Libraries Importation

```
from __future__ import print_function, division
from torchvision.datasets import EuroSAT
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import numpy as np
import torchvision
from torchvision import datasets, models, transforms
import matplotlib.pyplot as plt
import time
import os
import copy
import random
from torch.utils.data import DataLoader
from itertools import product
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
from torchcam.methods import SmoothGradCAMpp
from torchcam.utils import overlay_mask
from torchvision.transforms.functional import to_pil_image
```

Data Preprocessing

```
# Set random seeds for reproducibility
random.seed(42)
torch.manual_seed(42)
```

```
<torch._C.Generator at 0x7d0a5c4c68d0>
```

```
# Data augmentation and normalization for training
# Just normalization for validation and test
data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(224, scale=(0.8, 1.0)),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                             [0.229, 0.224, 0.225])
    ]),
    '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])
    ]),
}
```

```
# Can be used to wrap subsets and apply specific transforms to different subsets
class TransformSubset(torch.utils.data.Dataset):
    def __init__(self, subset, transform=None):
        self.subset = subset
        self.transform = transform
    def __getitem__(self, index):
        x, y = self.subset[index]
        if self.transform:
            x = self.transform(x)
        return x, y
```

```
    def __len__(self):
        return len(self.subset)


# Download the EuroSAT dataset.
data_dir = './data/eurosat'
eurosat_dataset = EuroSAT(root=data_dir, download=True)
```

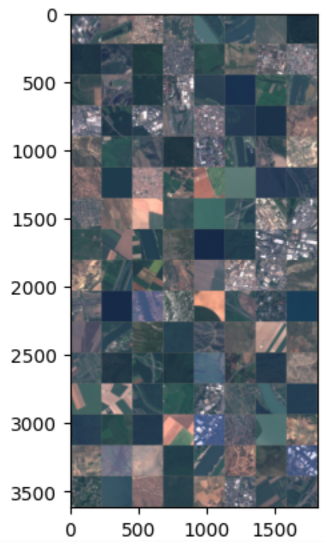
```
100%|██████████| 94.3M/94.3M [00:00<00:00, 357MB/s]
```

```
# Split dataset into train (49%), val (21%), and test (30%)
# train:val = 70:30
dataset_size = len(eurosat_dataset)
train_size = int(0.49 * dataset_size)
val_size = int(0.21 * dataset_size)
test_size = dataset_size - train_size - val_size


train_subset, val_subset, test_subset = torch.utils.data.random_split(eurosat_dataset, [train_size, val_size, test_size], generator=torch.Ge


# Wrap each subset with its corresponding transform
train_dataset = TransformSubset(train_subset, transform=data_transforms['train'])
val_dataset   = TransformSubset(val_subset,   transform=data_transforms['val'])
test_dataset  = TransformSubset(test_subset,  transform=data_transforms['test'])


# Create dataloaders
batch_size = 128
num_workers = 4
dataloaders = {
    'train': DataLoader(train_dataset, batch_size=batch_size, shuffle=True, num_workers=num_workers),
    'val':   DataLoader(val_dataset, batch_size=batch_size, shuffle=False, num_workers=num_workers),
    'test':  DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=num_workers)
}
dataset_sizes = {'train': len(train_dataset), 'val': len(val_dataset), 'test': len(test_dataset)}
class_names = eurosat_dataset.classes

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")


class_names
```

```
['AnnualCrop',
 'Forest',
 'HerbaceousVegetation',
 'Highway',
 'Industrial',
 'Pasture',
 'PermanentCrop',
 'Residential',
 'River',
 'SeaLake']
```

Visualization before going into training

```
# Can be used to visualize a batch of images
def imshow(inp, title=None):
    """Imshow for Tensor."""
    inp = inp.numpy().transpose((1, 2, 0))
    mean = np.array([0.485, 0.456, 0.406])
    std  = np.array([0.229, 0.224, 0.225])
    inp  = std * inp + mean
    inp  = np.clip(inp, 0, 1)
    plt.imshow(inp)
    plt.pause(0.001)


# Visualize a batch of training images
inputs, labels = next(iter(dataloaders['train']))
out = torchvision.utils.make_grid(inputs)
imshow(out, title=[class_names[x] for x in labels])
```



Model Selection and Architecture

```
# A custom CNN architecture
class CustomCNN(nn.Module):
    def __init__(self, dropout_rate=0.5):
        super(CustomCNN, self).__init__()
        # 3 convolutional blocks.
        self.features = nn.Sequential(
            # (3x224x224) to (32x112x112)
            nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            # (32x112x112) to (64x56x56)
            nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            # (64x56x56) to (128x28x28)
            nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )
        # Classifier with dropout regularization.
        self.classifier = nn.Sequential(
            nn.Dropout(0.5),  # Dropout regularizes by preventing overfitting.
            nn.Linear(128 * 28 * 28, 512),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(512, 10)
        )

    def forward(self, x):
        x = self.features(x)
        # Flatten the feature maps into a vector for the fully connected layers
        x = x.view(x.size(0), -1)
        x = self.classifier(x)
        return x
```

Model Training

```
def train_model(model, criterion, optimizer, scheduler, num_epochs=25, patience=5):

    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_val_loss = float('inf')
    patience_counter = 0
```

```
    for epoch in range(num_epochs):
        print('Epoch {}/{}'.format(epoch, num_epochs - 1))
        print('-' * 10)

        for phase in ['train', 'val']:
            if phase == 'train':
                scheduler.step()
                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]

            # Monitor training progress, including loss and accuracy
            print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss, epoch_acc))

            # EarlyStopping check
            if phase == 'val':
                if epoch_loss < best_val_loss:
                    best_val_loss = epoch_loss # Update best loss
                    best_model_wts = copy.deepcopy(model.state_dict()) # Update best model
                    patience_counter = 0  # Reset the counter because loss improves
                else:
                    patience_counter += 1 # Add on the counter bcause loss does not improve
                    if patience_counter >= patience: # If loss does not improve within 5 epochs
                        print('Early stopping triggered after {} epochs with no improvement in validation loss.'.format(patience))
                        model.load_state_dict(best_model_wts)
                        time_elapsed = time.time() - since
                        print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, time_elapsed % 60))
                        print('Best val Loss: {:.4f}'.format(best_val_loss))
                        return model # Termination
        print()

    time_elapsed = time.time() - since
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, time_elapsed % 60))
    print('Best val Loss: {:.4f}'.format(best_val_loss))
    model.load_state_dict(best_model_wts)
    return model
```

