In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

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

In [ ]:
```
import os
from PIL import Image
import pandas as pd
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
from torchvision.datasets import ImageFolder

data_path = r'/content/drive/MyDrive/data'

#Function to read images, labels, and file names
def read_images_and_labels(folder_path):
    images = []
    labels = []
    filenames = []
    for label in os.listdir(folder_path):
        label_path = os.path.join(folder_path, label)
        for file in os.listdir(label_path):
            file_path = os.path.join(label_path, file)
            img = Image.open(file_path)
            images.append(img)
            labels.append(label)
            filenames.append(file)
    return images, labels, filenames

train_images, train_labels, train_filenames = read_images_and_labels(os.pat
test_images, test_labels, test_filenames = read_images_and_labels(os.path.j
valid_images, valid_labels, valid_filenames = read_images_and_labels(os.pat

train_df = pd.DataFrame({'Image': train_images, 'Label': train_labels, 'Fil
test_df = pd.DataFrame({'Image': test_images, 'Label': test_labels, 'Filena
valid_df = pd.DataFrame({'Image': valid_images, 'Label': valid_labels, 'Fil
```

In [ ]:
```python
import random
import matplotlib.pyplot as plt

#Displaying few random images
def display_random_images(images, labels, filenames, num_images=5):
    random_indices = random.sample(range(len(images)), num_images)
    fig, axes = plt.subplots(1, num_images, figsize=(18, 3))

    for i, idx in enumerate(random_indices):
        axes[i].imshow(images[idx])
        axes[i].set_title(f"Label: {labels[idx]}\nFile: {filenames[idx]}")
        axes[i].axis('off')

    plt.show()

display_random_images(train_df['Image'], train_df['Label'], train_df['Filen
```

In [ ]:
```python
train_class_counts = train_df['Label'].value_counts()
test_class_counts = test_df['Label'].value_counts()
valid_class_counts = valid_df['Label'].value_counts()
```

In [ ]:
```python
train_class_counts
```

Out[6]:
```
AFRICAN PIED HORNBILL         187
ABBOTTS BOOBY                 180
AMERICAN AVOCET               179
ABYSSINIAN GROUND HORNBILL    179
AFRICAN PYGMY GOOSE           179
AMERICAN BITTERN              170
ABBOTTS BABBLER               166
ALPINE CHOUGH                 166
AMERICAN KESTREL              165
ALEXANDRINE PARAKEET          165
AFRICAN EMERALD CUCKOO        164
AMERICAN FLAMINGO             164
ALBERTS TOWHEE                161
AMERICAN COOT                 158
AFRICAN OYSTER CATCHER        155
ALTAMIRA YELLOWTHROAT         150
AFRICAN FIREFINCH             137
AFRICAN CROWNED CRANE         137
AMERICAN GOLDFINCH            133
ALBATROSS                     133
Name: Label, dtype: int64
```

In [ ]:
```
test_class_counts
```

Out[7]:
```
ALEXANDRINE PARAKEET          5
AMERICAN BITTERN              5
ABBOTTS BOOBY                 5
AFRICAN OYSTER CATCHER        5
AFRICAN EMERALD CUCKOO        5
ABBOTTS BABBLER               5
AFRICAN PIED HORNBILL         5
ALBATROSS                     5
AFRICAN PYGMY GOOSE           5
AFRICAN FIREFINCH             5
AFRICAN CROWNED CRANE         5
AMERICAN FLAMINGO             5
ALTAMIRA YELLOWTHROAT         5
AMERICAN COOT                 5
ALPINE CHOUGH                 5
AMERICAN GOLDFINCH            5
AMERICAN AVOCET               5
AMERICAN KESTREL              5
ALBERTS TOWHEE                5
ABYSSINIAN GROUND HORNBILL    5
Name: Label, dtype: int64
```

In [ ]:
```
valid_class_counts
```

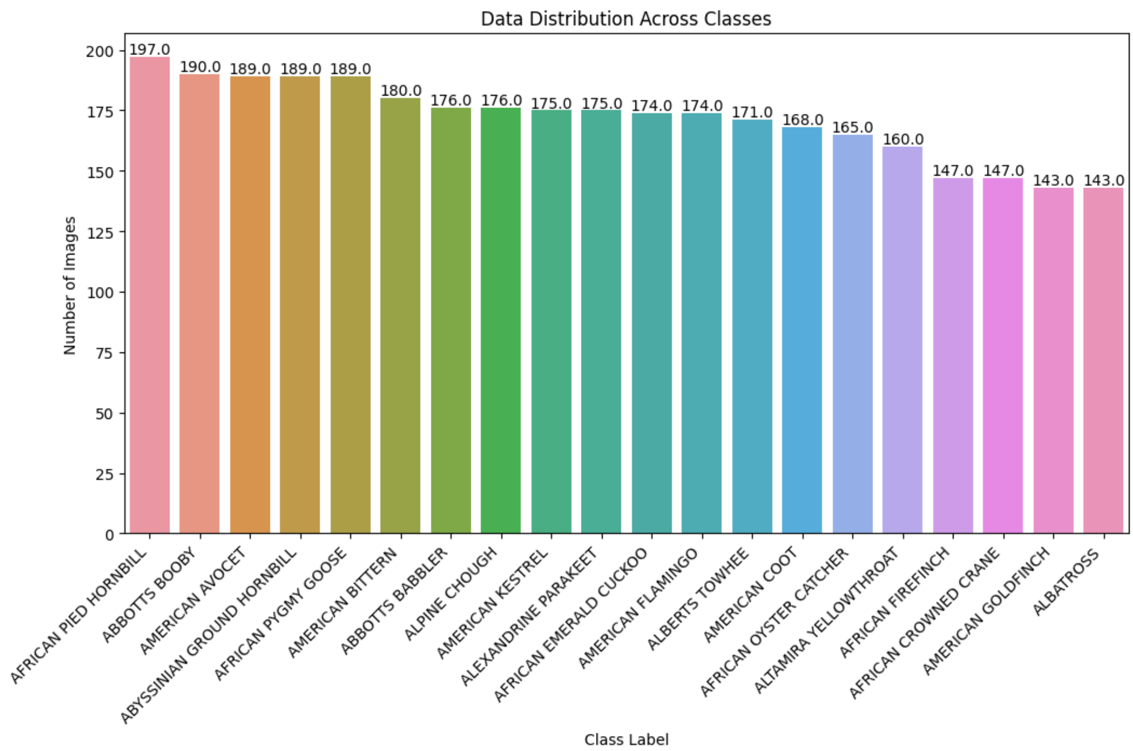
Out[8]:
```
ALTAMIRA YELLOWTHROAT         5
AMERICAN COOT                 5
AFRICAN CROWNED CRANE         5
ALBATROSS                     5
AFRICAN FIREFINCH             5
ABYSSINIAN GROUND HORNBILL    5
AFRICAN PYGMY GOOSE           5
ABBOTTS BOOBY                 5
AFRICAN PIED HORNBILL         5
ABBOTTS BABBLER               5
AFRICAN OYSTER CATCHER        5
ALEXANDRINE PARAKEET          5
AMERICAN AVOCET               5
AMERICAN BITTERN              5
ALBERTS TOWHEE                5
AMERICAN FLAMINGO             5
AMERICAN GOLDFINCH            5
ALPINE CHOUGH                 5
AMERICAN KESTREL              5
AFRICAN EMERALD CUCKOO        5
Name: Label, dtype: int64
```

