Masked_Autoencoder

April 5, 2024

[2]:
```
import os
import gc
import torch
import torch.nn as nn
import torch.nn.functional as F
import pandas as pd
import numpy as np
import h5py
import copy
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader, TensorDataset,␣
↪SubsetRandomSampler, ConcatDataset
from torchvision import transforms, utils, datasets
from torchmetrics import Accuracy
from sklearn.model_selection import KFold, StratifiedKFold, train_test_split
from torchvision.datasets import ImageFolder
from PIL import Image
import cv2
import pyarrow.parquet as pq
import seaborn as sns
from tqdm import tqdm
from statistics import mean
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn.preprocessing import StandardScaler
import csv
import torchvision
import ctypes
import torch.optim as optim
from torch.optim import Adam
from functools import partial
from einops import repeat, rearrange
from einops.layers.torch import Rearrange
from timm.models.vision_transformer import PatchEmbed, Block
from torch.optim import AdamW
from torch.optim.lr_scheduler import CosineAnnealingWarmRestarts,␣
↪CosineAnnealingLR, StepLR, ReduceLROnPlateau
from torch.cuda.amp import autocast, GradScaler
```

```python
from transformers import AutoModel, AutoTokenizer
from torch.utils.data.sampler import BatchSampler, Sampler
from skimage import io, transform
from torch.nn.utils import clip_grad_norm_

torch.manual_seed(42)
np.random.seed(42)
torch.cuda.manual_seed(42)

import warnings
warnings.filterwarnings("ignore")

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

[3]:
```python
file_path_1 = '/kaggle/input/mae-unlabeled/Dataset_Specific_Unlabelled.h5'
with h5py.File(file_path_1, 'r') as file:
    X_train = file["jet"][:]
    X_train = np.array(X_train)
```

[4]:
```python
X_train.shape
```

[4]: (60000, 125, 125, 8)

[5]:
```python
def get_2d_sincos_pos_embed(embed_dim, grid_size, cls_token=False):

    grid_h = np.arange(grid_size, dtype=np.float32)
    grid_w = np.arange(grid_size, dtype=np.float32)
    grid = np.meshgrid(grid_w, grid_h)  # here w goes first
    grid = np.stack(grid, axis=0)

    grid = grid.reshape([2, 1, grid_size, grid_size])
    pos_embed = get_2d_sincos_pos_embed_from_grid(embed_dim, grid)
    if cls_token:
        pos_embed = np.concatenate([np.zeros([1, embed_dim]), pos_embed],␣
↪axis=0)
    return pos_embed


def get_2d_sincos_pos_embed_from_grid(embed_dim, grid):
    assert embed_dim % 2 == 0

    emb_h = get_1d_sincos_pos_embed_from_grid(embed_dim // 2, grid[0])  # (H*W,␣
↪D/2)
    emb_w = get_1d_sincos_pos_embed_from_grid(embed_dim // 2, grid[1])  # (H*W,␣
↪D/2)

    emb = np.concatenate([emb_h, emb_w], axis=1) # (H*W, D)
```

```
    return emb


def get_1d_sincos_pos_embed_from_grid(embed_dim, pos):

    assert embed_dim % 2 == 0
    omega = np.arange(embed_dim // 2, dtype='float32')
    omega /= embed_dim / 2.
    omega = 1. / 10000**omega  # (D/2,)

    pos = pos.reshape(-1)  # (M,)
    out = np.einsum('m,d->md', pos, omega)  # (M, D/2), outer product

    emb_sin = np.sin(out) # (M, D/2)
    emb_cos = np.cos(out) # (M, D/2)

    emb = np.concatenate([emb_sin, emb_cos], axis=1)  # (M, D)
    return emb
```

[6]:
```
class Encoder(nn.Module):
    def __init__(self, img_size=224, patch_size=16, in_chans=8,
                 embed_dim=1024, depth=24, num_heads=16,
                 decoder_embed_dim=512, decoder_depth=8, decoder_num_heads=16,
                 mlp_ratio=4., norm_layer=nn.LayerNorm, norm_pix_loss=False):
        super().__init__()

        self.mask_ratio = 0.75
        self.patch_embed = PatchEmbed(img_size, patch_size, in_chans, embed_dim)
        num_patches = self.patch_embed.num_patches
        self.cls_token = nn.Parameter(torch.zeros(1, 1, embed_dim))
        self.pos_embed = nn.Parameter(torch.zeros(1, num_patches + 1,␣
↪embed_dim), requires_grad=False)  # fixed sin-cos embedding
        self.blocks = nn.ModuleList([
            Block(embed_dim, num_heads, mlp_ratio, qkv_bias=True,␣
↪norm_layer=norm_layer)
            for i in range(depth)])
        self.norm = norm_layer(embed_dim)
        self.initialize_weights()

    def initialize_weights(self):
        pos_embed = get_2d_sincos_pos_embed(self.pos_embed.shape[-1], int(self.
↪patch_embed.num_patches**.5), cls_token=True)
        self.pos_embed.data.copy_(torch.from_numpy(pos_embed).float().
↪unsqueeze(0))
        w = self.patch_embed.proj.weight.data
        torch.nn.init.xavier_uniform_(w.view([w.shape[0], -1]))
        torch.nn.init.normal_(self.cls_token, std=.02)
```

```
        self.apply(self._init_weights)

    def _init_weights(self, m):
        if isinstance(m, nn.Linear):
            torch.nn.init.xavier_uniform_(m.weight)
            if isinstance(m, nn.Linear) and m.bias is not None:
                nn.init.constant_(m.bias, 0)
        elif isinstance(m, nn.LayerNorm):
            nn.init.constant_(m.bias, 0)
            nn.init.constant_(m.weight, 1.0)

    def patchify(self, imgs):
        p = self.patch_embed.patch_size[0]
        assert imgs.shape[2] == imgs.shape[3] and imgs.shape[2] % p == 0
        h = w = imgs.shape[2] // p
        x = imgs.reshape(shape=(imgs.shape[0], 8, h, p, w, p))
        x = torch.einsum('nchpwq->nhwpqc', x)
        x = x.reshape(shape=(imgs.shape[0], h * w, p**2 * 8))
        return x

    def unpatchify(self, x):
        p = self.patch_embed.patch_size[0]
        h = w = int(x.shape[1]**.5)
        assert h * w == x.shape[1]
        x = x.reshape(shape=(x.shape[0], h, w, p, p, 8))
        x = torch.einsum('nhwpqc->nchpwq', x)
        imgs = x.reshape(shape=(x.shape[0], 8, h * p, h * p))
        return imgs

    def random_masking(self, x, mask_ratio):
        N, L, D = x.shape  # batch, length, dim
        len_keep = int(L * (1 - mask_ratio))
        noise = torch.rand(N, L, device=x.device)
        ids_shuffle = torch.argsort(noise, dim=1)  # ascend: small is keep,␣
↪large is remove
        ids_restore = torch.argsort(ids_shuffle, dim=1)
        ids_keep = ids_shuffle[:, :len_keep]
        x_masked = torch.gather(x, dim=1, index=ids_keep.unsqueeze(-1).
↪repeat(1, 1, D))
        mask = torch.ones([N, L], device=x.device)
        mask[:, :len_keep] = 0
        mask = torch.gather(mask, dim=1, index=ids_restore)
        return x_masked, mask, ids_restore

    def forward(self, x):
        imgs = self.patchify(x)
        x = self.patch_embed(x)
```

