In [ ]:
```
"""
Deep Learning Assignment 3
Conditional GAN Skeleton Code.
Adopted from public sources, customized and improved for this assignment.
"""

#import necessary modules
import torch
import torch.nn as nn
from torchvision import transforms, datasets
from torch import optim as optim
# for visualization
from matplotlib import pyplot as plt
import math
import numpy as np
```

In [ ]:
```
%load_ext tensorboard
import tensorflow as tf
import datetime
```

In [ ]:
```
# tells PyTorch to use an NVIDIA GPU, if one is available.
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# loading the dataset
training_parameters = {
    "img_size": 28,
    "n_epochs": 24, #24
    "batch_size": 64,
    "learning_rate_generator": 0.0002,
    "learning_rate_discriminator": 0.0002,
}
# define a transform to 1) scale the images and 2) convert them into tensors
transform = transforms.Compose([
    transforms.Resize(training_parameters['img_size']), # scales the smaller
    transforms.ToTensor(),
])

# load the dataset
train_loader = torch.utils.data.DataLoader(
    datasets.FashionMNIST(
        './data', # specifies the directory to download the datafiles to, re
        train = True,
        download = True,
        transform = transform),
    batch_size = training_parameters["batch_size"],
    shuffle=True
    )

# Fashion MNIST has 10 classes, just like MNIST. Here's what they correspond
label_descriptions = {
      0: 'T-shirt/top',
      1 : 'Trouser',
      2 : 'Pullover',
      3 : 'Dress',
      4 : 'Coat',
      5 : 'Sandal',
      6 : 'Shirt',
      7 : 'Sneaker',
      8 : 'Bag',
      9 : 'Ankle boot'
}
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train
-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train
-images-idx3-ubyte.gz to ./data/FashionMNIST/raw/train-images-idx3-ubyte.gz
100%|██████████| 26421880/26421880 [00:01<00:00, 15998023.58it/s]
Extracting ./data/FashionMNIST/raw/train-images-idx3-ubyte.gz to ./data/Fash
ionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train
-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train
-labels-idx1-ubyte.gz to ./data/FashionMNIST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 29515/29515 [00:00<00:00, 267152.26it/s]
Extracting ./data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to ./data/Fash
ionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-
images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-
images-idx3-ubyte.gz to ./data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz
100%|██████████| 4422102/4422102 [00:00<00:00, 5056578.21it/s]
Extracting ./data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to ./data/Fashi
onMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-
labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-
labels-idx1-ubyte.gz to ./data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 5148/5148 [00:00<00:00, 19611514.07it/s]
Extracting ./data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/Fashi
onMNIST/raw
```

In [ ]:

```python
# Create the Generator model class, which will be used to initialize the gen
class Generator(nn.Module):
  def __init__(self, input_dim, output_dim, num_labels=10): # to initialize
    super(Generator,self).__init__() # initialize the parent class
    # TODO (5.4) Turn this Generator into a Conditional Generator by
    # 1. Adjusting the input dimension of the first hidden layer.
    # 2. Modifying the input to the first hidden layer in the forward class.

    self.hidden_layer1 = nn.Sequential(
        nn.Linear(input_dim, 256),
        nn.LeakyReLU(0.2)
    )
    self.hidden_layer2 = nn.Sequential(
        nn.Linear(256, 512),
        nn.LeakyReLU(0.2)
    )
    self.hidden_layer3 = nn.Sequential(
        nn.Linear(512, 1024),
        nn.LeakyReLU(0.2)
    )
    self.hidden_layer4 = nn.Sequential(
        nn.Linear(1024, output_dim),
        nn.Tanh()
    )
  def forward(self, x, labels):

      output = self.hidden_layer1(x)
      output = self.hidden_layer2(output)
      output = self.hidden_layer3(output)
```

```
        output = self.hidden_layer4(output)
        return output.to(device)
```

In [ ]:
```
class Discriminator(nn.Module):
    def __init__(self, input_dim, output_dim=1, num_labels=None):
        super(Discriminator, self).__init__()

        #self.label_embedding = nn.Embedding(10, 10)
        # TODO (5.4) Modify this discriminator to function as a conditional
        self.hidden_layer1 = nn.Sequential(
            nn.Linear(input_dim, 1024),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.hidden_layer2 = nn.Sequential(
            nn.Linear(1024, 512),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.hidden_layer3 = nn.Sequential(
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.hidden_layer4 = nn.Sequential(
            nn.Linear(256, output_dim),
            nn.Sigmoid()
        )

    def forward(self, x, labels=None): # labels to be used in 5.4.

        output = self.hidden_layer1(x)
        output = self.hidden_layer2(output)
        output = self.hidden_layer3(output)
        output = self.hidden_layer4(output)
        return output.to(device)
```