Train the CNN Model

```
model_cnn = CustomCNN()
model_cnn = model_cnn.to(device)


# Set up loss function, optimizer, and learning rate scheduler.
criterion = nn.CrossEntropyLoss()
optimizer_cnn = optim.SGD(model_cnn.parameters(), lr=0.01, momentum=0.9)
scheduler_cnn = lr_scheduler.StepLR(optimizer_cnn, step_size=7, gamma=0.1)


# Train the CNN model
num_epochs = 25
```

```
model_cnn = train_model(model_cnn, criterion, optimizer_cnn, scheduler_cnn, num_epochs=num_epochs, patience=5)
```

```
Epoch 14/24
----------
train Loss: 0.8466 Acc: 0.7139
val Loss: 0.6784 Acc: 0.7820

Epoch 15/24
----------
train Loss: 0.8419 Acc: 0.7109
val Loss: 0.6782 Acc: 0.7820

Epoch 16/24
----------
train Loss: 0.8406 Acc: 0.7148
val Loss: 0.6840 Acc: 0.7792

Epoch 17/24
----------
train Loss: 0.8244 Acc: 0.7156
val Loss: 0.6746 Acc: 0.7832

Epoch 18/24
----------
train Loss: 0.8241 Acc: 0.7166
val Loss: 0.6664 Acc: 0.7869

Epoch 19/24
----------
train Loss: 0.8324 Acc: 0.7135
val Loss: 0.6524 Acc: 0.7885

Epoch 20/24
----------
train Loss: 0.8117 Acc: 0.7184
val Loss: 0.6710 Acc: 0.7868

Epoch 21/24
----------
train Loss: 0.8210 Acc: 0.7178
val Loss: 0.6680 Acc: 0.7852

Epoch 22/24
----------
train Loss: 0.8211 Acc: 0.7172
val Loss: 0.6865 Acc: 0.7785

Epoch 23/24
----------
train Loss: 0.8308 Acc: 0.7147
val Loss: 0.6631 Acc: 0.7854

Epoch 24/24
----------
train Loss: 0.8321 Acc: 0.7184
val Loss: 0.6688 Acc: 0.7862
Early stopping triggered after 5 epochs with no improvement in validation loss.
Training complete in 5m 55s
Best val Loss: 0.6524
```

Train a pre-trained ResNet18 model

```
# Load a pre-trained ResNet18 and modify the final layer for 10 classes
model_ft = models.resnet18(pretrained=True)
num_ftrs = model_ft.fc.in_features
model_ft.fc = nn.Linear(num_ftrs, 10)
model_ft = model_ft.to(device)

# Define loss function, optimizer, and learning rate scheduler
criterion = nn.CrossEntropyLoss()
optimizer_ft = optim.SGD(model_ft.parameters(), lr=0.001, momentum=0.9)
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)

# Train the model
num_epochs = 25
model_ft = train_model(model_ft, criterion, optimizer_ft, exp_lr_scheduler, num_epochs=num_epochs, patience=5)
```

```
val Loss: 0.0796 Acc: 0.9743
```

```
val Loss: 0.0796 Acc: 0.9743

Epoch 9/24
----------
train Loss: 0.0705 Acc: 0.9794
val Loss: 0.0779 Acc: 0.9743

Epoch 10/24
----------
train Loss: 0.0693 Acc: 0.9796
val Loss: 0.0770 Acc: 0.9743

Epoch 11/24
----------
train Loss: 0.0680 Acc: 0.9803
val Loss: 0.0768 Acc: 0.9758

Epoch 12/24
----------
train Loss: 0.0656 Acc: 0.9804
val Loss: 0.0765 Acc: 0.9741

Epoch 13/24
----------
train Loss: 0.0652 Acc: 0.9794
val Loss: 0.0751 Acc: 0.9757

Epoch 14/24
----------
train Loss: 0.0651 Acc: 0.9811
val Loss: 0.0752 Acc: 0.9746

Epoch 15/24
----------
train Loss: 0.0646 Acc: 0.9811
val Loss: 0.0782 Acc: 0.9741

Epoch 16/24
----------
train Loss: 0.0633 Acc: 0.9805
val Loss: 0.0782 Acc: 0.9748

Epoch 17/24
----------
train Loss: 0.0651 Acc: 0.9811
val Loss: 0.0793 Acc: 0.9746

Epoch 18/24
----------
train Loss: 0.0662 Acc: 0.9803
val Loss: 0.0773 Acc: 0.9755
Early stopping triggered after 5 epochs with no improvement in validation loss.
Training complete in 4m 8s
Best val Loss: 0.0751
```