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

all_df = pd.concat([train_df, test_df, valid_df], ignore_index=True)
plt.figure(figsize=(12, 6))
ax = sns.countplot(x='Label', data=all_df, order=all_df['Label'].value_coun

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get
                ha='center', va='center', fontsize=10, color='black', xytex
                textcoords='offset points')

plt.title('Data Distribution Across Classes')
plt.xlabel('Class Label')
plt.ylabel('Number of Images')
plt.xticks(rotation=45, ha='right')
plt.show()
```



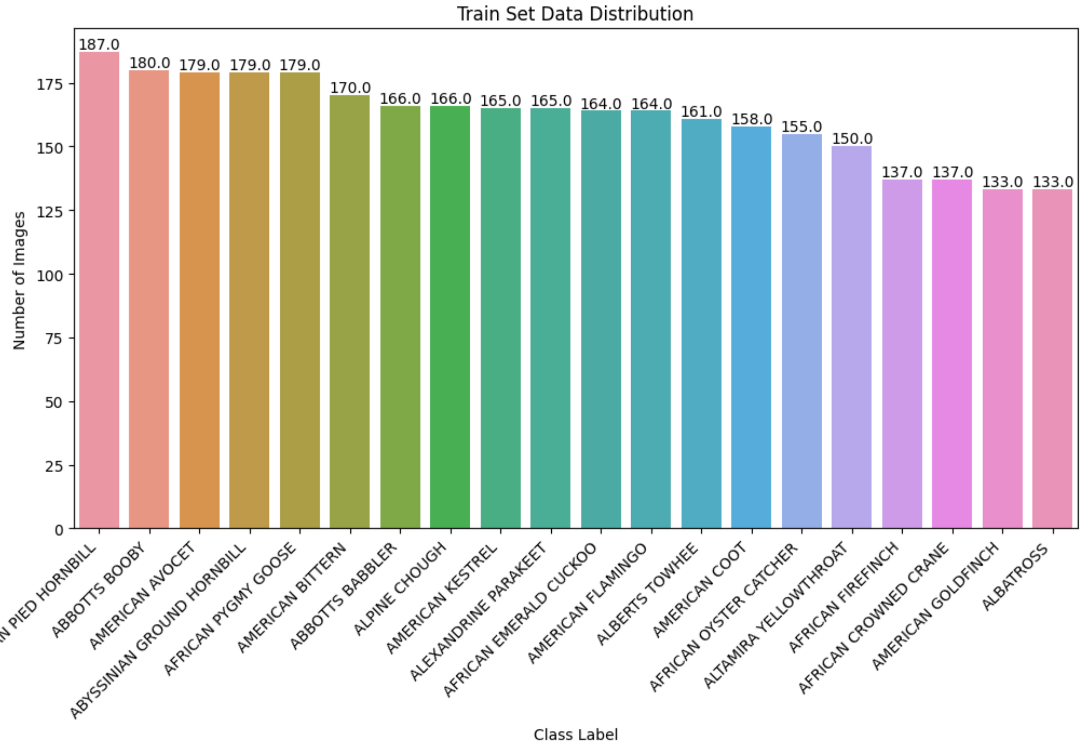
In [ ]:

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6))
ax = sns.countplot(x='Label', data=train_df, order=train_df['Label'].value_

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get
                ha='center', va='center', fontsize=10, color='black', xytex
                textcoords='offset points')

plt.title('Train Set Data Distribution')
plt.xlabel('Class Label')
plt.ylabel('Number of Images')
plt.xticks(rotation=45, ha='right')
plt.show()
```

