num_images):
        idx = np.random.randint(0, len(dataset))
        image, label = dataset[idx]
        axes[i].imshow(image.permute(1, 2, 0))
        axes[i].set_title(f"Class: {dataset.classes[label]}")
        axes[i].axis('off')
    plt.show()

print("Random Sample Images from Dataset:")
show_random_images(dataset)
```

```
Random Sample Images from Dataset:
```




```
# Visualize class distribution
from collections import Counter
def visualize_class_distribution(dataset):
    labels = [label for _, label in dataset]
    class_counts = Counter(labels)
    class_names = [dataset.classes[i] for i in class_counts.keys()]
    plt.figure(figsize=(12, 6))
    plt.bar(class_names, class_counts.values())
    plt.xticks(rotation=45)
    plt.title('Class Distribution')
    plt.show()
```

```
    plt.show()

visualize_class_distribution(dataset)
```




```
# Split Dataset
train_size = int(0.7 * len(dataset))
val_size = int(0.2 * len(dataset))
test_size = len(dataset) - train_size - val_size
train_dataset, val_dataset, test_dataset = random_split(dataset, [train_size, val_size, test_size])

batch_size = 32
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)
```

```
# Load Pre-trained ResNet18 Model
model = models.resnet18(pretrained=True)
model.fc = nn.Linear(model.fc.in_features, len(dataset.classes))
model.to(device)
```

```
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

```
# Define Loss, Optimizer, and Scheduler
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.0001)
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.5)
```

```
# Training Function
def train_model(model, train_loader, val_loader, epochs=10):
    train_losses, val_losses, val_accuracies = [], [], []

    for epoch in range(epochs):
        model.train()
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()

        val_loss, val_accuracy = validate_model(model, val_loader)
        train_losses.append(running_loss / len(train_loader))
        val_losses.append(val_loss)
        val_accuracies.append(val_accuracy)
        scheduler.step()

        print(f'Epoch {epoch+1}/{epochs}, Loss: {train_losses[-1]:.4f}, Val Acc: {val_accuracies[-1]:.2f}%')

    plot_metrics(train_losses, val_losses, val_accuracies)
```

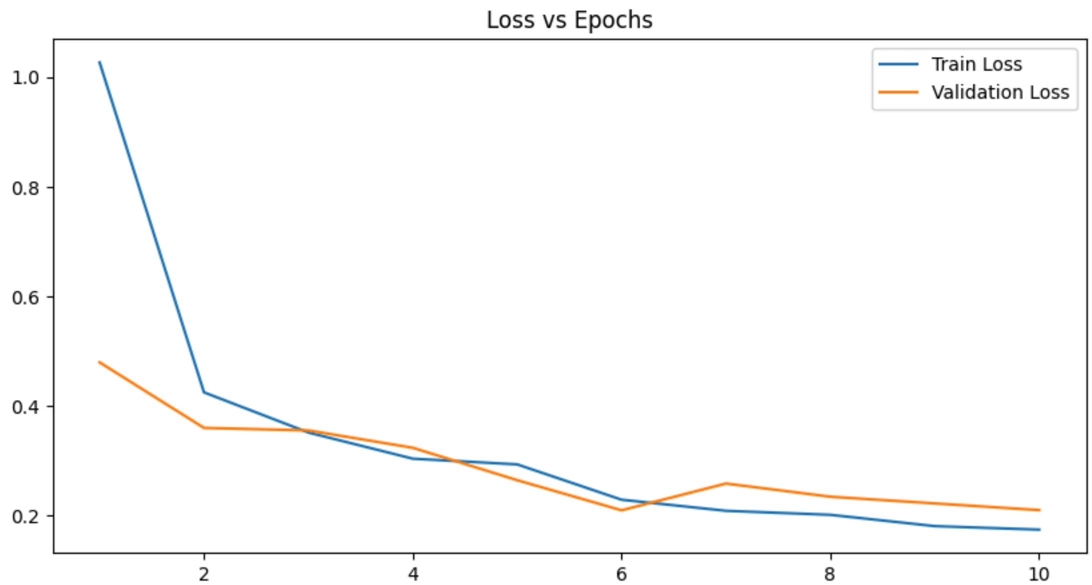
```
# validation Function
def validate_model(model, val_loader):
    model.eval()
    correct, total, val_loss = 0, 0, 0.0
    with torch.no_grad():
        for images, labels in val_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            loss = criterion(outputs, labels)
            val_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
```