Hyperparameter Tuning

```
# Can be used to obtain the accuracy
def evaluate_model(model, dataloader):
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for inputs, labels in dataloader:
            inputs = inputs.to(device)
            labels = labels.to(device)
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            total += labels.size(0)
            correct += torch.sum(preds == labels.data)
    return correct.double() / total


# Set parameter ranges for Grid Search
learning_rates = [0.001, 0.01]
optimizers = ['SGD', 'Adam']
dropout_rates = [0.3, 0.5]

num_epochs = 25
```

```
patience = 5

# Keep a record of the hyperparameters used and their impact on the model
experiment_log = []

for lr_val, opt_name, dropout_val in product(learning_rates, optimizers, dropout_rates):
    print("======================================")
    print("Running experiment with:")
    print("Learning Rate: {}".format(lr_val))
    print("Optimizer: {}".format(opt_name))
    print("Dropout Rate: {}".format(dropout_val))

    # Initiate the model with the current dropout rate
    model = CustomCNN(dropout_rate=dropout_val).to(device)

    criterion = nn.CrossEntropyLoss()

    # Set up the optimizer
    if opt_name == 'SGD':
        optimizer = optim.SGD(model.parameters(), lr=lr_val, momentum=0.9)
    elif opt_name == 'Adam':
        optimizer = optim.Adam(model.parameters(), lr=lr_val)

    scheduler = lr_scheduler.StepLR(optimizer, step_size=7, gamma=0.1)

    model = train_model(model, criterion, optimizer, scheduler, num_epochs=num_epochs, patience=patience)

    # Evaluate on the validation set
    val_acc = evaluate_model(model, dataloaders['val'])
    print("Final Validation Accuracy: {:.4f}".format(val_acc))

    # Keep the records
    experiment_log.append({
        'learning_rate': lr_val,
        'optimizer': opt_name,
        'dropout_rate': dropout_val,
        'val_accuracy': val_acc.item()
    })
    print("======================================\n")

# Display all records
print("----- Experiment Log -----")
for entry in experiment_log:
    print("LR: {learning_rate}, Optimizer: {optimizer}, Dropout: {dropout_rate} --> Val Acc: {val_accuracy:.4f}"
          .format(**entry))

# Determine the best configuration
best_experiment = max(experiment_log, key=lambda x: x['val_accuracy'])
print("\nBest Hyperparameters:")
print(best_experiment)
```

```
train Loss: 1.7147 Acc: 0.3598
val Loss: 1.5544 Acc: 0.4520

Epoch 23/24
----------
train Loss: 1.7150 Acc: 0.3613
val Loss: 1.5662 Acc: 0.4460

Epoch 24/24
----------
train Loss: 1.7253 Acc: 0.3587
val Loss: 1.5606 Acc: 0.4455

Training complete in 5m 58s
Best val Loss: 1.5544
Final Validation Accuracy: 0.4520
=======================================

----- Experiment Log -----
LR: 0.001, Optimizer: SGD, Dropout: 0.3 --> Val Acc: 0.8353
LR: 0.001, Optimizer: SGD, Dropout: 0.5 --> Val Acc: 0.8383
LR: 0.001, Optimizer: Adam, Dropout: 0.3 --> Val Acc: 0.7924
LR: 0.001, Optimizer: Adam, Dropout: 0.5 --> Val Acc: 0.7672
LR: 0.01, Optimizer: SGD, Dropout: 0.3 --> Val Acc: 0.7788
LR: 0.01, Optimizer: SGD, Dropout: 0.5 --> Val Acc: 0.7326
LR: 0.01, Optimizer: Adam, Dropout: 0.3 --> Val Acc: 0.1079
LR: 0.01, Optimizer: Adam, Dropout: 0.5 --> Val Acc: 0.4520

Best Hyperparameters:
{'learning_rate': 0.001, 'optimizer': 'SGD', 'dropout_rate': 0.5, 'val_accuracy': 0.8382716049382717}
```

```
# Train the CNN with the best hyperparameters
model_cnn = CustomCNN()
model_cnn = model_cnn.to(device)

criterion = nn.CrossEntropyLoss()
optimizer_cnn = optim.SGD(model_cnn.parameters(), lr=0.001, momentum=0.9)
scheduler_cnn = lr_scheduler.StepLR(optimizer_cnn, step_size=7, gamma=0.1)

num_epochs = 25
model_cnn = train_model(model_cnn, criterion, optimizer_cnn, scheduler_cnn, num_epochs=num_epochs, patience=5)
```

```
train Loss: 0.5054 Acc: 0.8205
```

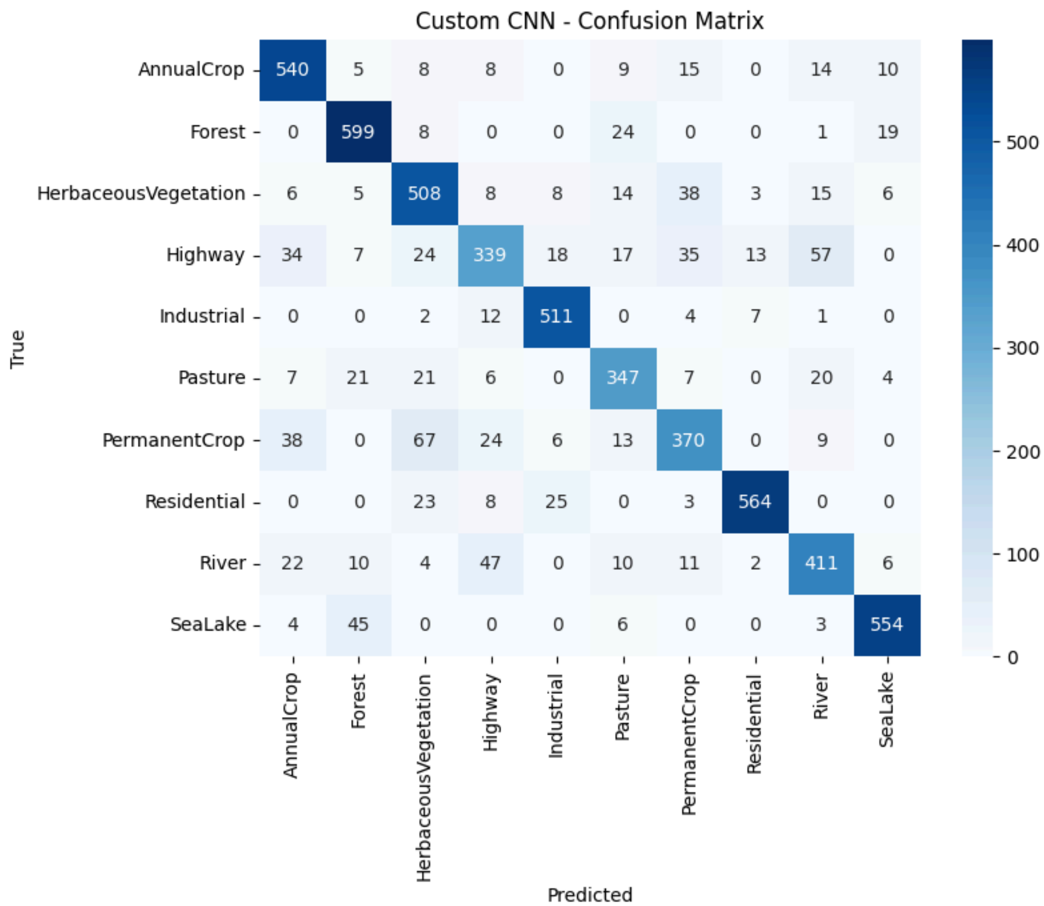
```
train Loss: 0.5054 Acc: 0.8205
val Loss: 0.4821 Acc: 0.8325

Epoch 18/24
----------
train Loss: 0.4954 Acc: 0.8274
val Loss: 0.4793 Acc: 0.8344

Epoch 19/24
----------
train Loss: 0.4933 Acc: 0.8275
val Loss: 0.4760 Acc: 0.8363
Early stopping triggered after 5 epochs with no improvement in validation loss.
Training complete in 4m 45s
Best val Loss: 0.4695
```