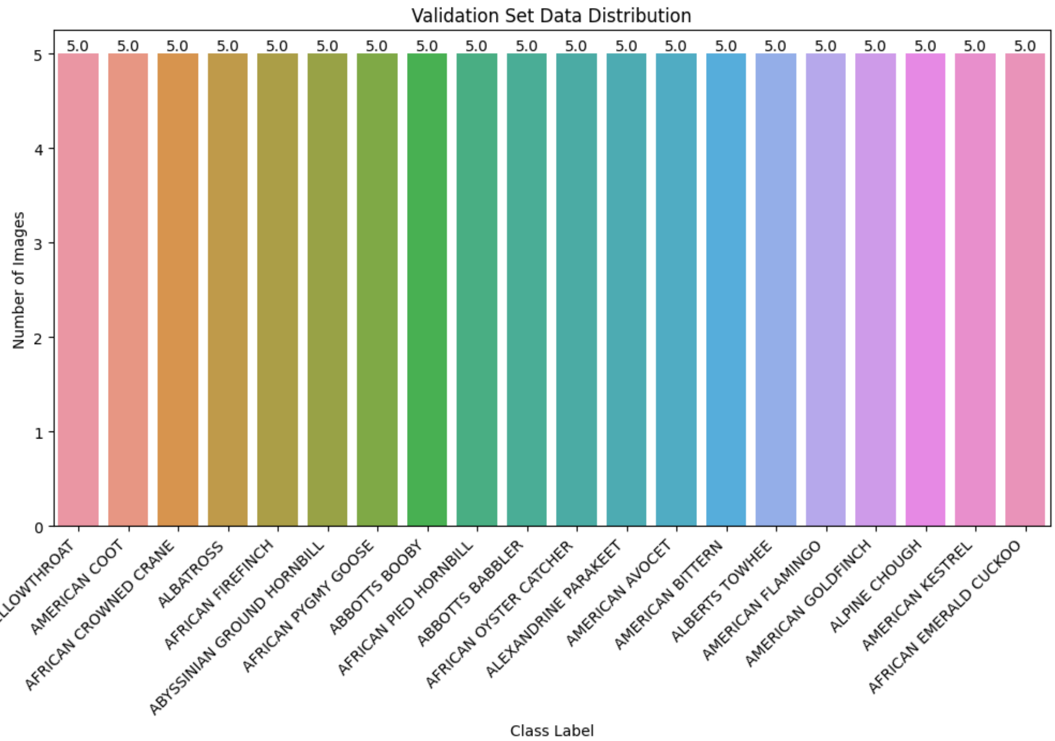


In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6))
ax = sns.countplot(x='Label', data=valid_df, order=valid_df['Label'].value_

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get
                ha='center', va='center', fontsize=10, color='black', xytex
                textcoords='offset points')

plt.title('Validation Set Data Distribution')
plt.xlabel('Class Label')
plt.ylabel('Number of Images')
plt.xticks(rotation=45, ha='right')
plt.show()
```

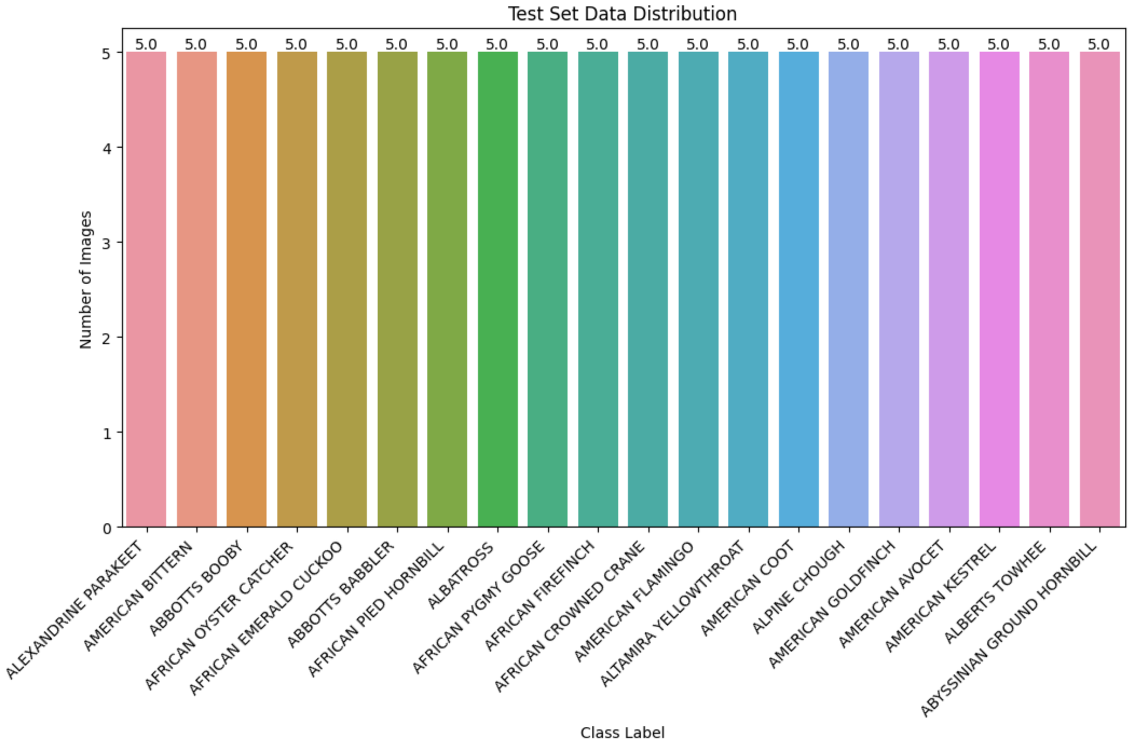


In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6))
ax = sns.countplot(x='Label', data=test_df, order=test_df['Label'].value_co

for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get
                ha='center', va='center', fontsize=10, color='black', xytex
                textcoords='offset points')

plt.title('Test Set Data Distribution')
plt.xlabel('Class Label')
plt.ylabel('Number of Images')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [ ]:
```
train_dataset_path = "/content/drive/MyDrive/data/train"

transform = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomAffine(degrees=0, scale=(0.8, 1.0))
])

for class_folder in os.listdir(train_dataset_path):
    class_folder_path = os.path.join(train_dataset_path, class_folder)

    augmented_image_paths = []

    for image_name in os.listdir(class_folder_path):
        image_path = os.path.join(class_folder_path, image_name)
        image = Image.open(image_path)

        augmented_image = transform(image)
        augmented_image_name = f"augmented_{image_name}"

