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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=T
```

```
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),
        transforms.RandomResizedCrop((100, 100), scale=(0.8, 1.0)),
        transforms.ToTensor(),
    ])


    test_transform = transforms.Compose([
        transforms.Resize((100, 100)),
        transforms.ToTensor(),
    ])



    batch_size = 16

    # Load data
    train_dataset = MyDataset(data_dir='/content/drive/MyDrive/AE_xray/train', transform=train_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 = 2500, hidden_size2 = 1000 , hidden_size3 = 500, hidden_size4 = 200, z_c
        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(0.5)
      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, hidd
        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)
      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)
```

```
#         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)
```

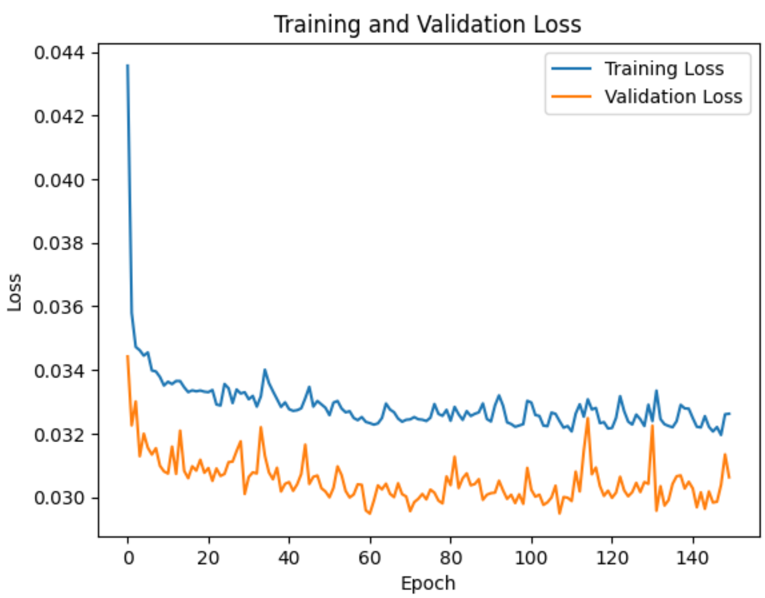
```
loss_fn = nn.MSELoss()
optimizer_enc = torch.optim.Adam(enc.parameters())
optimizer_dec = torch.optim.Adam(dec.parameters())
```

```
train_loss = []
val_loss = []
num_epochs = 150
checkpoint_path = "/content/drive/MyDrive/model/Autoencoder/dropout_xray_checkpoint_30z_5h_150e.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


total_batches_train = len(train_dl)
total_batches_valid = len(valid_dl)
for epoch in range(start_epoch,num_epochs+1):
    train_epoch_loss = 0
```

```
        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}'
        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
        # 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}, T

