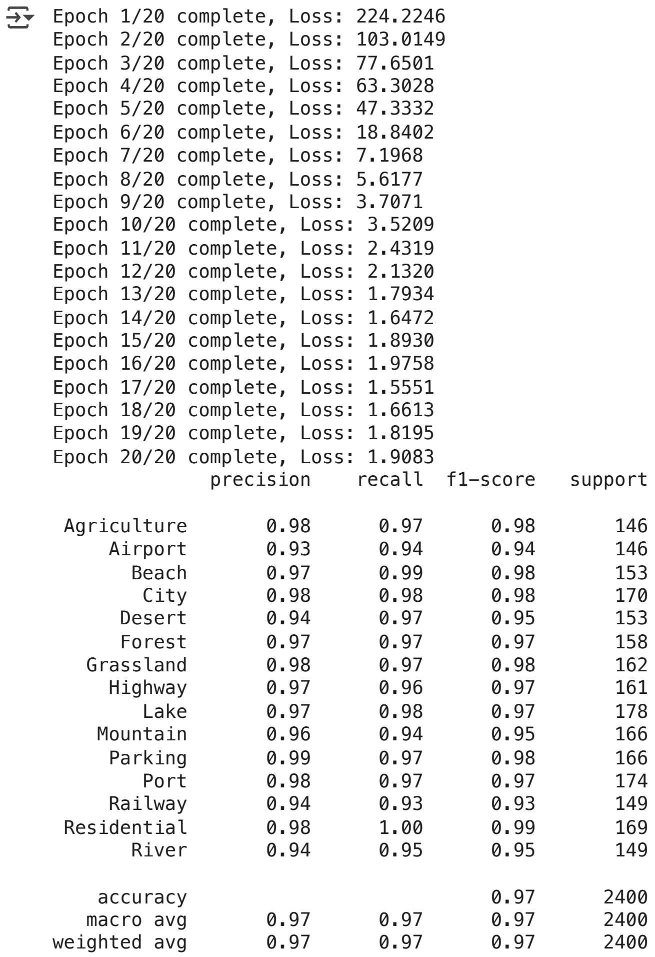
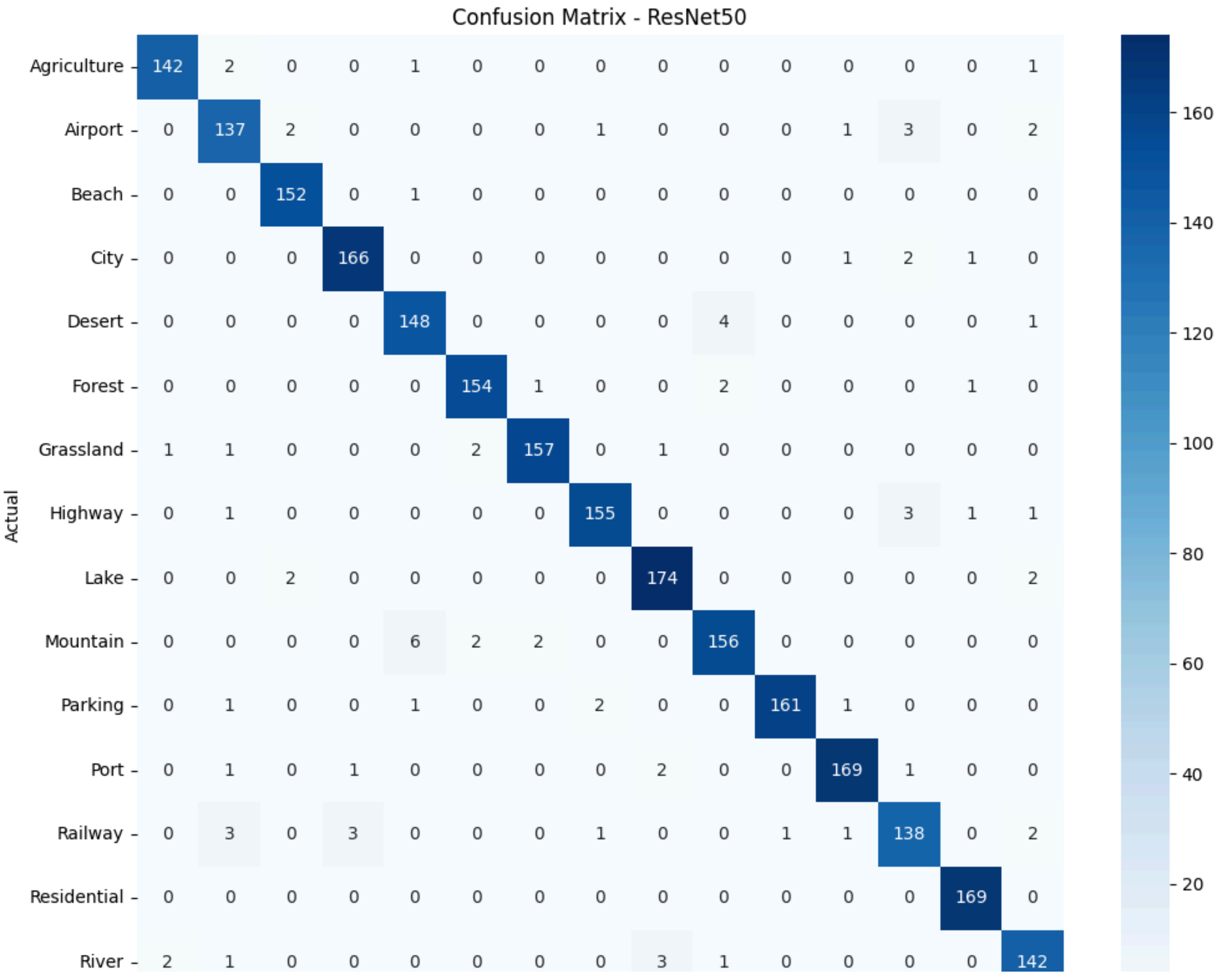
```
import os, torch, numpy as np, matplotlib.pyplot as plt, seaborn as sns
from torchvision import datasets, transforms, models
from torchvision.models import resnet50, ResNet50_Weights
from torch.utils.data import DataLoader, random_split
import torch.nn as nn
import torch.optim as optim
from torch.optim.lr_scheduler import StepLR
from sklearn.metrics import classification_report, confusion_matrix
import kagglehub

# Download dataset from Kaggle Hub
root_path = kagglehub.dataset_download("ankit1743/skyview-an-aerial-landscape-dataset")
data_path = os.path.join(root_path, "Aerial_Landscapes")

# Set device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Load pretrained ResNet-50 and modify final layer
weights = ResNet50_Weights.DEFAULT
model = resnet50(weights=weights)
model.fc = nn.Sequential(
    nn.Linear(model.fc.in_features, 512),
    nn.ReLU(),
    nn.Dropout(0.4),
    nn.Linear(512, 15)
)
model = model.to(device)

# Data augmentation and normalization
train_transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(15),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2),
    transforms.ToTensor(),
    transforms.Normalize([0.5]*3, [0.5]*3)
])
test_transform = weights.transforms()

# Load dataset
full_dataset = datasets.ImageFolder(data_path, transform=train_transform)
train_size = int(0.8 * len(full_dataset))
test_size = len(full_dataset) - train_size
train_dataset, test_dataset = random_split(full_dataset, [train_size, test_size])
test_dataset.dataset.transform = test_transform

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

# Define loss, optimizer, and scheduler
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
scheduler = StepLR(optimizer, step_size=5, gamma=0.1)