        augmented_image_path = os.path.join(class_folder_path, augmented_im
        augmented_image.save(augmented_image_path)
        augmented_image_paths.append(augmented_image_path)
```

In [ ]:
```
train_images_aug, train_labels_aug, train_filenames_aug = read_images_and_l
train_df_aug = pd.DataFrame({'Image': train_images_aug, 'Label': train_labe
```

In [ ]:
```
train_class_counts_aug = train_df_aug['Label'].value_counts()
train_class_counts_aug
```

Out[15]:
```
AFRICAN PIED HORNBILL        374
ABBOTTS BOOBY                360
AMERICAN AVOCET              358
ABYSSINIAN GROUND HORNBILL   358
AFRICAN PYGMY GOOSE          358
AMERICAN BITTERN             340
ABBOTTS BABBLER              332
ALPINE CHOUGH                332
AMERICAN KESTREL             330
ALEXANDRINE PARAKEET         330
AFRICAN EMERALD CUCKOO       328
AMERICAN FLAMINGO            328
ALBERTS TOWHEE               322
AMERICAN COOT                316
AFRICAN OYSTER CATCHER       310
ALTAMIRA YELLOWTHROAT        300
AFRICAN FIREFINCH            274
AFRICAN CROWNED CRANE        274
AMERICAN GOLDFINCH           266
ALBATROSS                    266
Name: Label, dtype: int64
```

In [ ]:
```
display_random_images(train_df_aug['Image'], train_df_aug['Label'], train_d
```

In [ ]:
```
import torch
from torchvision.transforms import v2 as transforms
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader, random_split

train_dataset_path = "/content/drive/MyDrive/data/train"
valid_dataset_path = "/content/drive/MyDrive/data/valid"
test_dataset_path = "/content/drive/MyDrive/data/test"

train_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])

valid_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])

test_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])

class CustomImageFolder(ImageFolder):
    def __init__(self, root, transform=None, class_to_index=None):
        super(CustomImageFolder, self).__init__(root, transform=transform)
        self.class_to_index = class_to_index

    def __getitem__(self, index):
        path, target = self.samples[index]
        image = self.loader(path)
        if self.transform is not None:
            image = self.transform(image)

        label = self.class_to_index[self.classes[target]]

        return image, label

class_to_index = {
    'AFRICAN PIED HORNBILL': 0,
    'ABBOTTS BOOBY': 1,
    'ABYSSINIAN GROUND HORNBILL': 2,
    'AMERICAN AVOCET': 3,
    'AFRICAN PYGMY GOOSE': 4,
    'AMERICAN BITTERN': 5,
    'ABBOTTS BABBLER': 6,
    'ALPINE CHOUGH': 7,
    'ALEXANDRINE PARAKEET': 8,
    'AMERICAN FLAMINGO': 9,
    'ALBERTS TOWHEE': 10,
    'AMERICAN COOT': 11,
    'AFRICAN OYSTER CATCHER': 12,
    'AMERICAN KESTREL': 13,
    'AFRICAN EMERALD CUCKOO': 14,
    'ALTAMIRA YELLOWTHROAT': 15,
    'AFRICAN FIREFINCH': 16,
    'AFRICAN CROWNED CRANE': 17,
    'ALBATROSS': 18,
    'AMERICAN GOLDFINCH': 19,
}
```

```
train_dataset = CustomImageFolder(train_dataset_path, transform=train_trans
valid_dataset = CustomImageFolder(valid_dataset_path, transform=valid_trans
test_dataset = CustomImageFolder(test_dataset_path, transform=test_transfor

batch_size = 32
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=Tru
val_loader = DataLoader(valid_dataset, batch_size=batch_size, shuffle=False
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False
```

In [ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import models
from tqdm import tqdm

class SimpleCNN(nn.Module):
    def __init__(self, num_classes):
        super(SimpleCNN, self).__init__()

        #Convolutional layers
        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)

        self.conv2 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)

        self.conv3 = nn.Conv2d(128, 256, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        #Fully connected layers
        self.fc1 = nn.Linear(256 * 28 * 28, 512)
        self.relu4 = nn.ReLU()
        self.fc2 = nn.Linear(512, num_classes)

    def forward(self, x):
        x = self.pool1(self.relu1(self.conv1(x)))
        x = self.pool2(self.relu2(self.conv2(x)))
        x = self.pool3(self.relu3(self.conv3(x)))

        x = x.view(x.size(0), -1)
        x = self.relu4(self.fc1(x))
        x = self.fc2(x)

        return x

num_classes = len(class_to_index)
cnn_model = SimpleCNN(num_classes)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
cnn_model = cnn_model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(cnn_model.parameters(), lr=0.00007)

#training loop
num_epochs = 10
for epoch in range(num_epochs):
    cnn_model.train()
    total_loss = 0.0
    correct_train = 0
    total_train = 0

    for inputs, labels in tqdm(train_loader, desc=f'Epoch {epoch + 1}/{num_
        inputs, labels = inputs.to(device), labels.to(device)
```

```
        optimizer.zero_grad()

        outputs = cnn_model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

        _, predicted = outputs.max(1)
        total_train += labels.size(0)
        correct_train += predicted.eq(labels).sum().item()

    avg_train_loss = total_loss / len(train_loader)
    train_accuracy = correct_train / total_train

    #validation Loop
    cnn_model.eval()
    total_val = 0
    correct_val = 0

    with torch.no_grad():
        for inputs, labels in tqdm(val_loader, desc=f'Validation'):
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = cnn_model(inputs)
            _, predicted = outputs.max(1)
            total_val += labels.size(0)
            correct_val += predicted.eq(labels).sum().item()

    val_accuracy = correct_val / total_val

    print(f'Epoch {epoch + 1}/{num_epochs}, '
          f'Training Loss: {avg_train_loss:.4f}, '
          f'Training Accuracy: {train_accuracy:.4f}, '
          f'Validation Accuracy: {val_accuracy:.4f}')

torch.save(cnn_model.state_dict(), 'CNN_model.pth')

cnn_model.eval()
total_test = 0
correct_test = 0

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc=f'Testing'):
        inputs, labels = inputs.to(device), labels.to(device)

        outputs = cnn_model(inputs)
        _, predicted1 = outputs.max(1)
        total_test += labels.size(0)
        correct_test += predicted1.eq(labels).sum().item()


test_accuracy = correct_test / total_test
print('-----------------------------------------------------------------------
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Epoch 1/10: 100%|██████████| 202/202 [00:34<00:00,  5.90it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  6.26it/s]
```

```
Epoch 1/10, Training Loss: 2.4802, Training Accuracy: 0.2319, Validation A
ccuracy: 0.4400

Epoch 2/10: 100%|██████████| 202/202 [00:33<00:00,  6.03it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  6.92it/s]

Epoch 2/10, Training Loss: 1.7099, Training Accuracy: 0.4875, Validation A
ccuracy: 0.6700

Epoch 3/10: 100%|██████████| 202/202 [00:33<00:00,  6.05it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.03it/s]

Epoch 3/10, Training Loss: 1.3609, Training Accuracy: 0.5954, Validation A
ccuracy: 0.7200

Epoch 4/10: 100%|██████████| 202/202 [00:33<00:00,  6.03it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.03it/s]

Epoch 4/10, Training Loss: 1.1134, Training Accuracy: 0.6688, Validation A
ccuracy: 0.8100

Epoch 5/10: 100%|██████████| 202/202 [00:33<00:00,  5.98it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.66it/s]

Epoch 5/10, Training Loss: 0.8875, Training Accuracy: 0.7433, Validation A
ccuracy: 0.7800

Epoch 6/10: 100%|██████████| 202/202 [00:34<00:00,  5.93it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  6.96it/s]

Epoch 6/10, Training Loss: 0.6999, Training Accuracy: 0.7912, Validation A
ccuracy: 0.8100

Epoch 7/10: 100%|██████████| 202/202 [00:33<00:00,  6.02it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  6.79it/s]

Epoch 7/10, Training Loss: 0.5042, Training Accuracy: 0.8570, Validation A
ccuracy: 0.7500

Epoch 8/10: 100%|██████████| 202/202 [00:33<00:00,  5.97it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.10it/s]

Epoch 8/10, Training Loss: 0.3518, Training Accuracy: 0.9049, Validation A
ccuracy: 0.7900

Epoch 9/10: 100%|██████████| 202/202 [00:33<00:00,  6.01it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.74it/s]

Epoch 9/10, Training Loss: 0.2234, Training Accuracy: 0.9473, Validation A
ccuracy: 0.8300

Epoch 10/10: 100%|██████████| 202/202 [00:33<00:00,  5.95it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.83it/s]

Epoch 10/10, Training Loss: 0.1467, Training Accuracy: 0.9706, Validation
Accuracy: 0.8200

Testing: 100%|██████████| 4/4 [00:00<00:00,  6.76it/s]

--------------------------------------------------------------------------
-------------
Test Accuracy: 0.7800
```