In [ ]:
```
discriminator = Discriminator(784,1).to(device) # initialize both models, an
generator = Generator(100,784).to(device)

discriminator_optimizer = optim.Adam(discriminator.parameters(), lr=training
generator_optimizer = optim.Adam(generator.parameters(), lr=training_paramet
```

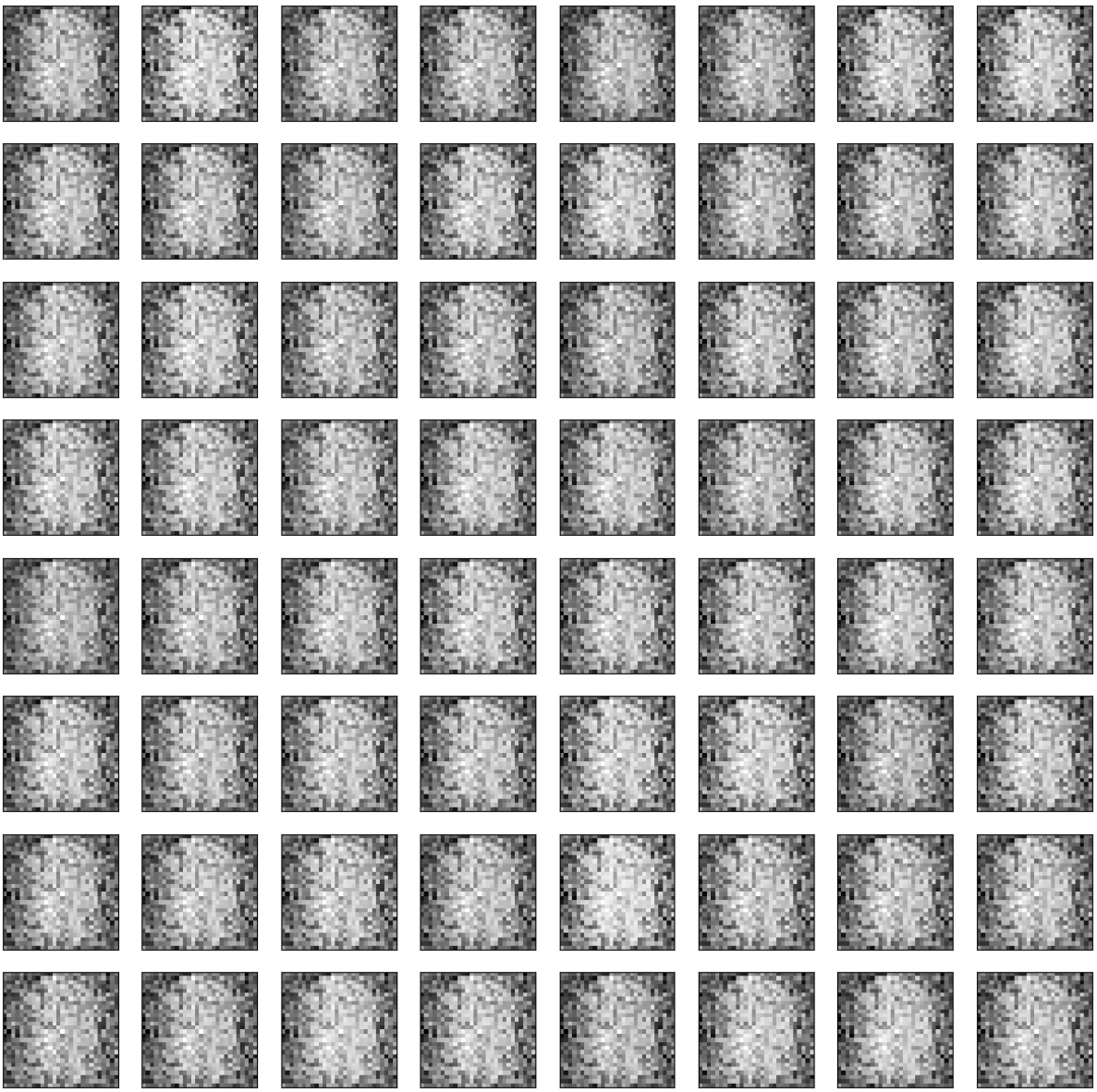
In [ ]:
```
# Establish convention for real and fake labels during training
real_label = 1.
fake_label = 0.
```