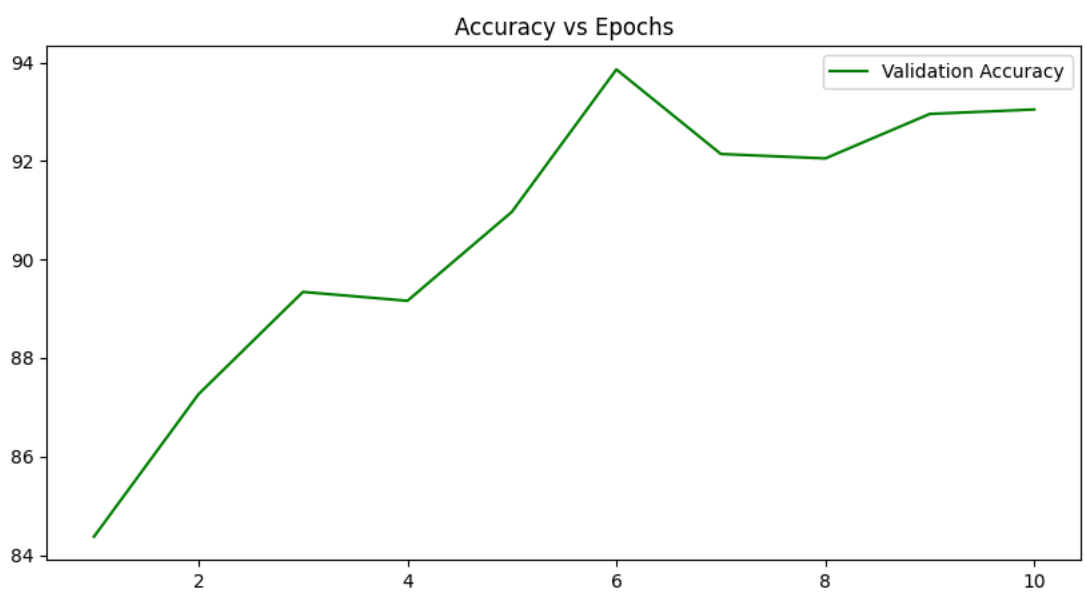
```
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    val_accuracy = 100 * correct / total
    return val_loss / len(val_loader), val_accuracy
```

```
Start coding or generate with AI.
```

```
# Plot metrics Function
def plot_metrics(train_losses, val_losses, val_accuracies):
    epochs = range(1, len(train_losses) + 1)

    # Loss Plot
    plt.figure(figsize=(10, 5))
    plt.plot(epochs, train_losses, label='Train Loss')
    plt.plot(epochs, val_losses, label='Validation Loss')
    plt.title('Loss vs Epochs')
    plt.legend()
    plt.show()

    # Accuracy Plot
    plt.figure(figsize=(10, 5))
    plt.plot(epochs, val_accuracies, label='Validation Accuracy', color='green')
    plt.title('Accuracy vs Epochs')
    plt.legend()
    plt.show()

train_model(model, train_loader, val_loader)
```

```
Epoch 1/10, Loss: 1.0271, Val Acc: 84.37%
Epoch 2/10, Loss: 0.4246, Val Acc: 87.26%
Epoch 3/10, Loss: 0.3512, Val Acc: 89.34%
Epoch 4/10, Loss: 0.3034, Val Acc: 89.16%
Epoch 5/10, Loss: 0.2930, Val Acc: 90.97%
Epoch 6/10, Loss: 0.2285, Val Acc: 93.86%
Epoch 7/10, Loss: 0.2082, Val Acc: 92.14%
Epoch 8/10, Loss: 0.2009, Val Acc: 92.05%
Epoch 9/10, Loss: 0.1802, Val Acc: 92.95%
Epoch 10/10, Loss: 0.1739, Val Acc: 93.04%
```

