```
from google.colab import drive
drive.mount('/content/drive')
     Mounted at /content/drive
import os
import time
import torch
import torch.nn as nn
import torchvision
from torchvision import datasets
from PIL import Image
from torchvision import transforms
from torch.utils.data import Dataset, DataLoader
import numpy as np
from tqdm import tqdm
import matplotlib.pyplot as plt
from sklearn.model selection import train test split
def aspect_ratio_preserving_resize(image, target_size):
    width, height = image.size
    target_width, target_height = target_size
    # Calculate the aspect ratio
    aspect_ratio = width / height
    if width > height:
        new_width = target_width
        new height = int(new width / aspect ratio)
    else:
        new height = target height
        new_width = int(new_height * aspect_ratio)
    # Perform the resize
    image = transforms.functional.resize(image, (new_height, new_width))
    # Create a new image with the target size and paste the resized image in the center
    new_image = Image.new("L", target_size)
    new_image.paste(image, ((target_width - new_width) // 2, (target_height - new_height) // 2))
    return new_image
class MyDataset(Dataset):
    def __init__(self, data_dir, transform=None):
        self.data_dir = data_dir
        self.transform = transform
        self.image paths = [os.path.join(data dir, file) for file in os.listdir(data dir)]
    def __len__(self):
        return len(self.image_paths)
    def __getitem__(self, idx):
        image path = self.image paths[idx]
        image = Image.open(image_path)
        # Apply aspect ratio-preserving resize
        resized_image = aspect_ratio_preserving_resize(image, (100, 100))
        if self.transform:
            transformed_image = self.transform(resized_image)
        else:
            transformed_image = resized_image
        return transformed_image
# Define your data transformation
train_transform = transforms.Compose([
    transforms.Resize((100, 100)),
    transforms.RandomHorizontalFlip(p=0.2),
    transforms.RandomVerticalFlip(p=0.2),
    transforms.RandomRotation(degrees=(5, 15)),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.2),
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transforms.RandomResizedCrop((100, 100), scale=(0.8, 1.0)),
    transforms.ToTensor(),
1)
test transform = transforms.Compose([
   transforms.Resize((100, 100)),
    transforms.ToTensor(),
1)
batch\_size = 16
# Load data
train dataset = MyDataset(data_dir='/content/drive/MyDrive/AE xray/train', transform=test transform)
test_dataset = MyDataset(data_dir='/content/drive/MyDrive/AE_xray/test', transform=test_transform)
train_data, valid_data = train_test_split(train_dataset, test_size=0.1, random_state=42)
# Dataloader
train dl = DataLoader(train data, batch size=batch size, shuffle=True)
valid_dl = DataLoader(valid_data, batch_size=batch_size, shuffle=True)
test_dl = DataLoader(test_dataset, batch_size=batch_size, shuffle=True)
class Encoder(nn.Module):
 def __init__(self , input_size = 10000 , hidden_size1 = 5000, hidden_size2 = 2000 , hidden_size3 = 1000, hidden_size4 = 500, z_
   super().__init__()
    self.fc1 = nn.Linear(input_size , hidden_size1)
   self.fc2 = nn.Linear(hidden_size1 , hidden_size2)
   self.fc3 = nn.Linear(hidden_size2 , hidden_size3)
   self.fc4 = nn.Linear(hidden_size3 , hidden_size4)
   self.fc5 = nn.Linear(hidden_size4 , z_dim)
    self.relu = nn.ReLU()
   self.dropout = nn.Dropout(0.2) # Add dropout with a 50% probability
 def forward(self, x):
   x = self.relu(self.fc1(x))
   x = self.dropout(x) # Apply dropout after the first layer
   x = self.relu(self.fc2(x))
   x = self.dropout(x) # Apply dropout after the second layer
   x = self.relu(self.fc3(x))
   x = self.dropout(x) # Apply dropout after the third layer
   x = self.relu(self.fc4(x))
   x = self.fc5(x)
    return x
class Decoder(nn.Module):
 def __init__(self , output_size = 10000 , hidden_size1 = 5000, hidden_size2 = 2000 , hidden_size3 = 1000, hidden_size4 = 500, z