# Track training loss
train_losses = []

# Training loop
for epoch in range(20):
    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()
    scheduler.step()
    train_losses.append(running_loss)
    print(f"Epoch {epoch+1}/20 complete, Loss: {running_loss:.4f}")

# Evaluation
model.eval()
all_preds, all_labels = [], []
with torch.no_grad():
    for images, labels in test_loader:
        images = images.to(device)
        outputs = model(images)
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_labels.extend(labels.numpy())

# Classification metrics
class_names = full_dataset.classes
print(classification_report(all_labels, all_preds, target_names=class_names))

# Confusion matrix
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(12, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names, yticklabels=class_names)
plt.title("Confusion Matrix - ResNet50")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Plot training loss curve
plt.figure(figsize=(8, 5))
plt.plot(range(1, len(train_losses) + 1), train_losses, marker='o')
plt.title("Training Loss Over Epochs")
plt.xlabel("Epoch")
plt.ylabel("Total Training Loss")
plt.grid(True)
plt.tight_layout()
plt.show()
```



```
Epoch 1/20 complete, Loss: 224.2246
Epoch 2/20 complete, Loss: 103.0149
Epoch 3/20 complete, Loss: 77.6501
Epoch 4/20 complete, Loss: 63.3028
Epoch 5/20 complete, Loss: 47.3332
Epoch 6/20 complete, Loss: 18.8402
Epoch 7/20 complete, Loss: 7.1968
Epoch 8/20 complete, Loss: 5.6177
Epoch 9/20 complete, Loss: 3.7071
Epoch 10/20 complete, Loss: 3.5209
Epoch 11/20 complete, Loss: 2.4319
Epoch 12/20 complete, Loss: 2.1320
Epoch 13/20 complete, Loss: 1.7934
Epoch 14/20 complete, Loss: 1.6472
Epoch 15/20 complete, Loss: 1.8930
Epoch 16/20 complete, Loss: 1.9758
Epoch 17/20 complete, Loss: 1.5551
