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

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cu12==11.4.5.107->torch) (12.6.85)
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>matplotlib) (1.17.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.11/dist-packages (from jinja2->torch) (3.0.2)
```

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

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

```python
import torch
import torch.nn as nn
import torch.optim as optim
```

```python
from torchvision import datasets, transforms, models
import os
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from torch.optim import lr_scheduler
from torchvision.models import regnet_y_8gf  # Latest RegNet variant

# Define data transformations for data augmentation and normalization
data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ColorJitter(brightness=0.2, contrast=0.2,
saturation=0.2, hue=0.2),
        transforms.RandomRotation(30),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224,
0.225])  # ImageNet mean and std
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224,
0.225])  # ImageNet mean and std
    ]),
}


# Define the data directory
data_dir = '/content/drive/MyDrive/Images'

# Create data loaders
image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x),
data_transforms[x]) for x in ['train', 'test']}
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x],
batch_size=16, shuffle=True, num_workers=4) for x in ['train',
'test']}
dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'test']}
print(dataset_sizes)

class_names = image_datasets['train'].classes
```

```
{'train': 3902, 'test': 977}
```

```
/usr/local/lib/python3.11/dist-packages/torch/utils/data/
dataloader.py:617: UserWarning: This DataLoader will create 4 worker
processes in total. Our suggested max number of worker in current
system is 2, which is smaller than what this DataLoader is going to
```

```
create. Please be aware that excessive worker creation might get
DataLoader running slow or even freeze, lower the worker number to
avoid potential slowness/freeze if necessary.
  warnings.warn(

# Load the pre-trained RegNetY model (you can choose different
variants of RegNet like 400MF, 8GF, etc.)
model = regnet_y_8gf(pretrained=True)

# Efficiently modify the final fully connected layer for 6 classes
model.fc = nn.Linear(model.fc.in_features, 6)

/usr/local/lib/python3.11/dist-packages/torchvision/models/
_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated
since 0.13 and may be removed in the future, please use 'weights'
instead.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:2
23: UserWarning: Arguments other than a weight enum or `None` for
'weights' are deprecated since 0.13 and may be removed in the future.
The current behavior is equivalent to passing
`weights=RegNet_Y_8GF_Weights.IMAGENET1K_V1`. You can also use
`weights=RegNet_Y_8GF_Weights.DEFAULT` to get the most up-to-date
weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/regnet_y_8gf-
d0d0e4a8.pth" to /root/.cache/torch/hub/checkpoints/regnet_y_8gf-
d0d0e4a8.pth
100%|██████████| 151M/151M [00:03<00:00, 49.7MB/s]

# Define the loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)  # Use Adam
optimizer for better convergence

# Learning Rate Scheduler (use cosine annealing for RegNet’s dynamic
scaling)
scheduler = lr_scheduler.CosineAnnealingLR(optimizer, T_max=10)

# Move the model to the GPU if available
device = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")
model = model.to(device)