Evaluation

Evaluate the CNN model

```python
model_cnn.eval()

all_labels_cnn = []
all_preds_cnn = []

with torch.no_grad():
    for inputs, labels in dataloaders['val']:
        inputs = inputs.to(device)
        outputs = model_cnn(inputs)
        _, preds = torch.max(outputs, 1)
        all_labels_cnn.extend(labels.cpu().numpy())
        all_preds_cnn.extend(preds.cpu().numpy())

# Compute overall accuracy for CNN
acc_cnn = np.mean(np.array(all_labels_cnn) == np.array(all_preds_cnn))
print("CNN Validation Accuracy: {:.4f}".format(acc_cnn))
print("\nClassification Report for CNN:")
print(classification_report(all_labels_cnn, all_preds_cnn, target_names=class_names))

# Plot confusion matrix for CNN
cm_cnn = confusion_matrix(all_labels_cnn, all_preds_cnn)
plt.figure(figsize=(8, 6))
sns.heatmap(cm_cnn, annot=True, fmt="d", cmap="Blues",
            xticklabels=class_names, yticklabels=class_names)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("CNN - Confusion Matrix")
plt.show()
```

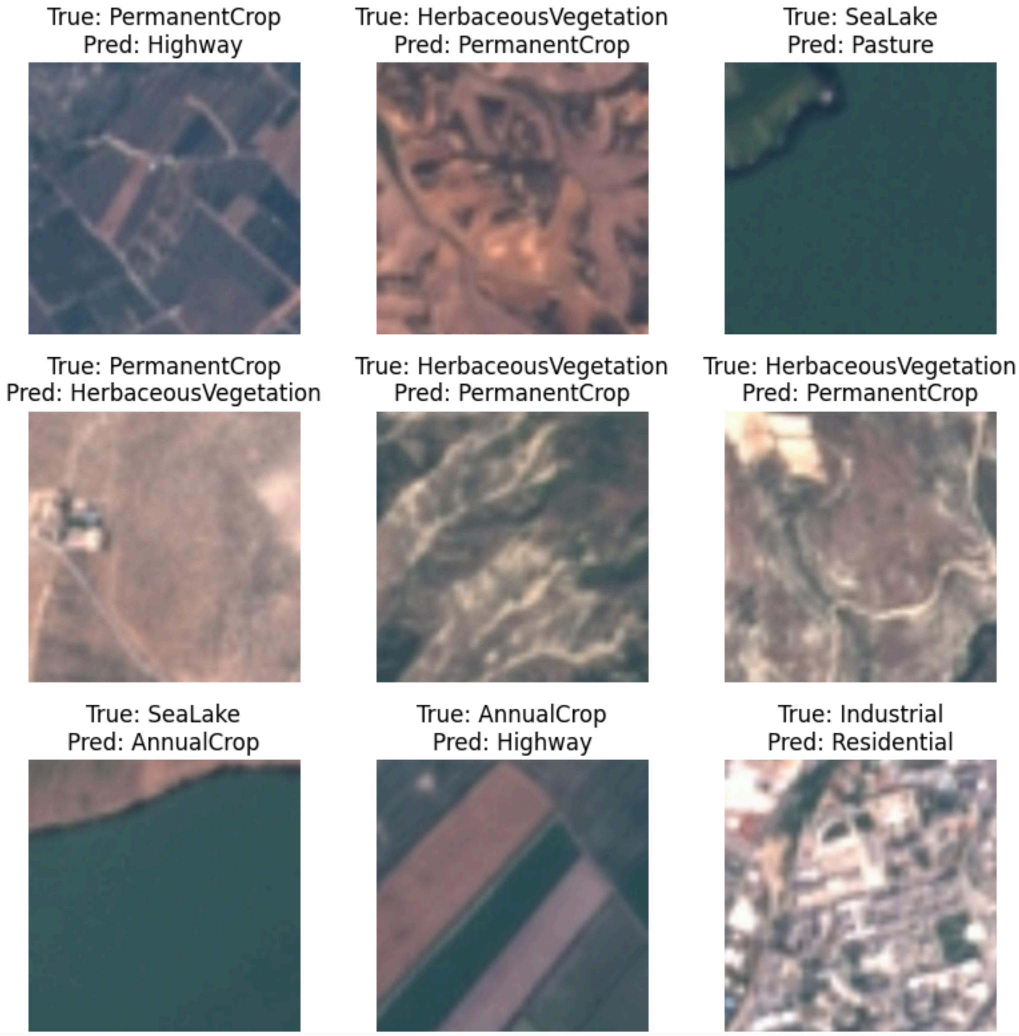
```
Custom CNN Validation Accuracy: 0.8365

Classification Report for Custom CNN:
                      precision    recall  f1-score   support

          AnnualCrop       0.83      0.89      0.86       609
              Forest       0.87      0.92      0.89       651
HerbaceousVegetation       0.76      0.83      0.80       611
             Highway       0.75      0.62      0.68       544
          Industrial       0.90      0.95      0.92       537
             Pasture       0.79      0.80      0.79       433
       PermanentCrop       0.77      0.70      0.73       527
         Residential       0.96      0.91      0.93       623
               River       0.77      0.79      0.78       523
             SeaLake       0.92      0.91      0.91       612

            accuracy                           0.84      5670
           macro avg       0.83      0.83      0.83      5670
        weighted avg       0.84      0.84      0.83      5670
```




```
def visualize_misclassifications(model, dataloader, num_images=16):
    model.eval()
    misclassified_imgs = []
    misclassified_labels = []
    misclassified_preds = []

    with torch.no_grad():
        for inputs, labels in dataloader:
            inputs = inputs.to(device)
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            # Identify misclassifications
            for i in range(len(labels)):
                if preds[i].cpu() != labels[i]:
                    misclassified_imgs.append(inputs[i].cpu())
                    misclassified_labels.append(labels[i].cpu().item())
                    misclassified_preds.append(preds[i].cpu().item())
                if len(misclassified_imgs) == num_images:
                    break
            if len(misclassified_imgs) == num_images:
```

```
                break

    # Plot misclassified images
    fig, axes = plt.subplots(int(num_images**0.5), int(num_images**0.5), figsize=(8, 8))
    for idx, ax in enumerate(axes.flatten()):
        img = misclassified_imgs[idx].numpy().transpose((1,2,0))
        # Denormalize
        mean = np.array([0.485, 0.456, 0.406])
        std  = np.array([0.229, 0.224, 0.225])
        img = std * img + mean
        img = np.clip(img, 0, 1)
        ax.imshow(img)
        ax.axis('off')
        ax.set_title(f"True: {class_names[misclassified_labels[idx]]}\nPred: {class_names[misclassified_preds[idx]]}")
    plt.tight_layout()
    plt.show()
```

```
visualize_misclassifications(model_cnn, dataloaders['test'], num_images=9)
```