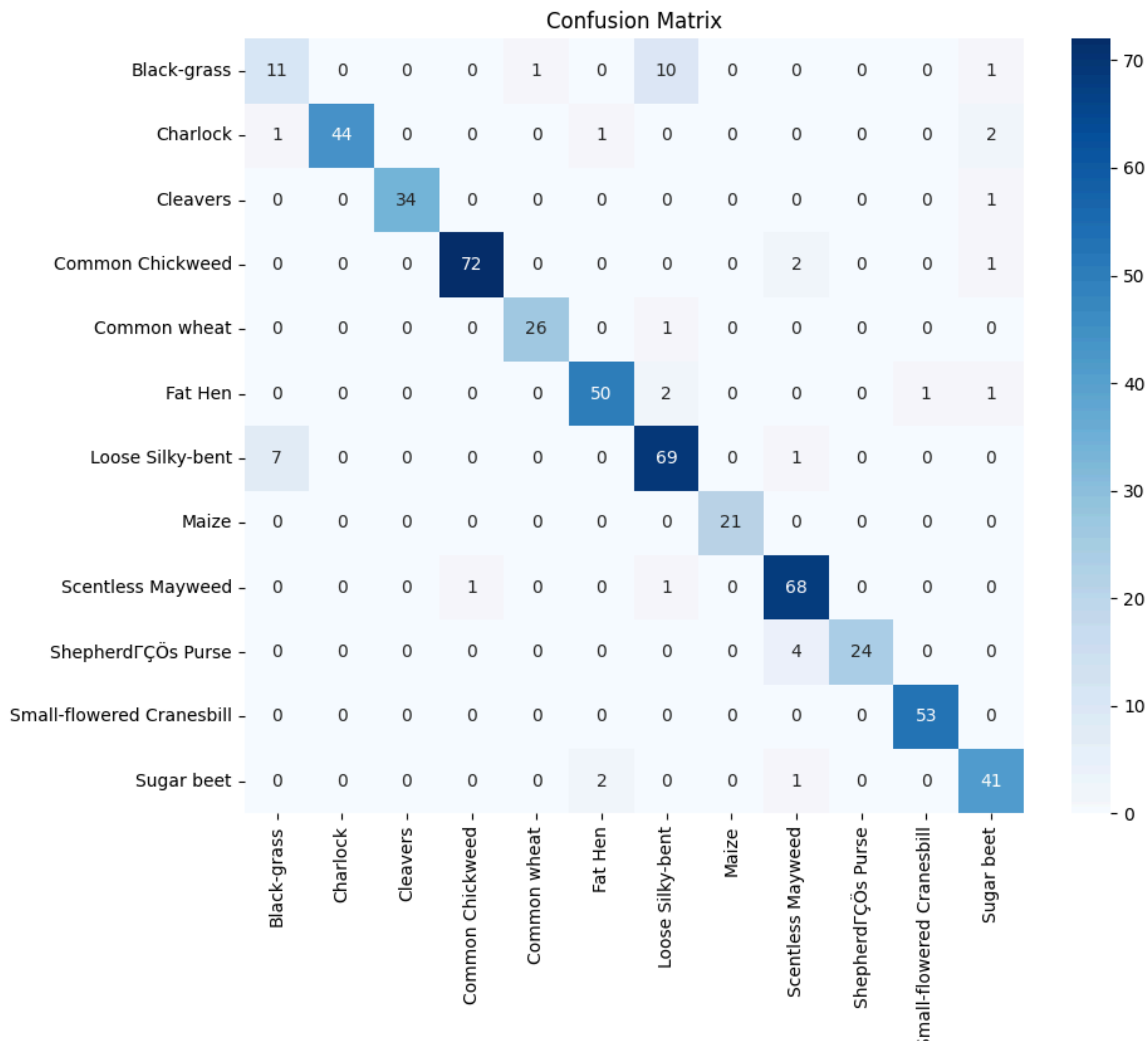





```
# Evaluate the Model
def evaluate_model(model, test_loader):
    model.eval()
    all_preds, all_labels = [], []
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs, 1)
            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    print("Classification Report:")
    print(classification_report(all_labels, all_preds, target_names=dataset.classes))

    # Confusion Matrix
    cm = confusion_matrix(all_labels, all_preds)
    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, cmap='Blues', xticklabels=dataset.classes, yticklabels=dataset.classes)
```

```
    plt.title("Confusion Matrix")
    plt.show()

evaluate_model(model, test_loader)
```