   super().__init__()
    self.fc1 = nn.Linear(z_dim , hidden_size4)
   self.fc2 = nn.Linear(hidden_size4 , hidden_size3)
   self.fc3 = nn.Linear(hidden_size3 , hidden_size2)
   self.fc4 = nn.Linear(hidden_size2 , hidden_size1)
   self.fc5 = nn.Linear(hidden_size1 , output_size)
   self.relu = nn.ReLU()
   self.dropout = nn.Dropout(0.5) # Add dropout with a 50% probability
  def forward(self, x):
    x = self.relu(self.fc1(x))
   x = self.dropout(x) # Apply dropout after the first layer
   x = self.relu(self.fc2(x))
   x = self.dropout(x) # Apply dropout after the second layer
   x = self.relu(self.fc3(x))
   x = self.dropout(x) # Apply dropout after the third layer
   x = self.relu(self.fc4(x))
   x = torch.sigmoid(self.fc5(x))
    return x
# class Encoder(nn.Module):
      def __init__(self, input_size=10000, hidden_size1=2500, hidden_size2=1000, hidden_size3=500, hidden_size4=200, z_dim=100):
#
          super().__init__()
#
          self.fc1 = nn.Linear(input_size, hidden_size1)
#
          self.fc2 = nn.Linear(hidden_size1, hidden_size2)
          self.fc3 = nn.Linear(hidden size2, hidden size3)
          self.fc4 = nn.Linear(hidden_size3, hidden_size4)
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self.fc5 = nn.Linear(hidden_size4, z_dim)
#
          self.relu = nn.ReLU()
#
          self.dropout = nn.Dropout(0.5) # Add dropout with a 50% probability
   # def forward(self, x):
         x = self.relu(self.fc1(x))
    #
          x = self.dropout(x) # Apply dropout after the first layer
         x = self.relu(self.fc2(x))
    #
         x = self.dropout(x) # Apply dropout after the second layer
          x = self.relu(self.fc3(x))
         x = self.dropout(x) # Apply dropout after the third layer
          x = self.relu(self.fc4(x))
         x = self.fc5(x)
   #
          return x
# class Decoder(nn.Module):
      def __init__(self, output_size=10000, hidden_size1=2500, hidden_size2=1000, hidden_size3=500, hidden_size4=200, z_dim=100):
#
          super().__init()
          self.fc1 = nn.Linear(z_dim, hidden_size4)
#
          self.fc2 = nn.Linear(hidden_size4, hidden_size3)
#
          self.fc3 = nn.Linear(hidden size3, hidden size2)
#
          self.fc4 = nn.Linear(hidden_size2, hidden_size1)
#
          self.fc5 = nn.Linear(hidden_size1, output_size)
          self.relu = nn.ReLU()
          self.dropout = nn.Dropout(0.5) # Add dropout with a 50% probability
    # def forward(self, x):
         x = self.relu(self.fc1(x))
         x = self.dropout(x) # Apply dropout after the first layer
         x = self.relu(self.fc2(x))
    #
         x = self.dropout(x) # Apply dropout after the second layer
         x = self.relu(self.fc3(x))
         x = self.dropout(x) # Apply dropout after the third layer
         x = self.relu(self.fc4(x))
         x = torch.sigmoid(self.fc5(x))
         return x
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
    device(type='cuda')
enc = Encoder().to(device)
dec = Decoder().to(device)
loss_fn = nn.MSELoss()
optimizer_enc = torch.optim.Adam(enc.parameters(), weight decay=1e-5)
optimizer_dec = torch.optim.Adam(dec.parameters(), weight_decay=1e-5)
train loss = []
val_loss = []
num epochs = 200
checkpoint_path = "/content/drive/MyDrive/model/Autoencoder/decay_dropout_xray_checkpoint_30z_5h_200e.pth"
# Check if a checkpoint exists to resume training
if os.path.exists(checkpoint_path):
  checkpoint = torch.load(checkpoint_path)
  enc.load_state_dict(checkpoint["enc_state_dict"])
 dec.load_state_dict(checkpoint["dec_state_dict"])
 optimizer_enc.load_state_dict(checkpoint["optimizer_enc_state_dict"])
 optimizer dec.load state dict(checkpoint["optimizer dec state dict"])
 train_loss = checkpoint["train_loss"]
 val_loss = checkpoint["val_loss"]
  start_epoch = checkpoint["epoch"] + 1 # Start from the next epoch after the loaded checkpoint
 print("Resume training from epoch", start epoch)
else:
  start_epoch = 1
    Resume training from epoch 13
total batches train = len(train dl)