```python
        x = x + self.pos_embed[:, 1:, :]
        x, mask, ids_restore = self.random_masking(x, self.mask_ratio)
        cls_token = self.cls_token + self.pos_embed[:, :1, :]
        cls_tokens = cls_token.expand(x.shape[0], -1, -1)
        x = torch.cat((cls_tokens, x), dim=1)
        for blk in self.blocks:
            x = blk(x)
        x = self.norm(x)
        return x, mask, ids_restore, imgs

class Decoder(nn.Module):
    def __init__(self, img_size=224, patch_size=16, in_chans=8,
                 embed_dim=1024, depth=24, num_heads=16,
                 decoder_embed_dim=512, decoder_depth=8, decoder_num_heads=16,
                 mlp_ratio=4., norm_layer=nn.LayerNorm, norm_pix_loss=False):
        super().__init__()

        self.num_patches = (img_size//patch_size)**2
        self.decoder_embed = nn.Linear(embed_dim, decoder_embed_dim, bias=True)
        self.mask_token = nn.Parameter(torch.zeros(1, 1, decoder_embed_dim))
        self.decoder_pos_embed = nn.Parameter(torch.zeros(1, self.num_patches + 1, decoder_embed_dim), requires_grad=False)  # fixed sin-cos embedding
        self.decoder_blocks = nn.ModuleList([
            Block(decoder_embed_dim, decoder_num_heads, mlp_ratio, qkv_bias=True, norm_layer=norm_layer)
            for i in range(decoder_depth)])

        self.decoder_norm = norm_layer(decoder_embed_dim)
        self.decoder_pred = nn.Linear(decoder_embed_dim, patch_size**2 * in_chans, bias=True)
        self.norm_pix_loss = norm_pix_loss

        self.initialize_weights()

    def initialize_weights(self):
        decoder_pos_embed = get_2d_sincos_pos_embed(self.decoder_pos_embed.shape[-1], int(self.num_patches**.5), cls_token=True)
        self.decoder_pos_embed.data.copy_(torch.from_numpy(decoder_pos_embed).float().unsqueeze(0))
        torch.nn.init.normal_(self.mask_token, std=.02)
        self.apply(self._init_weights)

    def _init_weights(self, m):
        if isinstance(m, nn.Linear):
            torch.nn.init.xavier_uniform_(m.weight)
            if isinstance(m, nn.Linear) and m.bias is not None:
                nn.init.constant_(m.bias, 0)
```

```
        elif isinstance(m, nn.LayerNorm):
            nn.init.constant_(m.bias, 0)
            nn.init.constant_(m.weight, 1.0)

    def patchify(self, imgs):
        p = self.patch_embed.patch_size[0]
        assert imgs.shape[2] == imgs.shape[3] and imgs.shape[2] % p == 0

        h = w = imgs.shape[2] // p
        x = imgs.reshape(shape=(imgs.shape[0], 8, h, p, w, p))
        x = torch.einsum('nchpwq->nhwpqc', x)
        x = x.reshape(shape=(imgs.shape[0], h * w, p**2 * 8))
        return x

    def unpatchify(self, x):
        p = self.patch_embed.patch_size[0]
        h = w = int(x.shape[1]**.5)
        assert h * w == x.shape[1]
        x = x.reshape(shape=(x.shape[0], h, w, p, p, 8))
        x = torch.einsum('nhwpqc->nchpwq', x)
        imgs = x.reshape(shape=(x.shape[0], 8, h * p, h * p))
        return imgs

    def forward(self, x, ids_restore):
        x = self.decoder_embed(x)
        mask_tokens = self.mask_token.repeat(x.shape[0], ids_restore.shape[1] + 1 - x.shape[1], 1)
        x_ = torch.cat([x[:, 1:, :], mask_tokens], dim=1)  # no cls token
        x_ = torch.gather(x_, dim=1, index=ids_restore.unsqueeze(-1).repeat(1, 1, x.shape[2]))  # unshuffle
        x = torch.cat([x[:, :1, :], x_], dim=1)
        x = x + self.decoder_pos_embed
        for blk in self.decoder_blocks:
            x = blk(x)
        x = self.decoder_norm(x)
        x = self.decoder_pred(x)
        x = x[:, 1:, :]
        return x

class Masked_VIT(nn.Module):
    def __init__(self, encoder, decoder, mask_ratio):
        super().__init__()

        self.encoder = encoder
        self.decoder = decoder
        self.mask_ratio = mask_ratio
```

```
    def forward(self, x):
        x, mask, ids_restore, imgs = self.encoder(x)
        pred = self.decoder(x, ids_restore)

        return imgs, pred, mask

def mae_vit_base_patch16_dec512d8b(img_size=125, mask_ratio = 0.75, **kwargs):
    encoder = Encoder(
        img_size=img_size, patch_size=5, embed_dim=768, depth=8, num_heads=12,
        decoder_embed_dim=512, decoder_depth=4, decoder_num_heads=16,
        mlp_ratio=4, norm_layer=partial(nn.LayerNorm, eps=1e-6), **kwargs)

    decoder = Decoder(
        img_size=img_size, patch_size=5, embed_dim=768, depth=8, num_heads=12,
        decoder_embed_dim=512, decoder_depth=4, decoder_num_heads=16,
        mlp_ratio=4, norm_layer=partial(nn.LayerNorm, eps=1e-6), **kwargs)

    model = Masked_VIT(encoder, decoder, mask_ratio)

    return model

model = mae_vit_base_patch16_dec512d8b(img_size=125, mask_ratio = 0.75)
```

[13]:
```
class Custom_Dataset(Dataset):
    def __init__(self, x, transform):
        self.x = x
        self.transform = transform

    def __len__(self):
        return self.x.shape[0]

    def __getitem__(self,idx):
        if torch.is_tensor(idx):
            idx = idx.tolist()
        img_1 = (self.x[idx])

        if self.transform:
            img_1 = self.transform(img_1)
        sample = {'img' : img_1}

        return sample

transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor()])