        # 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)
```

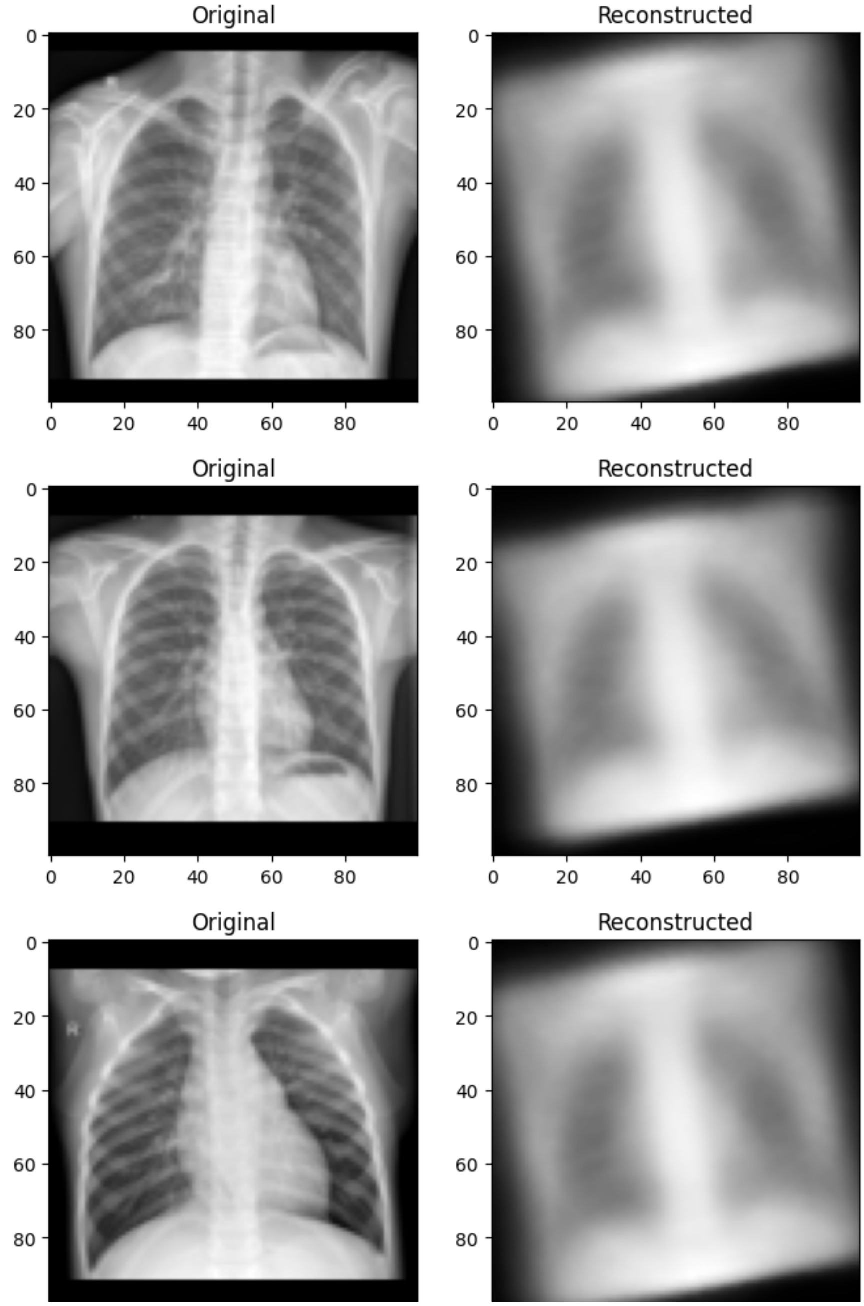
```
Epoch 140/150, Train_loss: 0.0328, Val_loss: 0.0305, Time taken: [1.82s]

Epoch 141/150, Train_loss: 0.0325, Val_loss: 0.0303, Time taken: [1.87s]

Epoch 142/150, Train_loss: 0.0322, Val_loss: 0.0297, Time taken: [1.83s]

Epoch 143/150, Train_loss: 0.0322, Val_loss: 0.0302, Time taken: [1.85s]

Epoch 144/150, Train_loss: 0.0325, Val_loss: 0.0296, Time taken: [1.87s]

Epoch 145/150, Train_loss: 0.0322, Val_loss: 0.0302, Time taken: [1.84s]

Epoch 146/150, Train_loss: 0.0321, Val_loss: 0.0298, Time taken: [1.83s]

Epoch 147/150, Train_loss: 0.0322, Val_loss: 0.0299, Time taken: [1.86s]

Epoch 148/150, Train_loss: 0.0320, Val_loss: 0.0304, Time taken: [1.85s]

Epoch 149/150, Train_loss: 0.0326, Val_loss: 0.0313, Time taken: [1.87s]

Epoch 150/150, Train_loss: 0.0326, Val_loss: 0.0306, Time taken: [1.85s]
```

```
# 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()
```




```
# Plot some original and reconstructed images
n_samples = 5  # Number of samples to visualize

with torch.no_grad():
    for i, batch in enumerate(test_dl):
        if i >= n_samples:
            break
        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')
        plt.imshow(reconstructed_image, cmap='gray')  # Convert to grayscale for display

        plt.show()
```


Original
Reconstructed
Original
Reconstructed
Original
Reconstructed