In [ ]:
```
#Loss_D - discriminator loss calculated as the sum of losses for the all rea

loss_func = nn.BCELoss() # Binary Cross Entropy Loss
def train_generator(batch_size):
    """
    Performs a training step on the generator by
        1. Generating fake images from random noise.
        2. Running the discriminator on the fake images.
        3. Computing loss on the result.
    :arg batch_size: the number of training examples in the current batch
    Returns the average generator loss over the batch.
    """
```

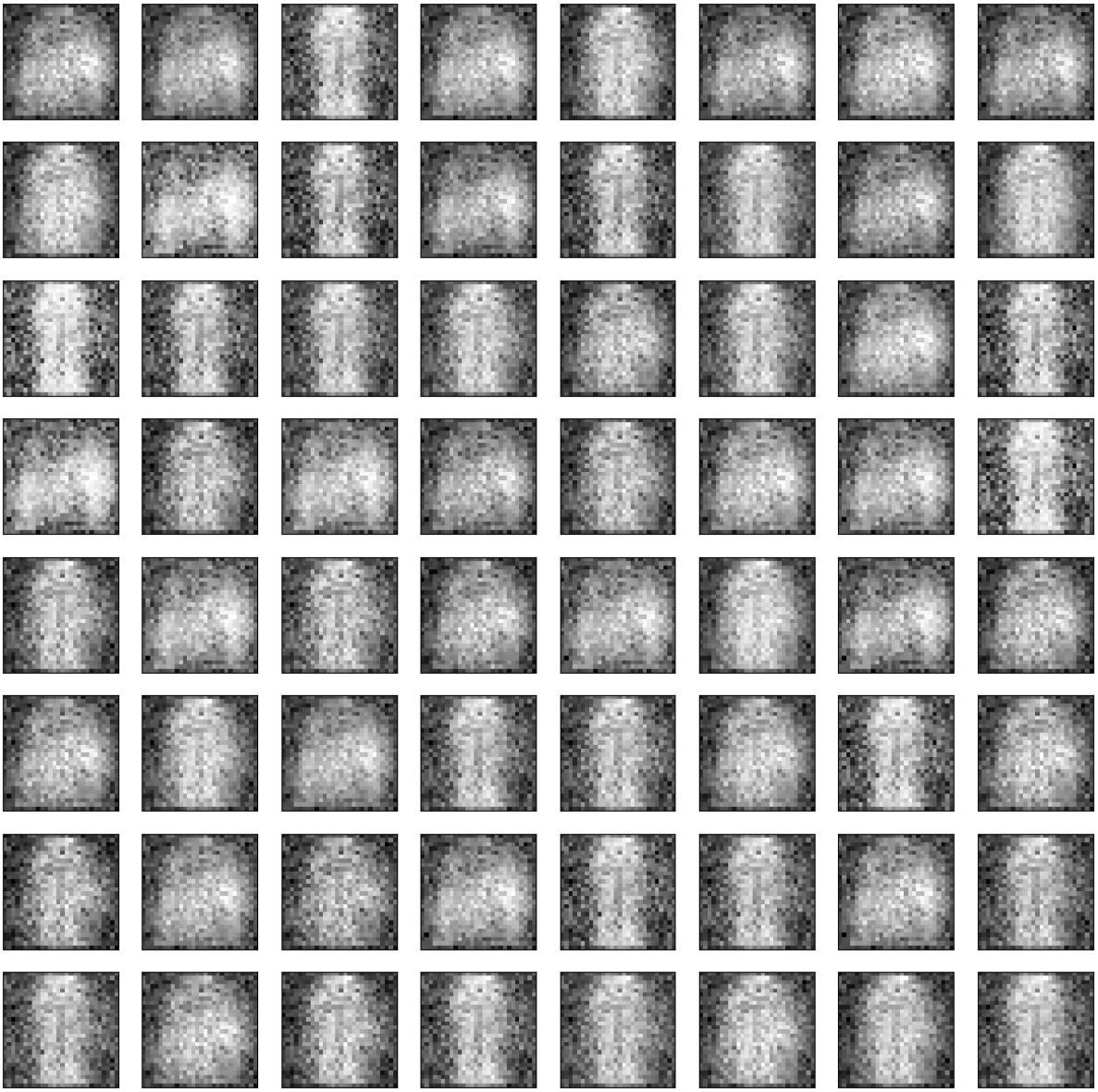
```
    # Start by zeroing the gradients of the optimizer
    generator_optimizer.zero_grad()
    # 1. Create a new batch of fake images (since the discriminator has just
    noise = torch.randn(batch_size,100).to(device) # whenever you create new
    generated_labels = torch.randint(0, 10, (batch_size,)).to(device)
    generator_output = generator(noise, labels = generated_labels)
    # 2. Run the discriminator on the fake images
    discriminator_output = discriminator(generator_output, labels = generate
    ###----copied----
    real_label_vector = torch.full((batch_size,), real_label, dtype=torch.fl
    real_label_vector = real_label_vector.view(-1, 1)
    #-------
    # 3. Compute the loss
    loss = loss_func(discriminator_output, real_label_vector)
    loss.backward()
    generator_optimizer.step()

    loss = loss.mean().item()
    return loss

def train_discriminator(batch_size, images, labels=None): # labels to be use
    """
    Performs a training step on the discriminator by
        1. Generating fake images from random noise.
        2. Running the discriminator on the fake images.
        3. Running the discriminator on the real images
        3. Computing loss on the results.
    :arg batch_size: the number of training examples in the current batch
    :arg images: the current batch of images, a tensor of size BATCH x 1 x 6
    :arg labels: the labels corresponding to images, a tensor of size BATCH
    Returns the average loss over the batch.
    """

    discriminator_optimizer.zero_grad()
    ###----fake images----###
    # 1. Create a new batch of fake images (since the discriminator has just
    noise = torch.randn(batch_size,100).to(device) # whenever you create new
    generated_labels = torch.randint(0, 10, (batch_size,)).to(device)
    generator_output = generator(noise, labels = generated_labels)
    # 2. Run the discriminator on the fake images
    discriminator_output = discriminator(generator_output, labels = generate
    # 3. Compute the loss
    fake_label_vector = torch.full((batch_size,), fake_label, dtype=torch.fl
    fake_label_vector = fake_label_vector.view(-1, 1)
    loss_fake = loss_func(discriminator_output, fake_label_vector)

    ###----real images----###
    # 1. Run the discriminator on the real images
    images = torch.flatten(images, start_dim=1)
    discriminator_output = discriminator(images, labels = labels)
    # 2. Compute the loss
    real_label_vector = torch.full((batch_size,), real_label, dtype=torch.fl
    real_label_vector = real_label_vector.view(-1, 1)
    loss_real = loss_func(discriminator_output, real_label_vector)

    #combine losses
    loss = loss_real + loss_fake
    loss.backward()
    discriminator_optimizer.step()

    loss = loss.mean().item()
    return loss
```