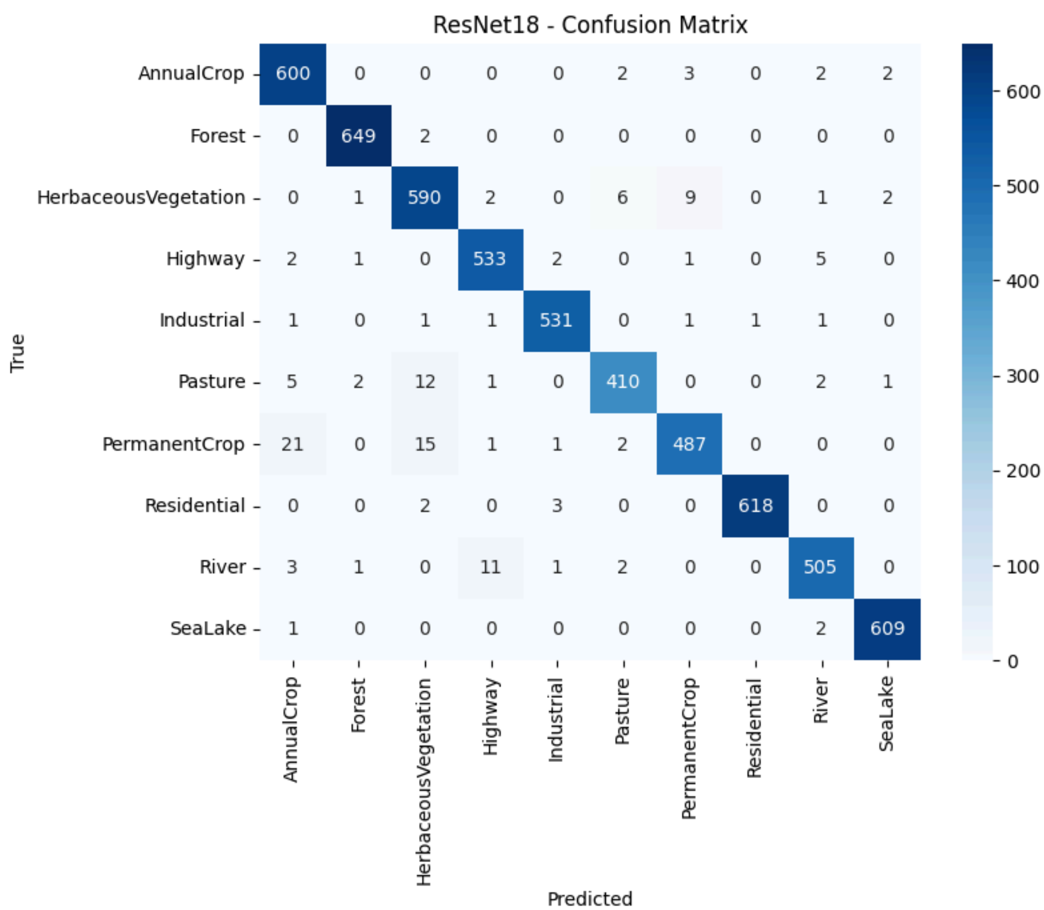


Evaluate the pre-trained ResNet18 model

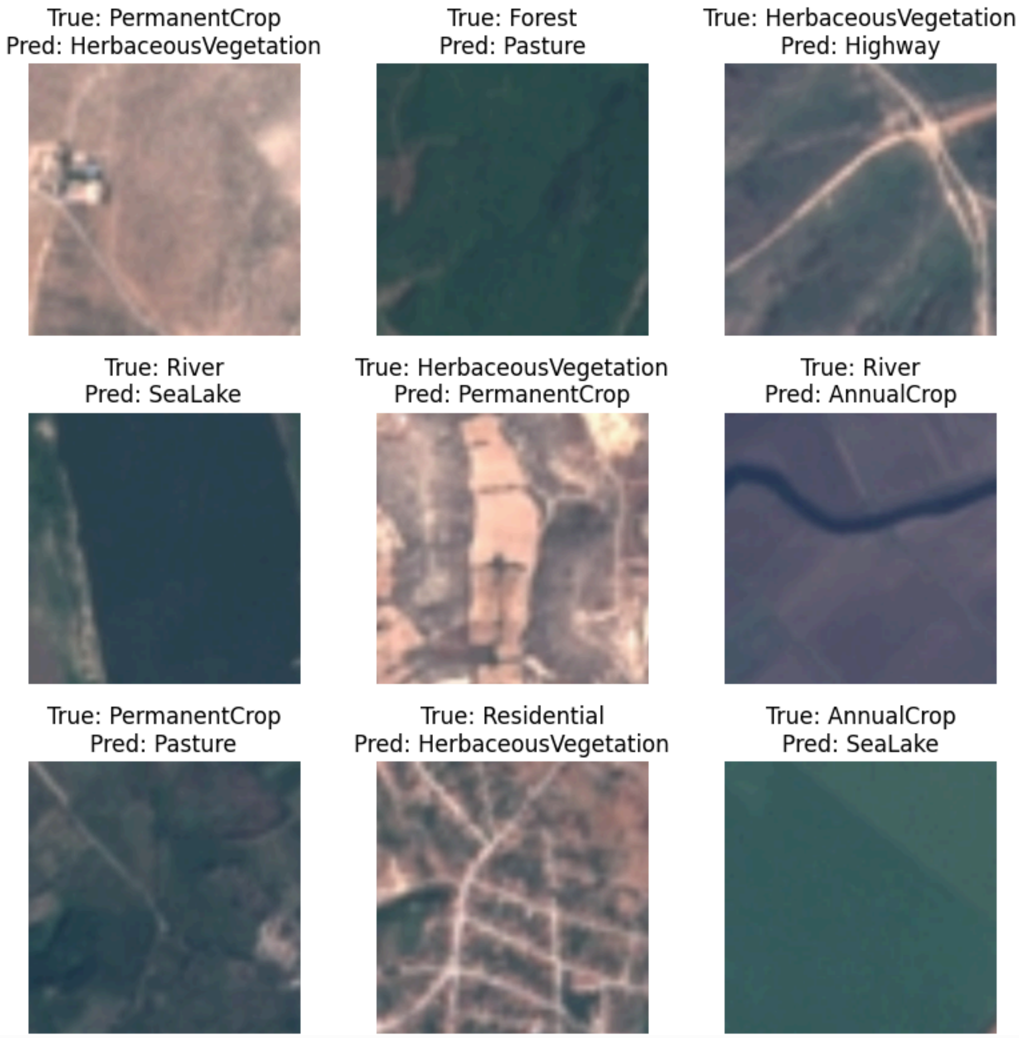
```
model_ft.eval()

all_labels_ft = []
all_preds_ft = []

with torch.no_grad():
    for inputs, labels in dataloaders['val']:
        inputs = inputs.to(device)
        outputs = model_ft(inputs)
        _, preds = torch.max(outputs, 1)
        all_labels_ft.extend(labels.cpu().numpy())
```

```
        all_preds_ft.extend(preds.cpu().numpy())

# Compute overall accuracy for ResNet18
acc_ft = np.mean(np.array(all_labels_ft) == np.array(all_preds_ft))
print("ResNet18 Validation Accuracy: {:.4f}".format(acc_ft))
print("\nClassification Report for ResNet18:")
print(classification_report(all_labels_ft, all_preds_ft, target_names=class_names))

# Plot confusion matrix for ResNet18
cm_ft = confusion_matrix(all_labels_ft, all_preds_ft)
plt.figure(figsize=(8, 6))
sns.heatmap(cm_ft, annot=True, fmt="d", cmap="Blues",
            xticklabels=class_names, yticklabels=class_names)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("ResNet18 - Confusion Matrix")
plt.show()
```

```
ResNet18 Validation Accuracy: 0.9757

Classification Report for ResNet18:
                      precision    recall  f1-score   support

          AnnualCrop       0.95      0.99      0.97       609
              Forest       0.99      1.00      0.99       651
HerbaceousVegetation       0.95      0.97      0.96       611
             Highway       0.97      0.98      0.98       544
          Industrial       0.99      0.99      0.99       537
             Pasture       0.97      0.95      0.96       433
       PermanentCrop       0.97      0.92      0.95       527
         Residential       1.00      0.99      1.00       623
               River       0.97      0.97      0.97       523
             SeaLake       0.99      1.00      0.99       612

            accuracy                           0.98      5670