In [ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import models
from tqdm import tqdm

class CustomResNet(nn.Module):
    def __init__(self, num_classes):
        super(CustomResNet, self).__init__()
        self.resnet = models.resnet18(pretrained=True)
        in_features = self.resnet.fc.in_features
        self.resnet.fc = nn.Linear(in_features, num_classes)

    def forward(self, x):
        return self.resnet(x)

num_classes = len(class_to_index)
resnet_model = CustomResNet(num_classes)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
resnet_model = resnet_model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(resnet_model.parameters(), lr=0.000001)

num_epochs = 10
for epoch in range(num_epochs):
    resnet_model.train()
    total_loss = 0.0
    correct_train = 0
    total_train = 0

    for inputs, labels in tqdm(train_loader, desc=f'Epoch {epoch + 1}/{num_
        inputs, labels = inputs.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs = resnet_model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

        _, predicted = outputs.max(1)
        total_train += labels.size(0)
        correct_train += predicted.eq(labels).sum().item()

    avg_train_loss = total_loss / len(train_loader)
    train_accuracy = correct_train / total_train

    resnet_model.eval()
    total_val = 0
    correct_val = 0

    with torch.no_grad():
        for inputs, labels in tqdm(val_loader, desc=f'Validation'):
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = resnet_model(inputs)
            _, predicted = outputs.max(1)
```

```
            total_val += labels.size(0)
            correct_val += predicted.eq(labels).sum().item()

    val_accuracy = correct_val / total_val

    print(f'Epoch {epoch + 1}/{num_epochs}, '
          f'Training Loss: {avg_train_loss:.4f}, '
          f'Training Accuracy: {train_accuracy:.4f}, '
          f'Validation Accuracy: {val_accuracy:.4f}')

torch.save(resnet_model.state_dict(), 'resnet_model.pth')

resnet_model.eval()
total_test = 0
correct_test = 0

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc=f'Testing'):
        inputs, labels = inputs.to(device), labels.to(device)

        outputs = resnet_model(inputs)
        _, predicted2 = outputs.max(1)
        total_test += labels.size(0)
        correct_test += predicted2.eq(labels).sum().item()


test_accuracy = correct_test / total_test
print('---------------------------------------------------------------------
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208:
UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may b
e removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223:
UserWarning: Arguments other than a weight enum or `None` for 'weights' ar
e deprecated since 0.13 and may be removed in the future. The current beha
vior is equivalent to passing `weights=ResNet18_Weights.IMAGENET1K_V1`. Yo
u can also use `weights=ResNet18_Weights.DEFAULT` to get the most up-to-da
te weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" t
o /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 138MB/s]
Epoch 1/10: 100%|██████████| 202/202 [00:24<00:00,  8.36it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.70it/s]

Epoch 1/10, Training Loss: 3.0789, Training Accuracy: 0.0536, Validation A
ccuracy: 0.1000

Epoch 2/10: 100%|██████████| 202/202 [00:24<00:00,  8.35it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.17it/s]

Epoch 2/10, Training Loss: 2.8651, Training Accuracy: 0.0994, Validation A
ccuracy: 0.2100

Epoch 3/10: 100%|██████████| 202/202 [00:24<00:00,  8.29it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.21it/s]

Epoch 3/10, Training Loss: 2.6606, Training Accuracy: 0.1859, Validation A
ccuracy: 0.3800
```

```
Epoch 4/10: 100%|██████████| 202/202 [00:23<00:00,  8.60it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  6.59it/s]