dataset = Custom_Dataset(X_train, transform = transform)
sample = dataset.__getitem__(0)
print((sample['img']).shape)
```

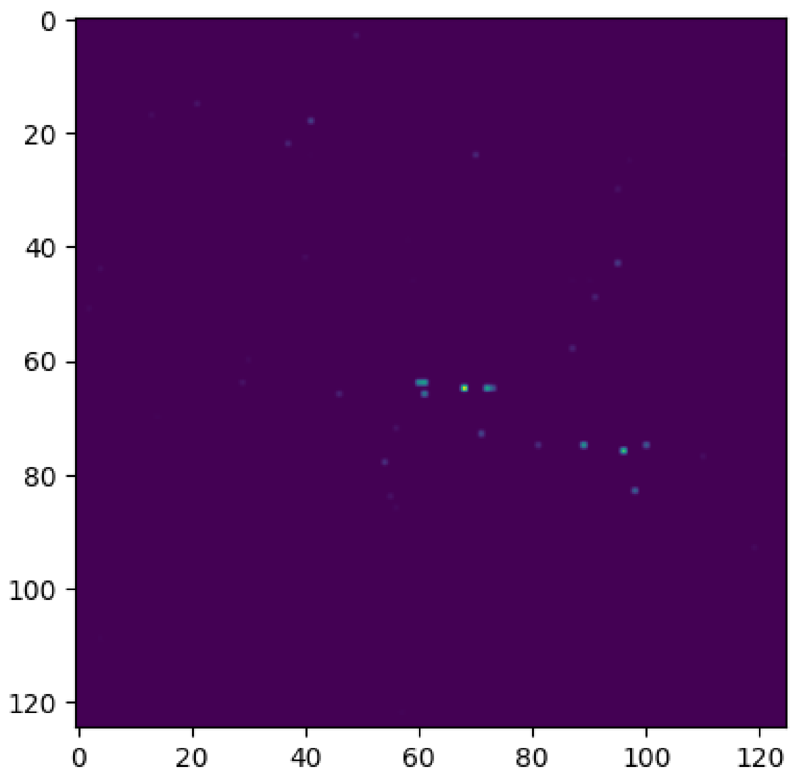
```
torch.Size([8, 125, 125])
```

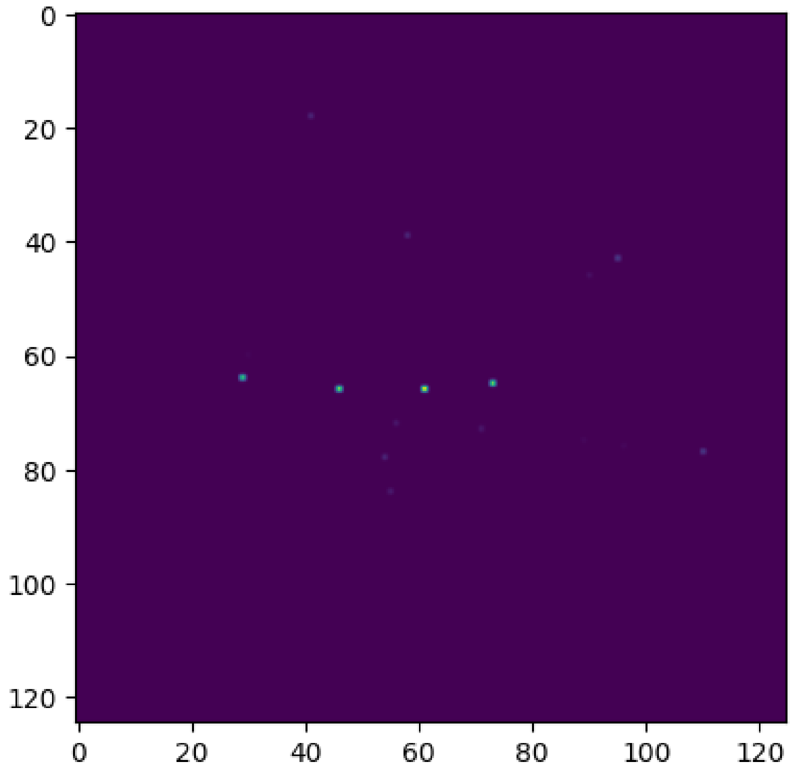
[14]:
```
sample = dataset.__getitem__(0)
print((sample['img']).shape)

img = sample['img'].permute(1,2,0)
img = img.cpu().detach().numpy()