           macro avg       0.98      0.97      0.97      5670
        weighted avg       0.98      0.98      0.98      5670
```




```
visualize_misclassifications(model_ft, dataloaders['test'], num_images=9)
```



Fine-Tuning

```
# Build a more sophisticated CNN architecture
class FineTunedCNN(nn.Module):
    def __init__(self, dropout_rate=0.5):
        super(FineTunedCNN, self).__init__()
        self.features = nn.Sequential(
            # 2 conv layers + pooling
            nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # 2 conv layers + pooling
            nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # 2 conv layers + pooling
            nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Conv2d(128, 128, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(128),
```

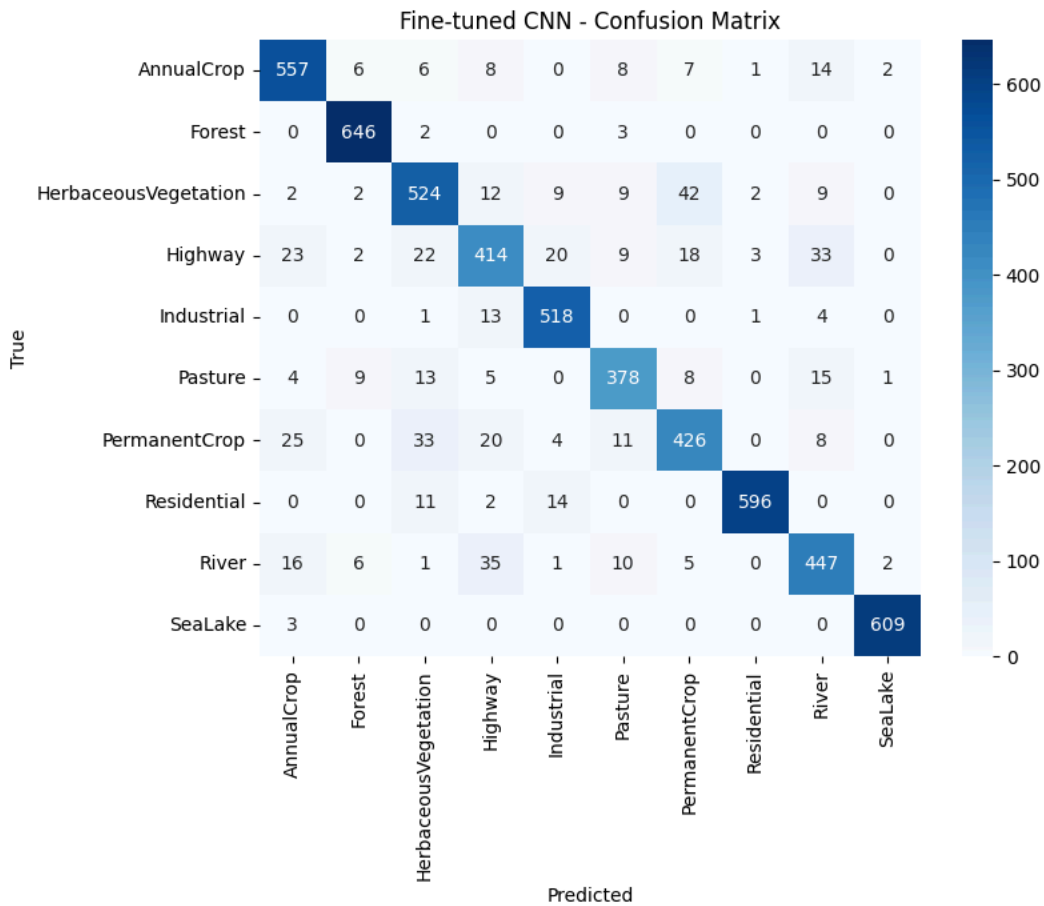
```
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            # 2 conv layers + pooling
            nn.Conv2d(128, 256, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )

        self.classifier = nn.Sequential(
            nn.Dropout(dropout_rate),
            nn.Linear(256 * 14 * 14, 512),
            nn.ReLU(inplace=True),
            nn.Dropout(dropout_rate),
            nn.Linear(512, 10)
        )

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.classifier(x)
        return x


model_fine_cnn = FineTunedCNN()
model_fine_cnn = model_fine_cnn.to(device)

criterion = nn.CrossEntropyLoss()
optimizer_fine_cnn = optim.SGD(model_fine_cnn.parameters(), lr=0.001, momentum=0.9)
scheduler_fine_cnn = lr_scheduler.StepLR(optimizer_fine_cnn, step_size=7, gamma=0.1)

# Train the new CNN model with the best hyperparameters defined in the previous section
num_epochs = 25
model_fine_cnn = train_model(model_fine_cnn, criterion, optimizer_fine_cnn, scheduler_fine_cnn, num_epochs=num_epochs, patience=5)
```

```
    train Loss: 0.3151 Acc: 0.8908
```