total hatches valid = len(valid dl)
```

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for epoch in range(start_epoch,num_epochs+1):
   train_epoch_loss = 0
   valid_epoch_loss = 0
   start_time = time.time()
   # Create a tqdm progress bar for the epoch
   epoch_progress = tqdm(enumerate(train_dl, 1), total=total_batches_train, desc=f'Epoch {epoch}/{num_epochs}', leave=False)
   for step, imgs in epoch_progress:
       imgs = imgs.to(device)
       imgs = imgs.flatten(1)
       latents = enc(imgs)
       output = dec(latents)
       loss = loss_fn(output, imgs)
       train epoch loss += loss.item()
       optimizer_enc.zero_grad()
       optimizer_dec.zero_grad()
       loss.backward()
       optimizer_enc.step()
       optimizer_dec.step()
   with torch.no_grad():
      for val_imgs in valid_dl:
       val_imgs = val_imgs.to(device)
       # val imgs = add noise(val imgs)
       val_imgs = val_imgs.flatten(1)
       val_reconstructed = dec(enc(val_imgs))
       step_loss = loss_fn(val_reconstructed, val_imgs)
       valid_epoch_loss += step_loss.item()
   # epoch_progress.set_description(f'Epoch {epoch}/{num_epochs}, Step {step}/{total_batches}, Train_step_loss: {loss.item():.4f
   # Calculate average loss
   train_epoch_loss /= total_batches_train
   valid_epoch_loss /= total_batches_valid
   train_loss.append(train_epoch_loss)
   val_loss.append(valid_epoch_loss)
   # Close the tqdm progress bar for the epoch
   epoch_progress.close()
   # Print the epoch loss after each epoch
   print('\n')
   print(f'Epoch {epoch}/{num_epochs}, Train_loss: {train_epoch_loss:.4f}, Val_loss: {valid_epoch_loss:.4f}, Time taken: [{time.
   # Save the model checkpoint along with training-related information
   checkpoint = {
       'epoch': epoch,
        'enc_state_dict': enc.state_dict(),
       'dec_state_dict':dec.state_dict(),
       'optimizer_enc_state_dict': optimizer_enc.state_dict(),
       'optimizer_dec_state_dict': optimizer_dec.state_dict(),
       'train_loss': train_loss,
       'val_loss': val_loss
   torch.save(checkpoint, checkpoint path)
```

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בμοτι τολίζως, ιιστι-τορρ: α.ατίτ, Λατ-τορρ: α.ατίτ, ιτιμε τακεμ: [4.302]
     Epoch 190/200, Train_loss: 0.0169, Val_loss: 0.0172, Time taken: [4.38s]
     Epoch 191/200, Train_loss: 0.0171, Val_loss: 0.0174, Time taken: [4.38s]
     Epoch 192/200, Train loss: 0.0171, Val loss: 0.0172, Time taken: [4.38s]
     Epoch 193/200, Train loss: 0.0171, Val loss: 0.0172, Time taken: [4.38s]
     Epoch 194/200, Train loss: 0.0170, Val loss: 0.0180, Time taken: [4.38s]
     Epoch 195/200, Train_loss: 0.0171, Val_loss: 0.0176, Time taken: [4.37s]
     Epoch 196/200, Train_loss: 0.0169, Val_loss: 0.0171, Time taken: [4.37s]
     Epoch 197/200, Train_loss: 0.0174, Val_loss: 0.0167, Time taken: [4.37s]
     Epoch 198/200, Train_loss: 0.0170, Val_loss: 0.0170, Time taken: [4.38s]
     Epoch 199/200, Train_loss: 0.0169, Val_loss: 0.0183, Time taken: [4.38s]
     Epoch 200/200, Train_loss: 0.0172, Val_loss: 0.0171, Time taken: [4.37s]
# checkpoint = torch.load(checkpoint path)
train loss = checkpoint['train loss']
valid_loss = checkpoint['val_loss']
plt.plot(train_loss, label='Training Loss')
plt.plot(valid_loss, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.show()
```

## Training and Validation Loss Training Loss Validation Loss 0.035 0.030 055 0.025 0.020 125 150 175 0 25 50 75 100 200 Epoch

```
batch = batch.to(device)
batch = batch.flatten(1)
reconstructed = dec(enc(batch))

original_image = batch[0].view(100,-1).cpu().numpy()
reconstructed_image = reconstructed[0].view(100,-1).cpu().numpy()

plt.figure(figsize=(8, 4))
plt.subplot(1, 2, 1)
plt.title('Original')
plt.imshow(original_image, cmap='gray') # Convert to grayscale for display

plt.subplot(1, 2, 2)
plt.title('Reconstructed_image, cmap='gray') # Convert to grayscale for display

plt.imshow(reconstructed_image, cmap='gray') # Convert to grayscale for display

plt.show()
```