for i in range(8):
    plt.imshow(img[:,:,i])
    plt.show()
```

```
torch.Size([8, 125, 125])
```

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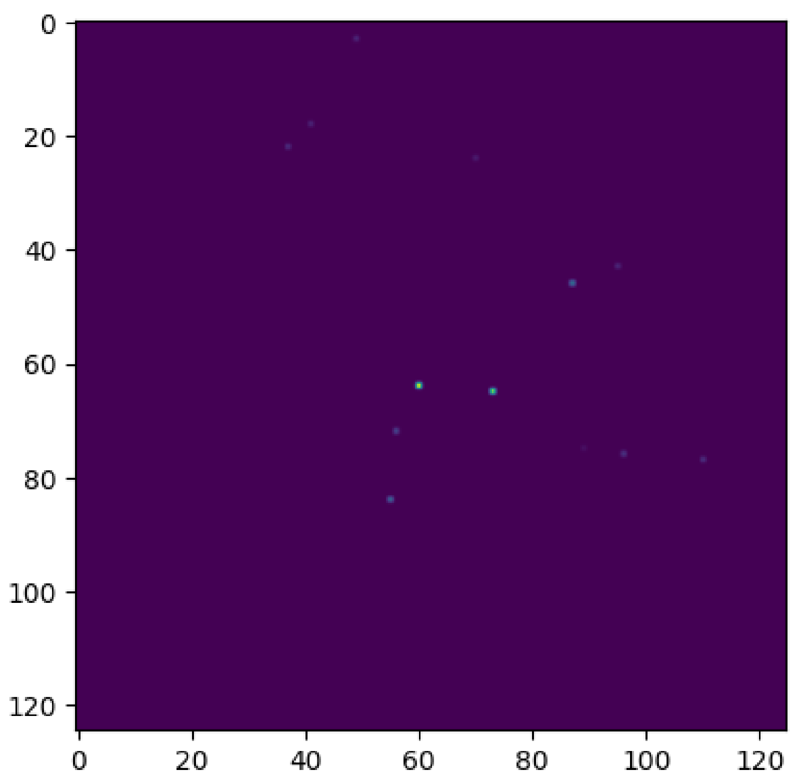
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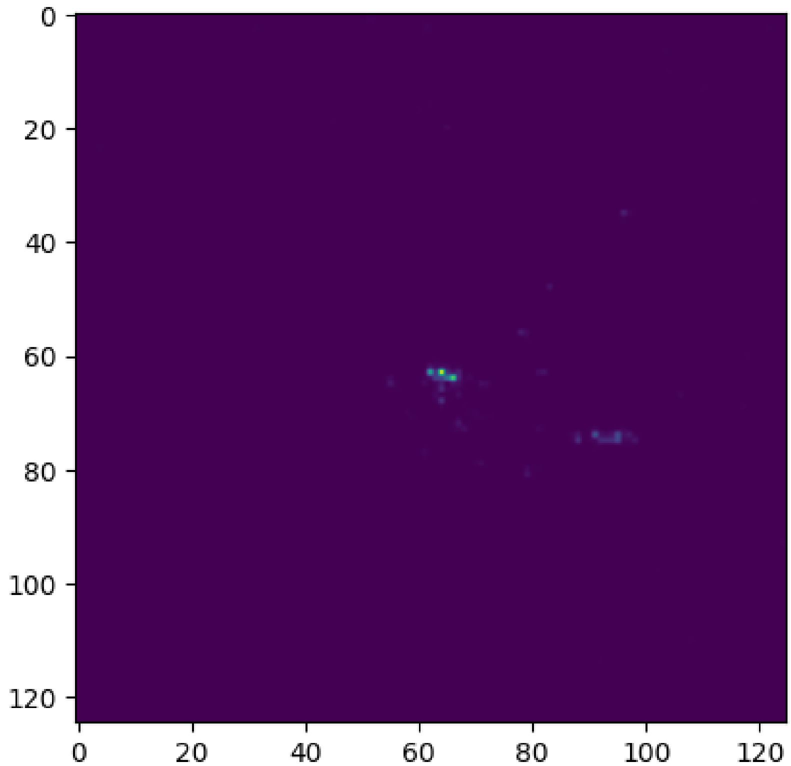
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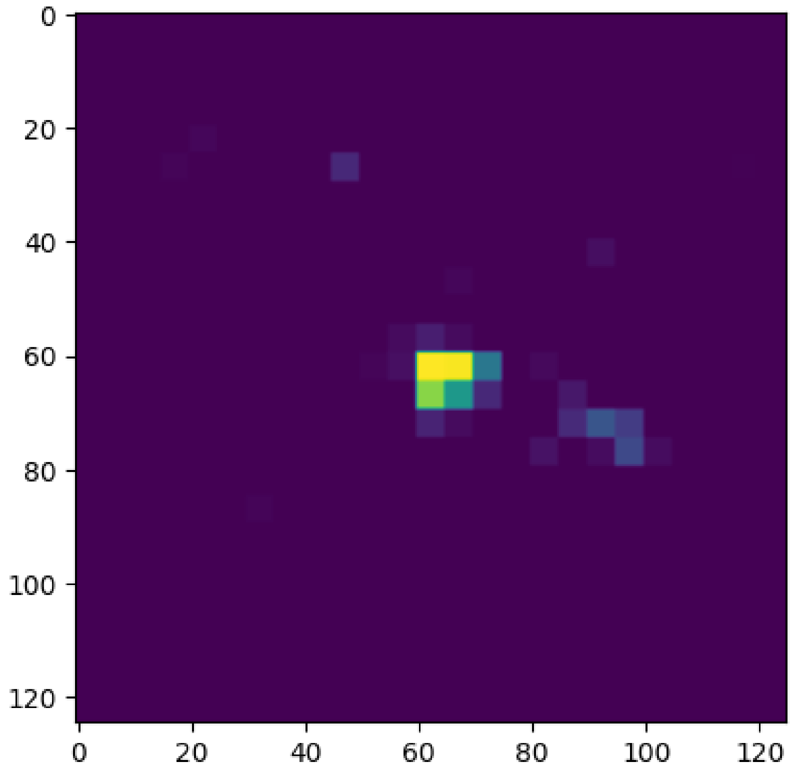

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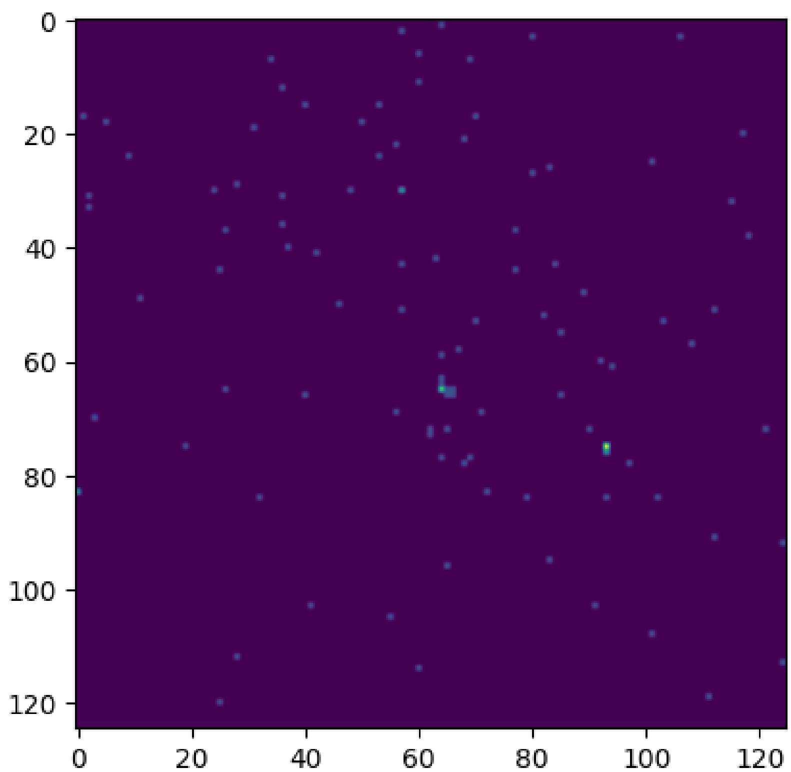