In [ ]:
```
for epoch in range(training_parameters['n_epochs']):
    G_loss = []  # for plotting the losses over time
    D_loss = []
    for batch, (imgs, labels) in enumerate(train_loader):
        batch_size = labels.shape[0]  # if the batch size doesn't evenly div
        #generator first training
        lossG = train_generator(batch_size)
        G_loss.append(lossG)
        #single discriminator training
        lossD = train_discriminator(batch_size, imgs, labels)
        D_loss.append(lossD)

        if ((batch + 1) % 500 == 0 and (epoch + 1) % 1 == 0):
            # Display a batch of generated images and print the loss
            print("Training Steps Completed: ", batch)
            with torch.no_grad():  # disables gradient computation to speed
                noise = torch.randn(batch_size, 100).to(device)
                fake_labels = torch.randint(0, 10, (batch_size,)).to(device)
                generated_data = generator(noise, fake_labels).cpu().view(ba

                # display generated images
                batch_sqrt = int(training_parameters['batch_size'] ** 0.5)
                fig, ax = plt.subplots(batch_sqrt, batch_sqrt, figsize=(15,
                for i, x in enumerate(generated_data):
                    #ax[math.floor(i / batch_sqrt)][i % batch_sqrt].set_titl
                    ax[math.floor(i / batch_sqrt)][i % batch_sqrt].imshow(x.
                    ax[math.floor(i / batch_sqrt)][i % batch_sqrt].get_xaxis
                    ax[math.floor(i / batch_sqrt)][i % batch_sqrt].get_yaxis
                plt.show()
                #fig.savefig(f"./results/CGAN_Generations_Epoch_{epoch}")
                #fig.savefig(f"pset/pset3/results/CGAN_Generations_Epoch_{ep
                fig.savefig(f"CGAN_Generations_Epoch_{epoch}")
                print(
                    f"Epoch {epoch}: loss_d: {torch.mean(torch.FloatTensor(D
```