# Training loop with dynamic scheduler and more efficient processing
num_epochs = 15
best_model_wts = model.state_dict()
best_acc = 0.0
train_losses, test_losses = [], []
train_accs, test_accs = [], []
```

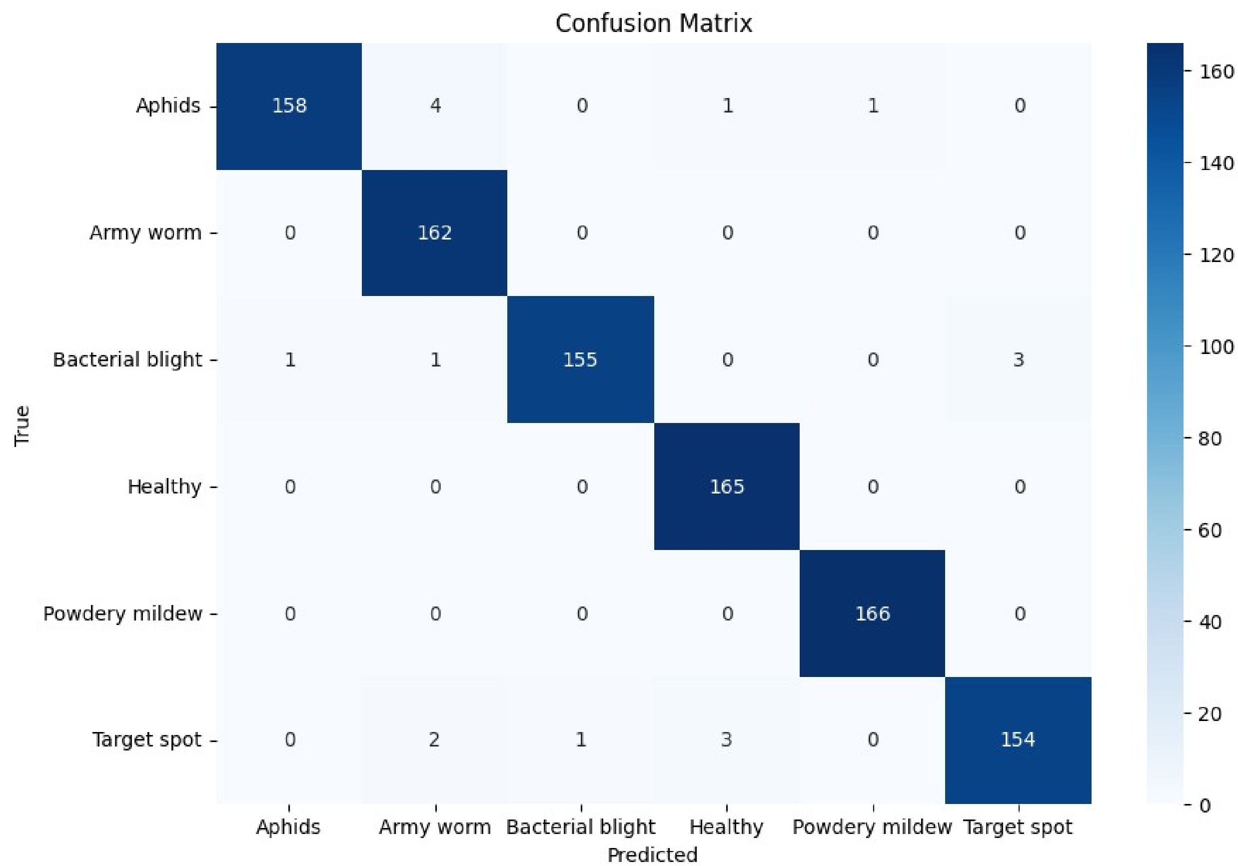
```python
for epoch in range(num_epochs):
    print(f'Epoch {epoch+1}/{num_epochs}')
    print('-' * 10)

    for phase in ['train', 'test']:
        if phase == 'train':
            model.train()
        else:
            model.eval()

        running_loss = 0.0
        running_corrects = 0

        for inputs, labels in dataloaders[phase]:
            inputs = inputs.to(device)
            labels = labels.to(device)

            optimizer.zero_grad()

            with torch.set_grad_enabled(phase == 'train'):
                outputs = model(inputs)
                _, preds = torch.max(outputs, 1)
                loss = criterion(outputs, labels)

                if phase == 'train':
                    loss.backward()
                    optimizer.step()

            running_loss += loss.item() * inputs.size(0)
            running_corrects += torch.sum(preds == labels.data)

        epoch_loss = running_loss / dataset_sizes[phase]
        epoch_acc = running_corrects.double() / dataset_sizes[phase]
        if phase == 'train':
            train_losses.append(epoch_loss)
            train_accs.append(epoch_acc)
        else:
            test_losses.append(epoch_loss)
            test_accs.append(epoch_acc)

        print(f'{phase} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

        # Deep copy the model if it achieves better performance
        if phase == 'test' and epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = model.state_dict()