Epoch 4/10, Training Loss: 2.4673, Training Accuracy: 0.3047, Validation A
ccuracy: 0.5300

Epoch 5/10: 100%|██████████| 202/202 [00:24<00:00,  8.23it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.11it/s]

Epoch 5/10, Training Loss: 2.2821, Training Accuracy: 0.4414, Validation A
ccuracy: 0.6500

Epoch 6/10: 100%|██████████| 202/202 [00:24<00:00,  8.38it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.64it/s]

Epoch 6/10, Training Loss: 2.1025, Training Accuracy: 0.5638, Validation A
ccuracy: 0.7600

Epoch 7/10: 100%|██████████| 202/202 [00:24<00:00,  8.39it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  6.88it/s]

Epoch 7/10, Training Loss: 1.9332, Training Accuracy: 0.6509, Validation A
ccuracy: 0.8500

Epoch 8/10: 100%|██████████| 202/202 [00:24<00:00,  8.25it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.21it/s]

Epoch 8/10, Training Loss: 1.7727, Training Accuracy: 0.7159, Validation A
ccuracy: 0.8900

Epoch 9/10: 100%|██████████| 202/202 [00:23<00:00,  8.54it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.79it/s]

Epoch 9/10, Training Loss: 1.6300, Training Accuracy: 0.7590, Validation A
ccuracy: 0.9600

Epoch 10/10: 100%|██████████| 202/202 [00:24<00:00,  8.28it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  7.17it/s]

Epoch 10/10, Training Loss: 1.5021, Training Accuracy: 0.7873, Validation
Accuracy: 0.9800

Testing: 100%|██████████| 4/4 [00:00<00:00,  6.87it/s]

--------------------------------------------------------------------------
-------------
Test Accuracy: 0.8900
```

In [ ]:
```
import torch
import torch.nn as nn
from tqdm import tqdm
from torchvision import transforms, datasets, models
from torch.utils.data import DataLoader, random_split

num_classes = len(train_dataset.classes)
densenet_model = models.densenet121(pretrained=True)
in_features = densenet_model.classifier.in_features
densenet_model.classifier = nn.Linear(in_features, num_classes)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
densenet_model = densenet_model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(densenet_model.parameters(), lr=0.000001)

#Training loop
num_epochs = 15
for epoch in range(num_epochs):

    densenet_model.train()
    total_loss = 0.0
    correct_train = 0
    total_train = 0

    for inputs, labels in tqdm(train_loader, desc=f'Epoch {epoch + 1}/{num_
        inputs, labels = inputs.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs = densenet_model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

        _, predicted = outputs.max(1)
        total_train += labels.size(0)
        correct_train += predicted.eq(labels).sum().item()

    avg_train_loss = total_loss / len(train_loader)
    train_accuracy = correct_train / total_train

    #Validation
    densenet_model.eval()
    total_val = 0
    correct_val = 0

    with torch.no_grad():
        for inputs, labels in tqdm(val_loader, desc=f'Validation'):
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = densenet_model(inputs)
            _, predicted = outputs.max(1)
            total_val += labels.size(0)
            correct_val += predicted.eq(labels).sum().item()

    val_accuracy = correct_val / total_val
```

```
    print(f'Epoch {epoch + 1}/{num_epochs}, '
          f'Training Loss: {avg_train_loss:.4f}, '
          f'Training Accuracy: {train_accuracy:.4f}, '
          f'Validation Accuracy: {val_accuracy:.4f}')

torch.save(densenet_model.state_dict(), 'densenet_model.pth')


#Testing Loop
densenet_model.eval()
total_test = 0
correct_test = 0

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc=f'Testing'):
        inputs, labels = inputs.to(device), labels.to(device)

        outputs = densenet_model(inputs)
        _, predicted3 = outputs.max(1)
        total_test += labels.size(0)
        correct_test += predicted3.eq(labels).sum().item()


test_accuracy = correct_test / total_test
print('---------------------------------------------------------------------------
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223:
UserWarning: Arguments other than a weight enum or `None` for 'weights' ar
e deprecated since 0.13 and may be removed in the future. The current beha
vior is equivalent to passing `weights=DenseNet121_Weights.IMAGENET1K_V1`.
You can also use `weights=DenseNet121_Weights.DEFAULT` to get the most up-
to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/densenet121-a639ec97.pt
h" to /root/.cache/torch/hub/checkpoints/densenet121-a639ec97.pth
100%|██████████| 30.8M/30.8M [00:00<00:00, 115MB/s]
Epoch 1/15: 100%|██████████| 202/202 [01:09<00:00,  2.90it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.66it/s]

Epoch 1/15, Training Loss: 3.0339, Training Accuracy: 0.0646, Validation A
ccuracy: 0.0600

Epoch 2/15: 100%|██████████| 202/202 [01:09<00:00,  2.91it/s]
Validation: 100%|██████████| 4/4 [00:01<00:00,  3.87it/s]

Epoch 2/15, Training Loss: 2.9110, Training Accuracy: 0.0974, Validation A
ccuracy: 0.0900

Epoch 3/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.02it/s]

Epoch 3/15, Training Loss: 2.7891, Training Accuracy: 0.1538, Validation A
ccuracy: 0.2000

Epoch 4/15: 100%|██████████| 202/202 [01:09<00:00,  2.90it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.28it/s]

Epoch 4/15, Training Loss: 2.6707, Training Accuracy: 0.2421, Validation A
ccuracy: 0.3000

Epoch 5/15: 100%|██████████| 202/202 [01:09<00:00,  2.90it/s]
Validation: 100%|██████████| 4/4 [00:01<00:00,  3.87it/s]
```

```
Epoch 5/15, Training Loss: 2.5532, Training Accuracy: 0.3346, Validation A
ccuracy: 0.4400

Epoch 6/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.16it/s]

Epoch 6/15, Training Loss: 2.4373, Training Accuracy: 0.4289, Validation A
ccuracy: 0.5800

Epoch 7/15: 100%|██████████| 202/202 [01:09<00:00,  2.90it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.29it/s]