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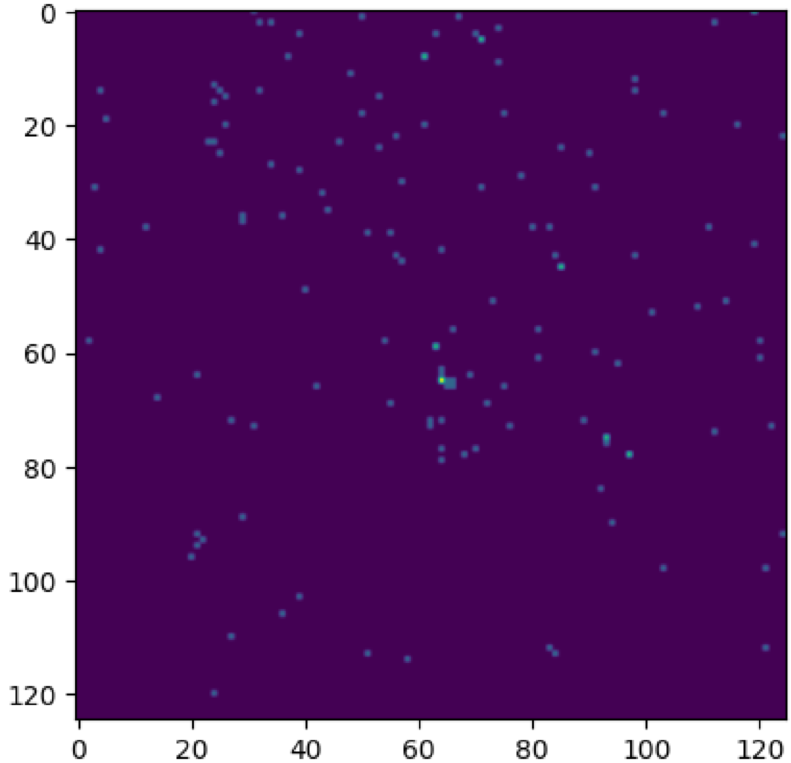
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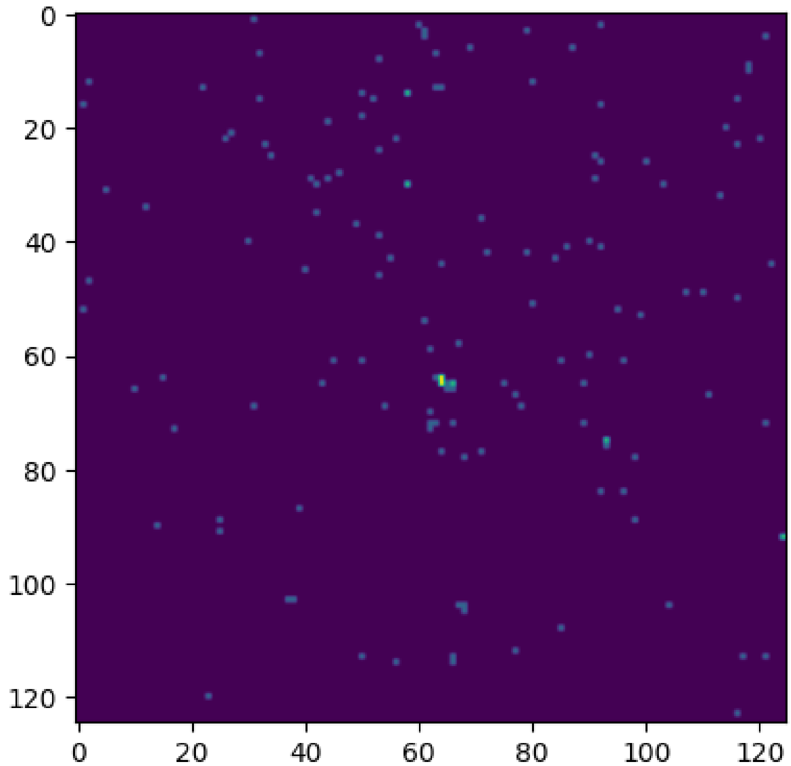
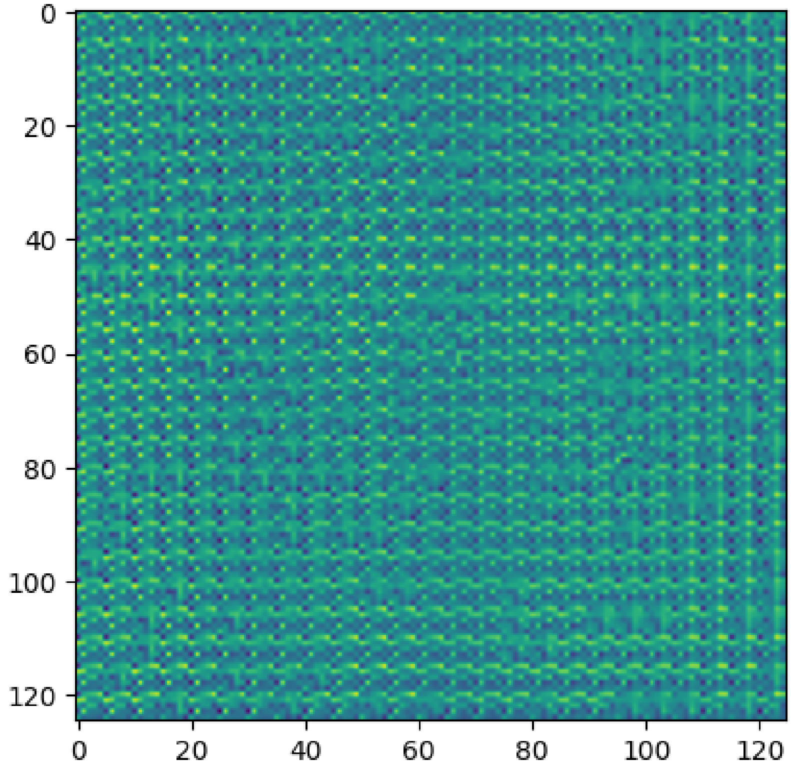


[15]:
```
imgs, pred, ind = model(sample['img'].unsqueeze(0).to(device))
def unpatchify(x):
    p = 5
    h = w = int(x.shape[1]**.5)
    assert h * w == x.shape[1]
    x = x.reshape(shape=(x.shape[0], h, w, p, p, 8))
    x = torch.einsum('nhwpqc->nchpwq', x)
    imgs = x.reshape(shape=(x.shape[0], 8, h * p, h * p))
    return imgs