    scheduler.step()  # Update learning rate using cosine annealing
```

```python
# Load best model weights
model.load_state_dict(best_model_wts)
```

```
Epoch 1/15
----------
train Loss: 0.8761 Acc: 0.6991
test Loss: 0.7128 Acc: 0.7851
Epoch 2/15
----------
train Loss: 0.5385 Acc: 0.8175
test Loss: 0.3064 Acc: 0.8915
Epoch 3/15
----------
train Loss: 0.4485 Acc: 0.8432
test Loss: 0.1877 Acc: 0.9314
Epoch 4/15
----------
train Loss: 0.3551 Acc: 0.8842
test Loss: 0.1486 Acc: 0.9529
Epoch 5/15
----------
train Loss: 0.3039 Acc: 0.8949
test Loss: 0.1022 Acc: 0.9683
Epoch 6/15
----------
train Loss: 0.2500 Acc: 0.9188
test Loss: 0.0527 Acc: 0.9826
Epoch 7/15
----------
train Loss: 0.2000 Acc: 0.9341
test Loss: 0.0382 Acc: 0.9867
Epoch 8/15
----------
train Loss: 0.1709 Acc: 0.9441
test Loss: 0.0461 Acc: 0.9846
Epoch 9/15
----------
train Loss: 0.1333 Acc: 0.9564
test Loss: 0.0397 Acc: 0.9785
Epoch 10/15
----------
train Loss: 0.1092 Acc: 0.9634
test Loss: 0.0342 Acc: 0.9826
Epoch 11/15
----------
train Loss: 0.0915 Acc: 0.9669
test Loss: 0.0376 Acc: 0.9826
Epoch 12/15
----------
train Loss: 0.1070 Acc: 0.9654
```

```
test Loss: 0.0304 Acc: 0.9867
Epoch 13/15
----------
train Loss: 0.1126 Acc: 0.9618
test Loss: 0.0342 Acc: 0.9857
Epoch 14/15
----------
train Loss: 0.1325 Acc: 0.9526
test Loss: 0.0424 Acc: 0.9836
Epoch 15/15
----------
train Loss: 0.1871 Acc: 0.9400
test Loss: 0.0641 Acc: 0.9826

<All keys matched successfully>

# Save the trained model
torch.save(model.state_dict(), 'best_classification_model_regnet.pth')

# Evaluate model performance
def evaluate_model(model, dataloader):
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for inputs, labels in dataloaders['test']:  # Using test set
for evaluation
            inputs = inputs.to(device)
            labels = labels.to(device)
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    cm = confusion_matrix(all_labels, all_preds)
    cr = classification_report(all_labels, all_preds,
target_names=class_names)
    return cm, cr

# Get confusion matrix and classification report
cm, cr = evaluate_model(model, dataloaders['test'])
print("Classification Report:\n", cr)

Classification Report:
                   precision    recall  f1-score   support

          Aphids       0.99      0.96      0.98       164
       Army worm       0.96      1.00      0.98       162
Bacterial blight       0.99      0.97      0.98       160
         Healthy       0.98      1.00      0.99       165
```

```
Powdery mildew       0.99      1.00      1.00       166
   Target spot       0.98      0.96      0.97       160

      accuracy                           0.98       977
     macro avg       0.98      0.98      0.98       977
  weighted avg       0.98      0.98      0.98       977


# Visualize Confusion Matrix
plt.figure(figsize=(10, 7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=class_names, yticklabels=class_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```




```
from PIL import Image
# Example image prediction with probabilities
image_path = '/content/target.jpeg'  # Replace with your test image
path
image = Image.open(image_path)
preprocess = transforms.Compose([
```

```python
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])
input_tensor = preprocess(image)
input_batch = input_tensor.unsqueeze(0).to(device)

# Perform inference
model.eval()
with torch.no_grad():
    output = model(input_batch)
    probabilities = torch.nn.functional.softmax(output, dim=1)
    confidence, predicted_class = torch.max(probabilities, 1)

# Get predicted class and probability
predicted_class_name = class_names[predicted_class.item()]
predicted_prob = probabilities[0][predicted_class].item()

print(f'The predicted class is: {predicted_class_name} with a
confidence of {predicted_prob:.4f}')

# Show the image with prediction
plt.imshow(np.array(image))
plt.axis('off')
plt.text(10, 10, f'Predicted: {predicted_class_name}
({predicted_prob*100:.2f}%)', fontsize=12, color='white',
backgroundcolor='red')
plt.show()
```

```
The predicted class is: Target spot with a confidence of 0.7808
```


```
# Ensure all tensors in train_accs and test_accs are converted to
Python floats
train_accs = [acc.cpu().item() if isinstance(acc, torch.Tensor) else
acc for acc in train_accs]
test_accs = [acc.cpu().item() if isinstance(acc, torch.Tensor) else
acc for acc in test_accs]

# Plotting
epochs = range(1, num_epochs + 1)
plt.figure(figsize=(12, 5))

# Loss plot
plt.subplot(1, 2, 1)
plt.plot(epochs, train_losses, label='Train Loss')
plt.plot(epochs, test_losses, label='Test Loss')
plt.title('Loss Curve')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Accuracy plot
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accs, label='Train Accuracy')
plt.plot(epochs, test_accs, label='Test Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
```

```
plt.legend()

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