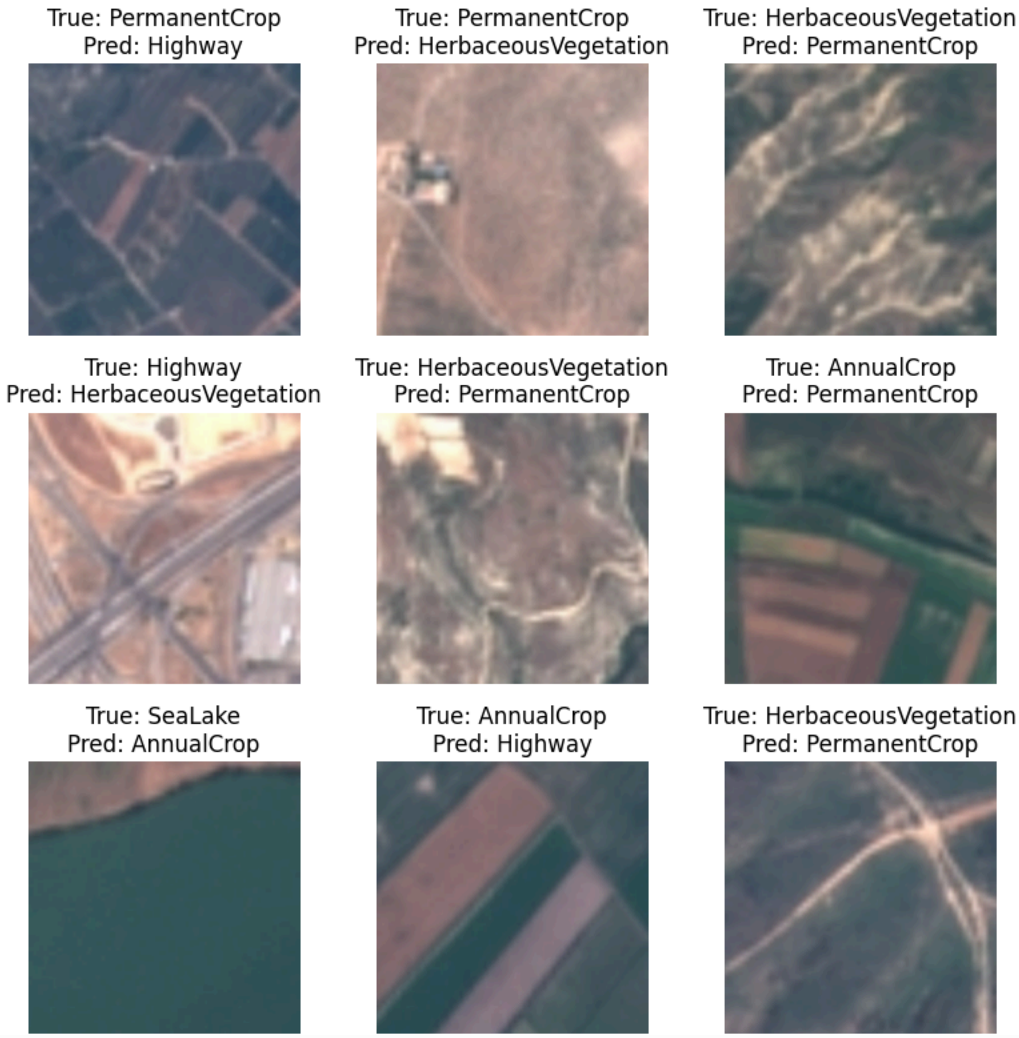
```
train Loss: 0.3151 Acc: 0.8908
val Loss: 0.2926 Acc: 0.8995

Epoch 22/24
----------
train Loss: 0.3128 Acc: 0.8930
val Loss: 0.2940 Acc: 0.9000

Epoch 23/24
----------
train Loss: 0.3135 Acc: 0.8922
val Loss: 0.2940 Acc: 0.8981
Early stopping triggered after 5 epochs with no improvement in validation loss.
Training complete in 8m 34s
Best val Loss: 0.2874
```

```
model_fine_cnn.eval()

all_labels_cnn = []
all_preds_cnn = []

with torch.no_grad():
    for inputs, labels in dataloaders['val']:
        inputs = inputs.to(device)
        outputs = model_fine_cnn(inputs)
        _, preds = torch.max(outputs, 1)
        all_labels_cnn.extend(labels.cpu().numpy())
        all_preds_cnn.extend(preds.cpu().numpy())

acc_cnn = np.mean(np.array(all_labels_cnn) == np.array(all_preds_cnn))
print("Fine-tuned CNN Validation Accuracy: {:.4f}".format(acc_cnn))
print("\nClassification Report for Fine-tuned CNN:")
print(classification_report(all_labels_cnn, all_preds_cnn, target_names=class_names))

cm_cnn = confusion_matrix(all_labels_cnn, all_preds_cnn)
plt.figure(figsize=(8, 6))
sns.heatmap(cm_cnn, annot=True, fmt="d", cmap="Blues",
            xticklabels=class_names, yticklabels=class_names)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Fine-tuned CNN - Confusion Matrix")
plt.show()
```

```
Fine-tuned CNN Validation Accuracy: 0.9021

Classification Report for Fine-tuned CNN:
                      precision    recall  f1-score   support

          AnnualCrop       0.88      0.91      0.90       609
              Forest       0.96      0.99      0.98       651
HerbaceousVegetation       0.85      0.86      0.86       611
             Highway       0.81      0.76      0.79       544
          Industrial       0.92      0.96      0.94       537
             Pasture       0.88      0.87      0.88       433
       PermanentCrop       0.84      0.81      0.82       527
         Residential       0.99      0.96      0.97       623
               River       0.84      0.85      0.85       523
             SeaLake       0.99      1.00      0.99       612

            accuracy                           0.90      5670
           macro avg       0.90      0.90      0.90      5670
        weighted avg       0.90      0.90      0.90      5670
```