Epoch 7/15, Training Loss: 2.3275, Training Accuracy: 0.5152, Validation A
ccuracy: 0.6600

Epoch 8/15: 100%|██████████| 202/202 [01:09<00:00,  2.91it/s]
Validation: 100%|██████████| 4/4 [00:01<00:00,  3.89it/s]

Epoch 8/15, Training Loss: 2.2179, Training Accuracy: 0.5912, Validation A
ccuracy: 0.7400

Epoch 9/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.10it/s]

Epoch 9/15, Training Loss: 2.1119, Training Accuracy: 0.6543, Validation A
ccuracy: 0.7700

Epoch 10/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.08it/s]

Epoch 10/15, Training Loss: 2.0081, Training Accuracy: 0.7020, Validation
Accuracy: 0.8400

Epoch 11/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:01<00:00,  4.00it/s]

Epoch 11/15, Training Loss: 1.9078, Training Accuracy: 0.7419, Validation
Accuracy: 0.8700

Epoch 12/15: 100%|██████████| 202/202 [01:09<00:00,  2.90it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.64it/s]

Epoch 12/15, Training Loss: 1.8111, Training Accuracy: 0.7735, Validation
Accuracy: 0.8800

Epoch 13/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  5.16it/s]

Epoch 13/15, Training Loss: 1.7216, Training Accuracy: 0.7977, Validation
Accuracy: 0.8900

Epoch 14/15: 100%|██████████| 202/202 [01:09<00:00,  2.90it/s]
Validation: 100%|██████████| 4/4 [00:00<00:00,  4.90it/s]

Epoch 14/15, Training Loss: 1.6379, Training Accuracy: 0.8140, Validation
Accuracy: 0.9200

Epoch 15/15: 100%|██████████| 202/202 [01:09<00:00,  2.89it/s]
Validation: 100%|██████████| 4/4 [00:01<00:00,  3.86it/s]

Epoch 15/15, Training Loss: 1.5520, Training Accuracy: 0.8309, Validation
Accuracy: 0.9000

Testing: 100%|██████████| 4/4 [00:01<00:00,  3.86it/s]
```

```
--------------------------------------------------------------------------------
Test Accuracy: 0.9200
```

In [ ]:
```
!pip install timm
```

```
Collecting timm
  Downloading timm-0.9.12-py3-none-any.whl (2.2 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.2/2.2 MB 6.7 MB/s eta 0:0
0:00
Requirement already satisfied: torch>=1.7 in /usr/local/lib/python3.10/dis
t-packages (from timm) (2.1.0+cu118)
Requirement already satisfied: torchvision in /usr/local/lib/python3.10/di
st-packages (from timm) (0.16.0+cu118)
Requirement already satisfied: pyyaml in /usr/local/lib/python3.10/dist-pa
ckages (from timm) (6.0.1)
Requirement already satisfied: huggingface-hub in /usr/local/lib/python3.1
0/dist-packages (from timm) (0.19.4)
Requirement already satisfied: safetensors in /usr/local/lib/python3.10/di
st-packages (from timm) (0.4.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-
packages (from torch>=1.7->timm) (3.13.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python
3.10/dist-packages (from torch>=1.7->timm) (4.5.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-pac
kages (from torch>=1.7->timm) (1.12)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-
packages (from torch>=1.7->timm) (3.2.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-pa
ckages (from torch>=1.7->timm) (3.1.2)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-pa
ckages (from torch>=1.7->timm) (2023.6.0)
Requirement already satisfied: triton==2.1.0 in /usr/local/lib/python3.10/
dist-packages (from torch>=1.7->timm) (2.1.0)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from huggingface-hub->timm) (2.31.0)
Requirement already satisfied: tqdm>=4.42.1 in /usr/local/lib/python3.10/d
ist-packages (from huggingface-hub->timm) (4.66.1)
Requirement already satisfied: packaging>=20.9 in /usr/local/lib/python3.1
0/dist-packages (from huggingface-hub->timm) (23.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-pac
kages (from torchvision->timm) (1.23.5)
Requirement already satisfied: pillow!=8.3.*,>=5.3.0 in /usr/local/lib/pyt
hon3.10/dist-packages (from torchvision->timm) (9.4.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.1
0/dist-packages (from jinja2->torch>=1.7->timm) (2.1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/
python3.10/dist-packages (from requests->huggingface-hub->timm) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/d
ist-packages (from requests->huggingface-hub->timm) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python
3.10/dist-packages (from requests->huggingface-hub->timm) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python
3.10/dist-packages (from requests->huggingface-hub->timm) (2023.11.17)
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/d
ist-packages (from sympy->torch>=1.7->timm) (1.3.0)
Installing collected packages: timm
Successfully installed timm-0.9.12
```

In [ ]:
```
import timm
```