Epoch 18/20 complete, Loss: 1.6613
Epoch 19/20 complete, Loss: 1.8195
Epoch 20/20 complete, Loss: 1.9083
              precision    recall  f1-score   support

 Agriculture       0.98      0.97      0.98       146
     Airport       0.93      0.94      0.94       146
       Beach       0.97      0.99      0.98       153
        City       0.98      0.98      0.98       170
      Desert       0.94      0.97      0.95       153
      Forest       0.97      0.97      0.97       158
   Grassland       0.98      0.97      0.98       162
     Highway       0.97      0.96      0.97       161
        Lake       0.97      0.98      0.97       178
    Mountain       0.96      0.94      0.95       166
     Parking       0.99      0.97      0.98       166
        Port       0.98      0.97      0.97       174
     Railway       0.94      0.93      0.93       149
 Residential       0.98      1.00      0.99       169
       River       0.94      0.95      0.95       149

    accuracy                           0.97      2400
   macro avg       0.97      0.97      0.97      2400
weighted avg       0.97      0.97      0.97      2400
```



Confusion Matrix - ResNet50

Agriculture	142	2	0	0	1	0	0	0	0	0	0	0	0	0	1
Airport	0	137	2	0	0	0	0	1	0	0	0	1	3	0	2
Beach	0	0	152	0	1	0	0	0	0	0	0	0	0	0	0
City	0	0	0	166	0	0	0	0	0	0	0	1	2	1	0
Desert	0	0	0	0	148	0	0	0	0	4	0	0	0	0	1
Forest	0	0	0	0	0	154	1	0	0	2	0	0	0	1	0
Grassland	1	1	0	0	0	2	157	0	1	0	0	0	0	0	0
Highway	0	1	0	0	0	0	0	155	0	0	0	0	3	1	1
Lake	0	0	2	0	0	0	0	0	174	0	0	0	0	0	2
Mountain	0	0	0	0	6	2	2	0	0	156	0	0	0	0	0
Parking	0	1	0	0	1	0	0	2	0	0	161	1	0	0	0
Port	0	1	0	1	0	0	0	0	2	0	0	169	1	0	0
Railway	0	3	0	3	0	0	0	1	0	0	1	1	138	0	2
Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	169	0
River	2	1	0	0	0	0	0	0	3	1	0	0	0	0	142