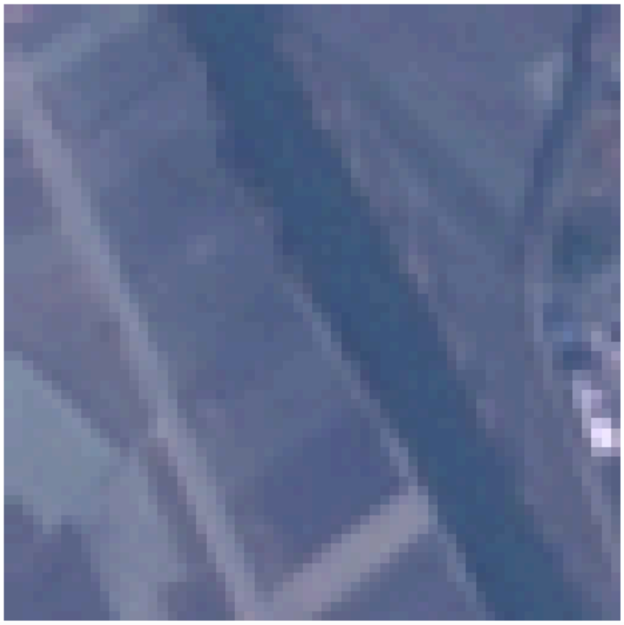

```
visualize_misclassifications(model_fine_cnn, dataloaders['test'], num_images=9)
```



GradCam to understand what regions the model is paying attention to

```
# Untransformed validation dataset
val_dataset_raw = TransformSubset(val_subset, transform=None)

# Get the first image and its label from the raw validation dataset.
original_img, original_label = val_dataset_raw[0]

# Display the original image and its label
plt.figure(figsize=(6, 6))
plt.imshow(original_img)
plt.title(f"Original Validation Image - Label: {original_label}")
plt.axis("off")
plt.show()
```

Original Validation Image - Label: 8

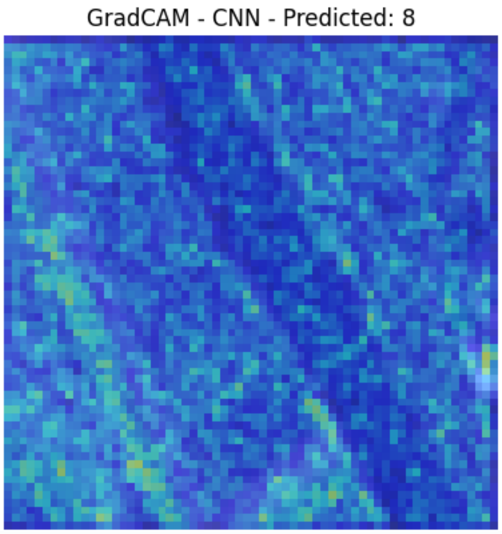


```
preprocess = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])

# Preprocess the image
input_tensor = preprocess(original_img).unsqueeze(0)
```

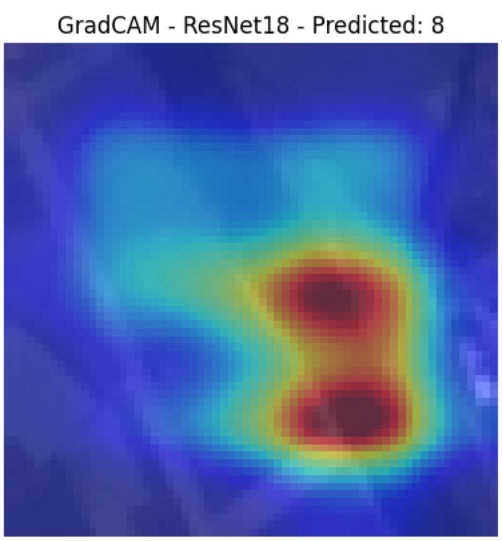
```
input_tensor.shape
```

```
torch.Size([1, 3, 224, 224])
```

```
with SmoothGradCAMpp(model_fine_cnn, target_layer="features.8") as cam_extractor:
    input_tensor = input_tensor.to(device)
    out = model_fine_cnn(input_tensor)
    pred_class = out.squeeze(0).argmax().item()
    activation_map = cam_extractor(pred_class, out)

result = overlay_mask(original_img,
                      to_pil_image(activation_map[0].squeeze(0), mode='F'), alpha=0.5)

plt.imshow(result)
plt.axis('off')
plt.title(f"GradCAM - CNN - Predicted: {pred_class}")
plt.show()
```




```
with SmoothGradCAMpp(model_ft, target_layer="layer4") as cam_extractor:
    input_tensor = input_tensor.to(device)
    out = model_ft(input_tensor)
    pred_class = out.squeeze(0).argmax().item()
    activation_map = cam_extractor(pred_class, out)

result = overlay_mask(original_img,
                      to_pil_image(activation_map[0].squeeze(0), mode='F'), alpha=0.5)

plt.imshow(result)
plt.axis('off')
plt.title(f"GradCAM - ResNet18 - Predicted: {pred_class}")
plt.show()
```



Final Model Testing

```
test_acc = evaluate_model(model_fine_cnn, dataloaders['test'])
print('Test Accuracy for the fine-tuned CNN model: {:.4f}'.format(test_acc))
```

```
Test Accuracy for the fine-tuned CNN model: 0.8995
```

```
test_acc = evaluate_model(model_ft, dataloaders['test'])
print('Test Accuracy for the pre-trained ResNet18 model: {:.4f}'.format(test_acc))
```

```
Test Accuracy for the pre-trained ResNet18 model: 0.9716
```

```
# make sure everything is printing
```


```
# make sure everything is printing
```