```
model.safetensors:   0%|          | 0.00/346M [00:00<?, ?B/s]
```

In [ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from tqdm import tqdm
import torch
import torch.nn as nn
from torchvision import transforms
from torchvision.models import vision_transformer
from torch.utils.data import DataLoader
from torchvision.datasets import ImageFolder

#vit_model = vision_transformer.vit_base_patch16_224(pretrained=True)
vit_model = timm.create_model("vit_base_patch16_224", pretrained=True)
num_classes = len(class_to_index)
vit_model.head = nn.Linear(in_features=vit_model.head.in_features, out_feat

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
vit_model = vit_model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(vit_model.parameters(), lr=0.0005)

# Training Loop
num_epochs = 12
for epoch in range(num_epochs):
    # Training
    vit_model.train()
    total_loss = 0.0
    correct_train = 0
    total_train = 0

    for inputs, labels in tqdm(train_loader, desc=f'Epoch {epoch + 1}/{num_
        inputs, labels = inputs.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs = vit_model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

        _, predicted = outputs.max(1)
        total_train += labels.size(0)
        correct_train += predicted.eq(labels).sum().item()

    avg_train_loss = total_loss / len(train_loader)
    train_accuracy = correct_train / total_train

    # Validation
    vit_model.eval()
    total_val = 0
    correct_val = 0

    with torch.no_grad():
        for inputs, labels in tqdm(val_loader, desc=f'Validation'):
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = vit_model(inputs)
            _, predicted = outputs.max(1)
```

```
                total_val += labels.size(0)
                correct_val += predicted.eq(labels).sum().item()

        val_accuracy = correct_val / total_val

        print(f'Epoch {epoch + 1}/{num_epochs}, '
              f'Training Loss: {avg_train_loss:.4f}, '
              f'Training Accuracy: {train_accuracy:.4f}, '
              f'Validation Accuracy: {val_accuracy:.4f}')

# Testing loop
vit_model.eval()
total_test = 0
correct_test = 0

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc=f'Testing'):
        inputs, labels = inputs.to(device), labels.to(device)

        outputs = vit_model(inputs)
        _, predicted4 = outputs.max(1)
        total_test += labels.size(0)
        correct_test += predicted4.eq(labels).sum().item()

test_accuracy = correct_test / total_test
print('-----------------------------------------------------------------------
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Epoch 1/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.58it/s]

Epoch 1/12, Training Loss: 2.9648, Training Accuracy: 0.0923, Validation A
ccuracy: 0.2200

Epoch 2/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.23it/s]

Epoch 2/12, Training Loss: 2.3795, Training Accuracy: 0.2288, Validation A
ccuracy: 0.3100

Epoch 3/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.64it/s]

Epoch 3/12, Training Loss: 1.8166, Training Accuracy: 0.4181, Validation A
ccuracy: 0.4700

Epoch 4/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.61it/s]

Epoch 4/12, Training Loss: 1.5329, Training Accuracy: 0.5074, Validation A
ccuracy: 0.5900

Epoch 5/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.39it/s]

Epoch 5/12, Training Loss: 1.4064, Training Accuracy: 0.5507, Validation A
ccuracy: 0.5900

Epoch 6/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.27it/s]

Epoch 6/12, Training Loss: 1.3105, Training Accuracy: 0.5745, Validation A
ccuracy: 0.6600
```

```
Epoch 7/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.65it/s]

Epoch 7/12, Training Loss: 1.2174, Training Accuracy: 0.6089, Validation A
ccuracy: 0.6400

Epoch 8/12: 100%|██████████| 202/202 [03:39<00:00,  1.09s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.61it/s]

Epoch 8/12, Training Loss: 1.1218, Training Accuracy: 0.6475, Validation A
ccuracy: 0.6400

Epoch 9/12: 100%|██████████| 202/202 [03:38<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.60it/s]

Epoch 9/12, Training Loss: 1.0854, Training Accuracy: 0.6495, Validation A
ccuracy: 0.6300

Epoch 10/12: 100%|██████████| 202/202 [03:39<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.23it/s]

Epoch 10/12, Training Loss: 1.0472, Training Accuracy: 0.6622, Validation
Accuracy: 0.7500

Epoch 11/12: 100%|██████████| 202/202 [03:39<00:00,  1.09s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.44it/s]

Epoch 11/12, Training Loss: 0.9825, Training Accuracy: 0.6871, Validation
Accuracy: 0.6700

Epoch 12/12: 100%|██████████| 202/202 [03:39<00:00,  1.08s/it]
Validation: 100%|██████████| 4/4 [00:01<00:00,  2.60it/s]

Epoch 12/12, Training Loss: 0.9486, Training Accuracy: 0.6927, Validation
Accuracy: 0.6900

Testing: 100%|██████████| 4/4 [00:01<00:00,  2.57it/s]

--------------------------------------------------------------------------
-------------
Test Accuracy: 0.7400
```

In [ ]:
```
import numpy as np
from scipy.stats import mode

pred_cnn = []
pred_res = []
pred_den = []
pred_vit = []
all_ground_truth_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc=f'Testing'):
        inputs, labels = inputs.to(device), labels.to(device)

        all_ground_truth_labels.append(labels)

        outputs_cnn = cnn_model(inputs)
        _, predicted1 = outputs_cnn.max(1)
        pred_cnn.extend(predicted1.cpu().numpy())

        outputs_res = resnet_model(inputs)
        _, predicted2 = outputs_res.max(1)
        pred_res.extend(predicted2.cpu().numpy())

        outputs_den = densenet_model(inputs)
        _, predicted3 = outputs_den.max(1)
        pred_den.extend(predicted3.cpu().numpy())

        outputs_vit = vit_model(inputs)
        _, predicted4 = outputs_vit.max(1)
        pred_vit.extend(predicted4.cpu().numpy())

pred_cnn = np.array(pred_cnn)
pred_res = np.array(pred_res)
pred_den = np.array(pred_den)
pred_vit = np.array(pred_vit)

ground_truth_labels = np.concatenate([labels.cpu().numpy() for labels in al

accuracy_cnn = np.mean(pred_cnn == ground_truth_labels)
accuracy_res = np.mean(pred_res == ground_truth_labels)
accuracy_den = np.mean(pred_den == ground_truth_labels)
accuracy_vit = np.mean(pred_vit == ground_truth_labels)

print(f"\nCNN Model Accuracy: {accuracy_cnn * 100:.2f}%")
print(f"ResNet Model Accuracy: {accuracy_res * 100:.2f}%")
print(f"DenseNet Model Accuracy: {accuracy_den * 100:.2f}%")
print(f"ViT Model Accuracy: {accuracy_vit * 100:.2f}%")

all_predictions = np.stack([pred_cnn, pred_res, pred_den], axis=1)

ensemble_predictions, _ = mode(all_predictions, axis=1)
ensemble_accuracy = np.mean(ensemble_predictions.flatten() == ground_truth_

print(f"Ensemble Accuracy: {ensemble_accuracy * 100:.2f}%")
```

```
Testing: 100%|██████████| 4/4 [00:02<00:00,  1.96it/s]
```

```
CNN Model Accuracy: 78.00%
ResNet Model Accuracy: 89.00%
DenseNet Model Accuracy: 92.00%
ViT Model Accuracy: 74.00%
Ensemble Accuracy: 93.00%
```