pred = unpatchify(pred)
pred = pred.reshape((8, 125, 125))
img = pred.permute(1,2,0)
img = img.cpu().detach().numpy()

for i in range(8):
    plt.imshow(img[:,:,i])
    plt.show()
```



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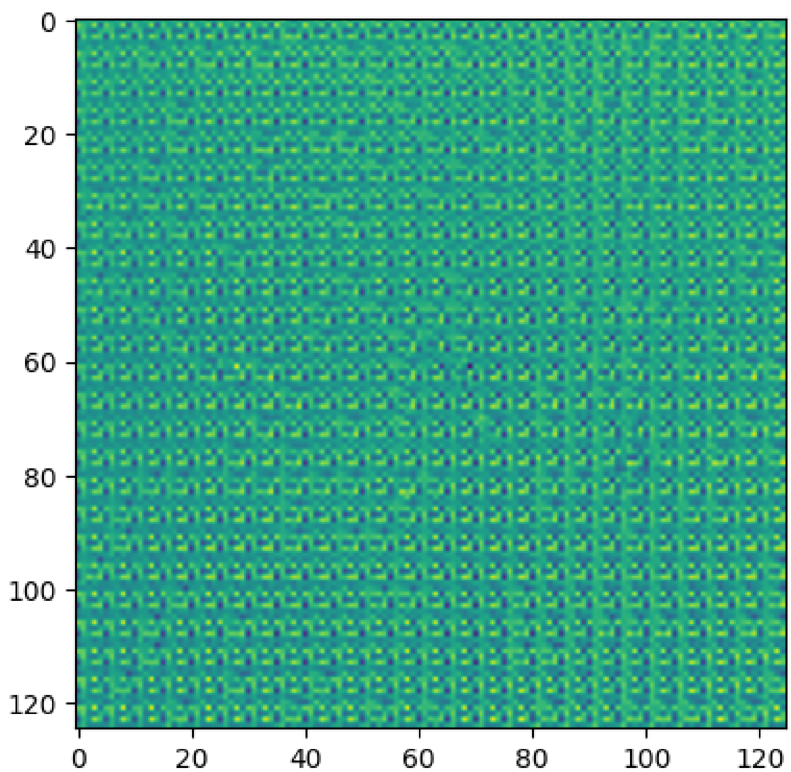

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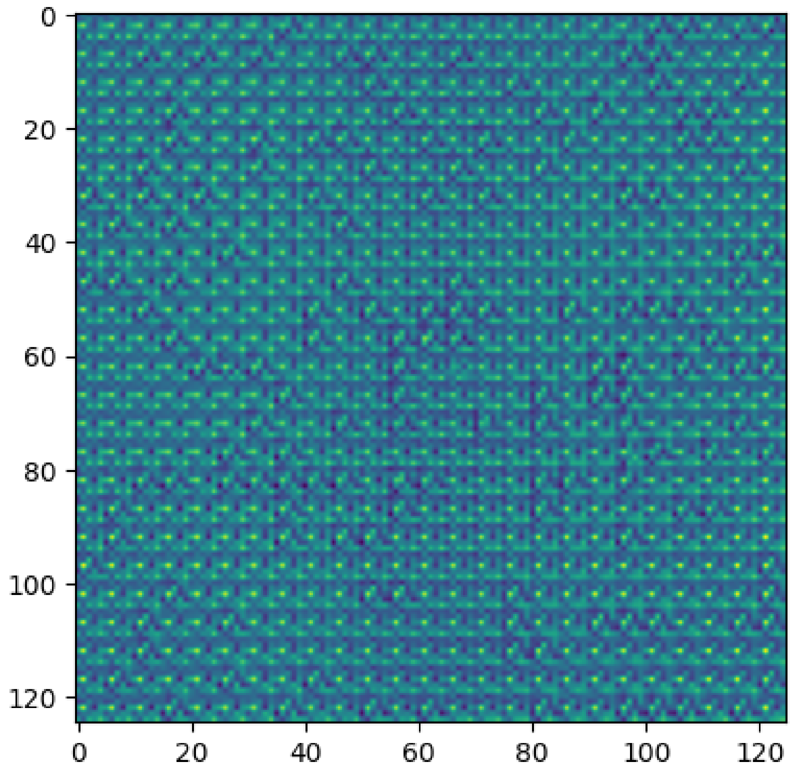
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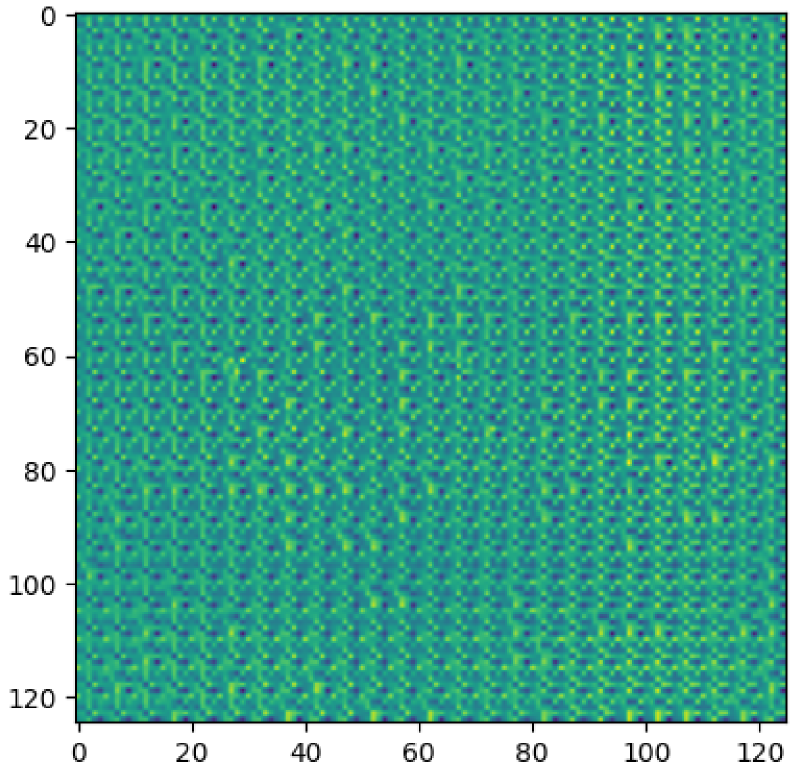
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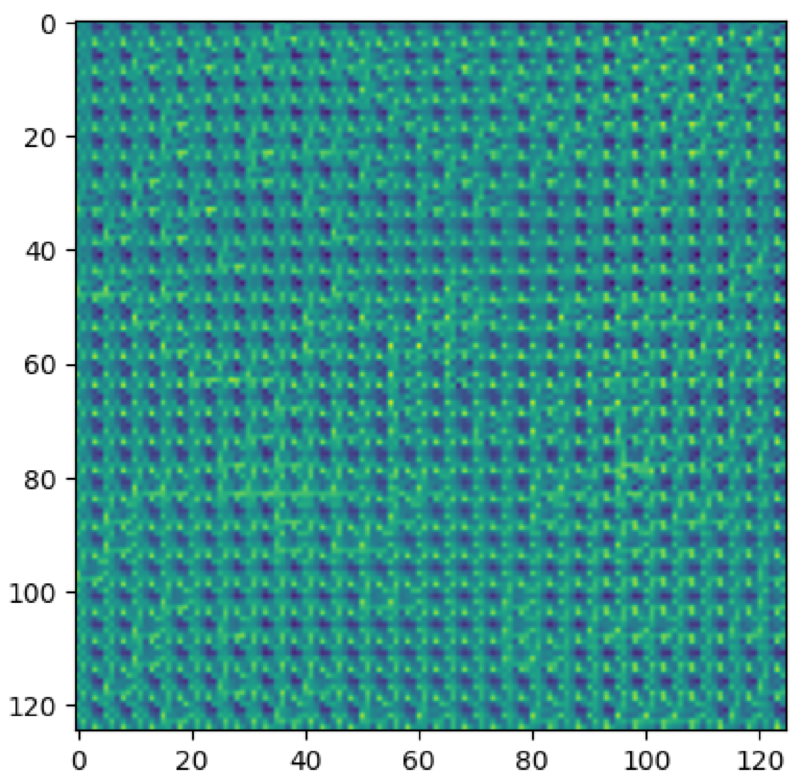
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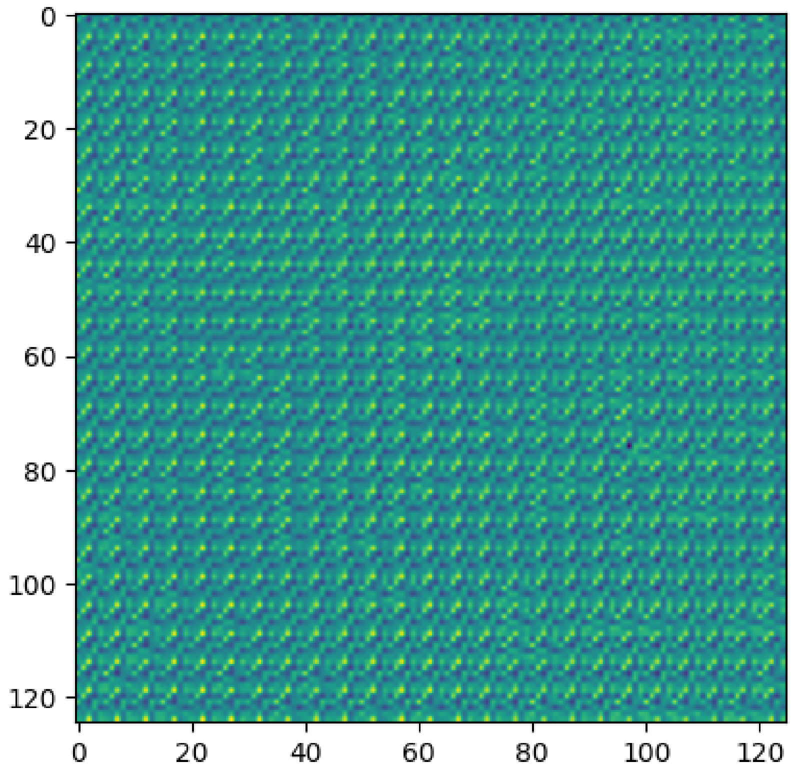
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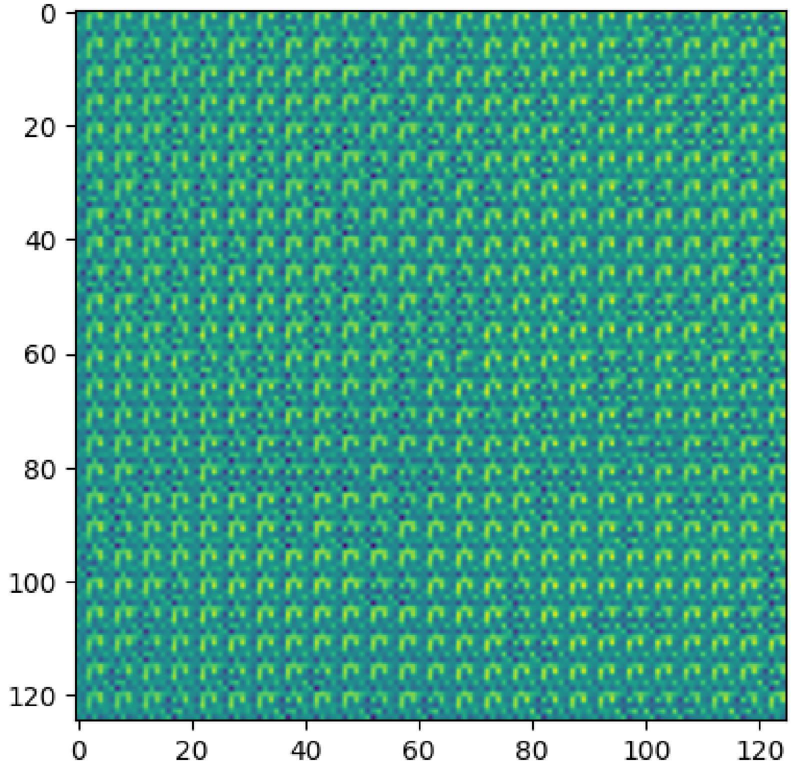

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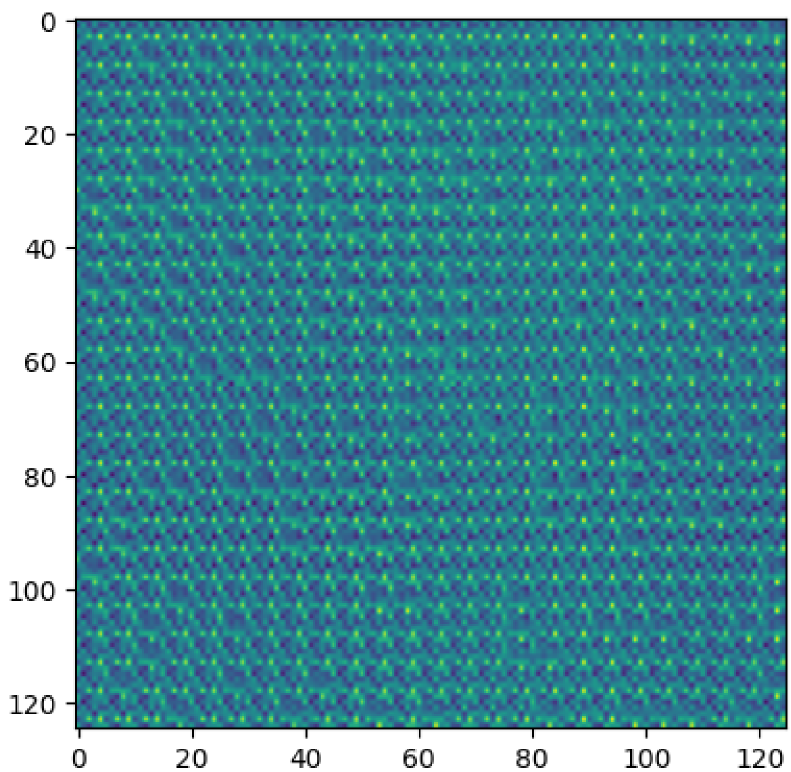

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[17]:
```python
def custom_loss(imgs, pred, mask):