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

              Black-grass       0.58      0.48      0.52        23
                 Charlock       1.00      0.92      0.96        48
                 Cleavers       1.00      0.97      0.99        35
         Common Chickweed       0.99      0.96      0.97        75
             Common wheat       0.96      0.96      0.96        27
                  Fat Hen       0.94      0.93      0.93        54
         Loose Silky-bent       0.83      0.90      0.86        77
                    Maize       1.00      1.00      1.00        21
        Scentless Mayweed       0.89      0.97      0.93        70
          ShepherdΓÇÖs Purse       1.00      0.86      0.92        28
Small-flowered Cranesbill       0.98      1.00      0.99        53
               Sugar beet       0.87      0.93      0.90        44

                 accuracy                           0.92       555
                macro avg       0.92      0.91      0.91       555
             weighted avg       0.92      0.92      0.92       555
```

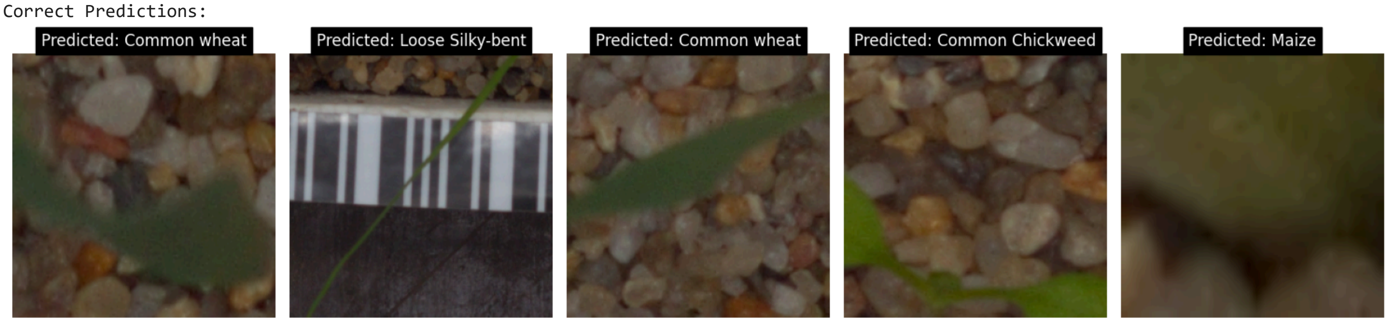



```
# Show image Function
import matplotlib.pyplot as plt

def show_images(images, num_images=5, correct=True):
    """
    Display a list of images with their predicted labels.
    If correct is False, display the true and predicted labels.
```

```
    """
    fig, axes = plt.subplots(1, num_images, figsize=(15, 5))

    for i in range(num_images):
        if i >= len(images):
            break

        if correct:
            image, predicted = images[i]
            label_text = f"Predicted: {dataset.classes[predicted]}"
        else:
            image, predicted, true_label = images[i]
            label_text = (f"Predicted: {dataset.classes[predicted]}\n"
                          f"True: {dataset.classes[true_label]}")

        # Display the image
        axes[i].imshow(image.permute(1, 2, 0).numpy())
        axes[i].set_title(label_text, fontsize=12, color='white', backgroundcolor='black')
        axes[i].axis('off')

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

```
def show_predictions(model, data_loader, num_images=5):
    model.eval()
    correct_images, incorrect_images = [], []

    with torch.no_grad():
        for images, labels in data_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs, 1)
            for i in range(len(labels)):
                if predicted[i] == labels[i]:
                    correct_images.append((images[i].cpu(), predicted[i]))
                else:
                    incorrect_images.append((images[i].cpu(), predicted[i], labels[i]))

    print("\nCorrect Predictions:")
    show_images(correct_images, num_images, correct=True)
    print("\nIncorrect Predictions:")
    show_images(incorrect_images, num_images, correct=False)

# Run the visualization
show_predictions(model, test_loader)
```

```
Correct Predictions:
```




```
Incorrect Predictions:
```