    target = imgs
    loss = (pred - target) ** 2
    loss = loss.mean(dim=-1)
    loss = (loss * mask).sum() / mask.sum()
    return loss
```

[19]:
```python
class CFG:
    lr = 1.5e-4
    weight_decay = 5e-2
    num_epochs = 100
    batch_size = 64
```

[23]:
```python
train_size = int(0.8 * len(dataset))
val_size = len(dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(dataset,␣
 ↪[train_size, val_size])
train_loader = DataLoader(train_dataset, batch_size=CFG.batch_size,␣
 ↪shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=CFG.batch_size, shuffle=False)
```

[24]:
```python
optimizer = AdamW(model.parameters(), lr=CFG.lr, weight_decay=CFG.weight_decay)
scheduler = CosineAnnealingWarmRestarts(optimizer, T_0=40, T_mult=2)
model = mae_vit_base_patch16_dec512d8b(img_size=125)
```

[25]:
```python
train_losses = []
val_losses = []
model = model.to(device)
for epoch in range(CFG.num_epochs):
    train_loss = 0.0
    val_loss = 0.0

    model.train()
    for batch in tqdm(train_loader, desc=f'Epoch {epoch+1}/{CFG.num_epochs}␣
 ↪(Train)', unit='batch'):
        inputs = batch['img'].to(device).float()

        optimizer.zero_grad()
        imgs, outputs, ind = model(inputs)
        loss = custom_loss(imgs, outputs, ind)
        loss.backward()
        optimizer.step()
```

```
        train_loss += loss.item()

    train_loss /= len(train_loader)
    train_losses.append(train_loss)

    model.eval()
    with torch.no_grad():
        for batch in tqdm(val_loader, desc=f'Epoch {epoch+1}/{CFG.num_epochs}␣
↪(Val)', unit='batch'):
            val_inputs = batch['img'].to(device).float()

            imgs, val_outputs, ind = model(val_inputs)
            loss = custom_loss(imgs, val_outputs, ind)
            val_loss += loss.item()

    val_loss /= len(val_loader)
    val_losses.append(val_loss)

    scheduler.step()

    print(f'Epoch {epoch+1}/{CFG.num_epochs}, Train Loss: {train_loss:.4f}, Val␣
↪Loss: {val_loss:.4f}')
    torch.save(model, f'./best_model.pth')
```

```
Epoch 1/80 (Train): 100%|      | 750/750 [08:13<00:00,  1.52batch/s]
Epoch 1/80 (Val): 100%|      | 188/188 [00:42<00:00,  4.43batch/s]

Epoch 1/80, Train Loss: 0.9470, Val Loss: 0.9181

Epoch 2/80 (Train): 100%|      | 750/750 [08:19<00:00,  1.50batch/s]
Epoch 2/80 (Val): 100%|      | 188/188 [00:43<00:00,  4.32batch/s]

Epoch 2/80, Train Loss: 0.9194, Val Loss: 0.9170

Epoch 3/80 (Train): 100%|      | 750/750 [08:16<00:00,  1.51batch/s]
Epoch 3/80 (Val): 100%|      | 188/188 [00:42<00:00,  4.44batch/s]

Epoch 3/80, Train Loss: 0.9157, Val Loss: 0.9147

Epoch 4/80 (Train): 100%|      | 750/750 [08:14<00:00,  1.52batch/s]
Epoch 4/80 (Val): 100%|      | 188/188 [00:42<00:00,  4.41batch/s]

Epoch 4/80, Train Loss: 0.9123, Val Loss: 0.9100

Epoch 5/80 (Train): 100%|      | 750/750 [08:17<00:00,  1.51batch/s]
Epoch 5/80 (Val): 100%|      | 188/188 [00:42<00:00,  4.43batch/s]

Epoch 5/80, Train Loss: 0.9102, Val Loss: 0.9075

Epoch 6/80 (Train):  64%|       | 479/750 [05:16<02:53,  1.56batch/s]IOPub
message rate exceeded.
The Jupyter server will temporarily stop sending output
```

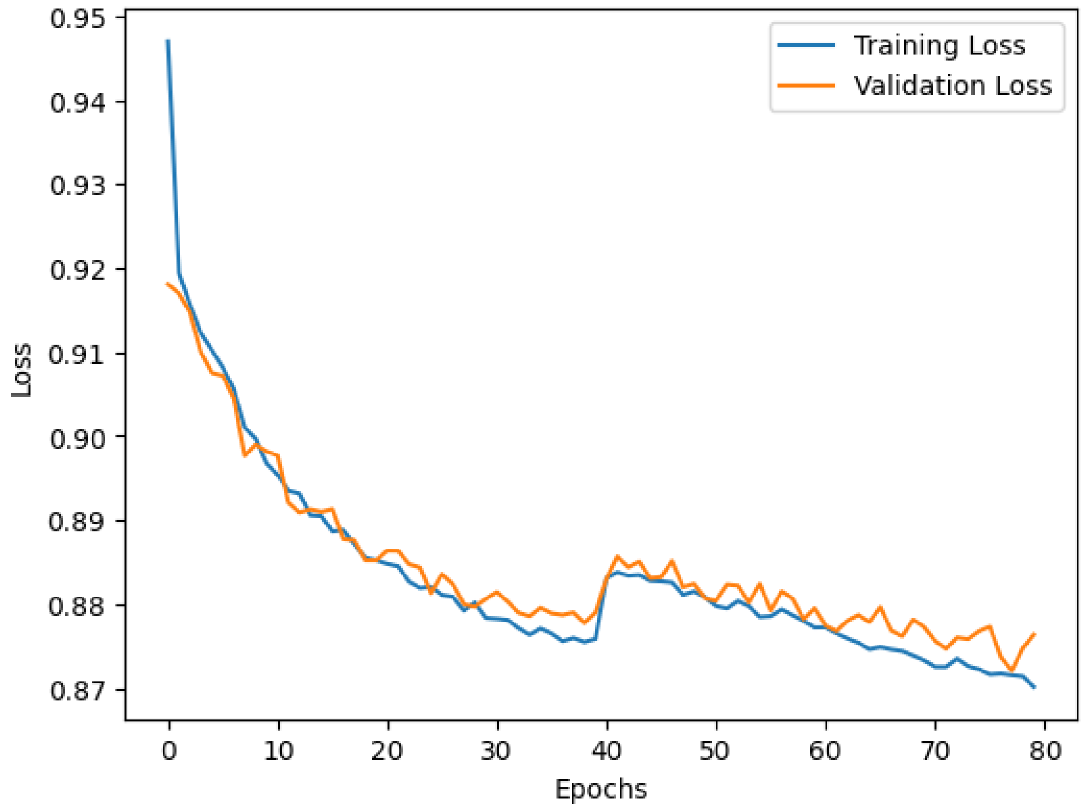
```
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--ServerApp.iopub_msg_rate_limit`.

Current values:
ServerApp.iopub_msg_rate_limit=1000.0 (msgs/sec)
ServerApp.rate_limit_window=3.0 (secs)

Epoch 7/80 (Val): 100%|     | 188/188 [00:42<00:00,  4.45batch/s]

Epoch 7/80, Train Loss: 0.9056, Val Loss: 0.9045

Epoch 8/80 (Train): 100%|     | 750/750 [08:18<00:00,  1.50batch/s]
Epoch 8/80 (Val): 100%|     | 188/188 [00:41<00:00,  4.48batch/s]

Epoch 8/80, Train Loss: 0.9010, Val Loss: 0.8977

Epoch 9/80 (Train): 100%|     | 750/750 [08:14<00:00,  1.52batch/s]
Epoch 9/80 (Val): 100%|     | 188/188 [00:42<00:00,  4.45batch/s]

Epoch 9/80, Train Loss: 0.8997, Val Loss: 0.8990

Epoch 10/80 (Train): 100%|     | 750/750 [08:13<00:00,  1.52batch/s]
Epoch 10/80 (Val): 100%|     | 188/188 [00:41<00:00,  4.51batch/s]

Epoch 10/80, Train Loss: 0.8967, Val Loss: 0.8982

Epoch 11/80 (Train): 100%|     | 750/750 [08:16<00:00,  1.51batch/s]
Epoch 11/80 (Val): 100%|     | 188/188 [00:42<00:00,  4.38batch/s]

Epoch 11/80, Train Loss: 0.8954, Val Loss: 0.8977

Epoch 12/80 (Train): 100%|     | 750/750 [08:16<00:00,  1.51batch/s]
Epoch 12/80 (Val): 100%|     | 188/188 [00:42<00:00,  4.47batch/s]

Epoch 12/80, Train Loss: 0.8935, Val Loss: 0.8921

Epoch 13/80 (Train): 100%|     | 750/750 [08:22<00:00,  1.49batch/s]
Epoch 13/80 (Val): 100%|     | 188/188 [00:42<00:00,  4.44batch/s]

Epoch 13/80, Train Loss: 0.8932, Val Loss: 0.8909

Epoch 14/80 (Train): 100%|     | 750/750 [08:15<00:00,  1.51batch/s]
Epoch 14/80 (Val): 100%|     | 188/188 [00:41<00:00,  4.53batch/s]

Epoch 14/80, Train Loss: 0.8906, Val Loss: 0.8913

Epoch 15/80 (Train): 100%|     | 750/750 [08:19<00:00,  1.50batch/s]
Epoch 15/80 (Val): 100%|     | 188/188 [00:43<00:00,  4.36batch/s]

Epoch 15/80, Train Loss: 0.8905, Val Loss: 0.8910

Epoch 16/80 (Train):  74%|     | 555/750 [06:09<02:10,  1.49batch/s]IOPub
message rate exceeded.
The Jupyter server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
```

```
`--ServerApp.iopub_msg_rate_limit`.

Current values:
ServerApp.iopub_msg_rate_limit=1000.0 (msgs/sec)
ServerApp.rate_limit_window=3.0 (secs)

Epoch 45/80 (Train): 100%|     | 750/750 [08:45<00:00,  1.43batch/s]
Epoch 45/80 (Val): 100%|     | 188/188 [00:46<00:00,  4.03batch/s]

Epoch 45/80, Train Loss: 0.8828, Val Loss: 0.8831

Epoch 46/80 (Train): 100%|     | 750/750 [08:40<00:00,  1.44batch/s]
Epoch 46/80 (Val): 100%|     | 188/188 [00:44<00:00,  4.24batch/s]

Epoch 46/80, Train Loss: 0.8827, Val Loss: 0.8832

Epoch 47/80 (Val): 100%|     | 188/188 [00:46<00:00,  4.03batch/s]s]

Epoch 47/80, Train Loss: 0.8826, Val Loss: 0.8851

Epoch 48/80 (Train): 100%|     | 750/750 [08:44<00:00,  1.43batch/s]
Epoch 48/80 (Val): 100%|     | 188/188 [00:46<00:00,  4.04batch/s]

Epoch 48/80, Train Loss: 0.8811, Val Loss: 0.8820

Epoch 49/80 (Train): 100%|     | 750/750 [08:57<00:00,  1.40batch/s]
Epoch 49/80 (Val): 100%|     | 188/188 [00:46<00:00,  4.05batch/s]

Epoch 49/80, Train Loss: 0.8815, Val Loss: 0.8824

Epoch 50/80 (Train): 100%|     | 750/750 [08:43<00:00,  1.43batch/s]
Epoch 50/80 (Val):  94%|     | 176/188 [00:43<00:03,  3.86batch/s]IOPub
message rate exceeded.
The Jupyter server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--ServerApp.iopub_msg_rate_limit`.

Current values:
ServerApp.iopub_msg_rate_limit=1000.0 (msgs/sec)
ServerApp.rate_limit_window=3.0 (secs)
```

[27]:
```
encoder = model.module.encoder
torch.save(encoder, 'encoder.pth')
torch.save(model.module, 'model.pth')
```

[32]:
```
plt.plot(train_losses, label='Training Loss')
plt.plot(val_losses, label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

```
plt.show()
```



Training Loss
Validation Loss
Loss
Epochs
0.95
0.94
0.93
0.92
0.91
0.90
0.89
0.88
0.87
0
10
20
30
40
50
60
70
80