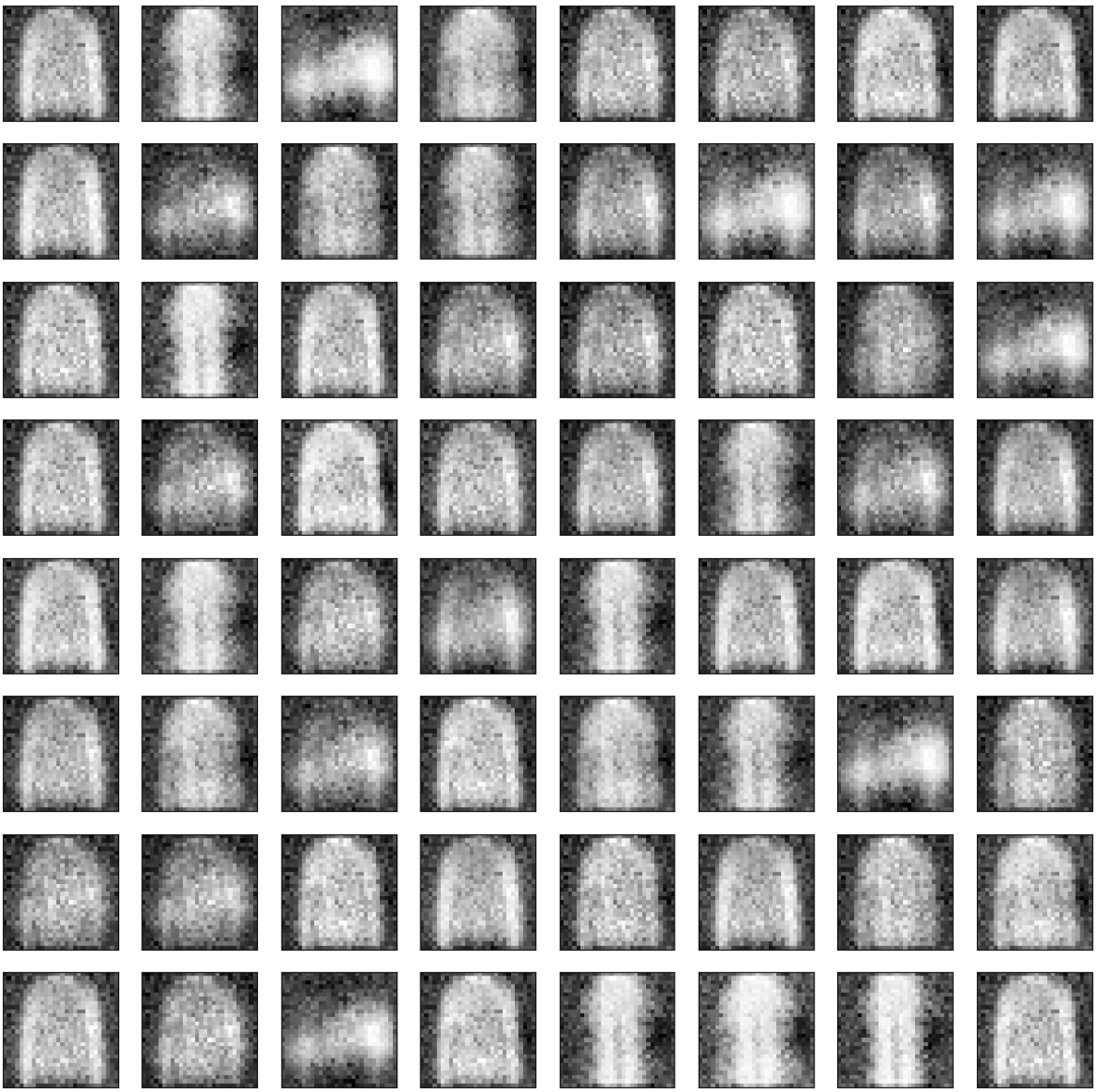
```
Training Steps Completed:  499
```



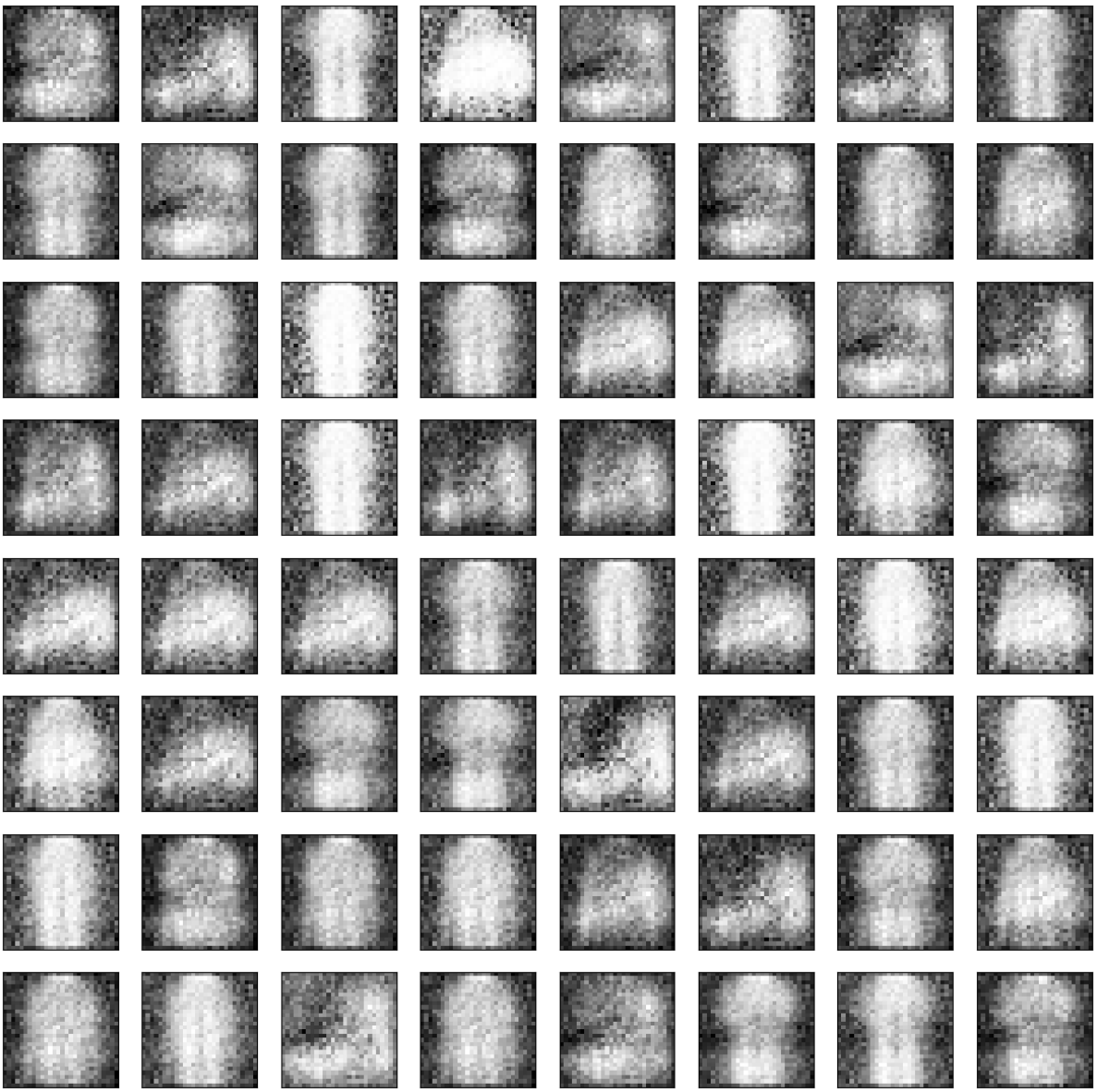
```
Epoch 0: loss_d: 1.225581407546997, loss_g: 1.4263771772384644
Training Steps Completed:  499
```



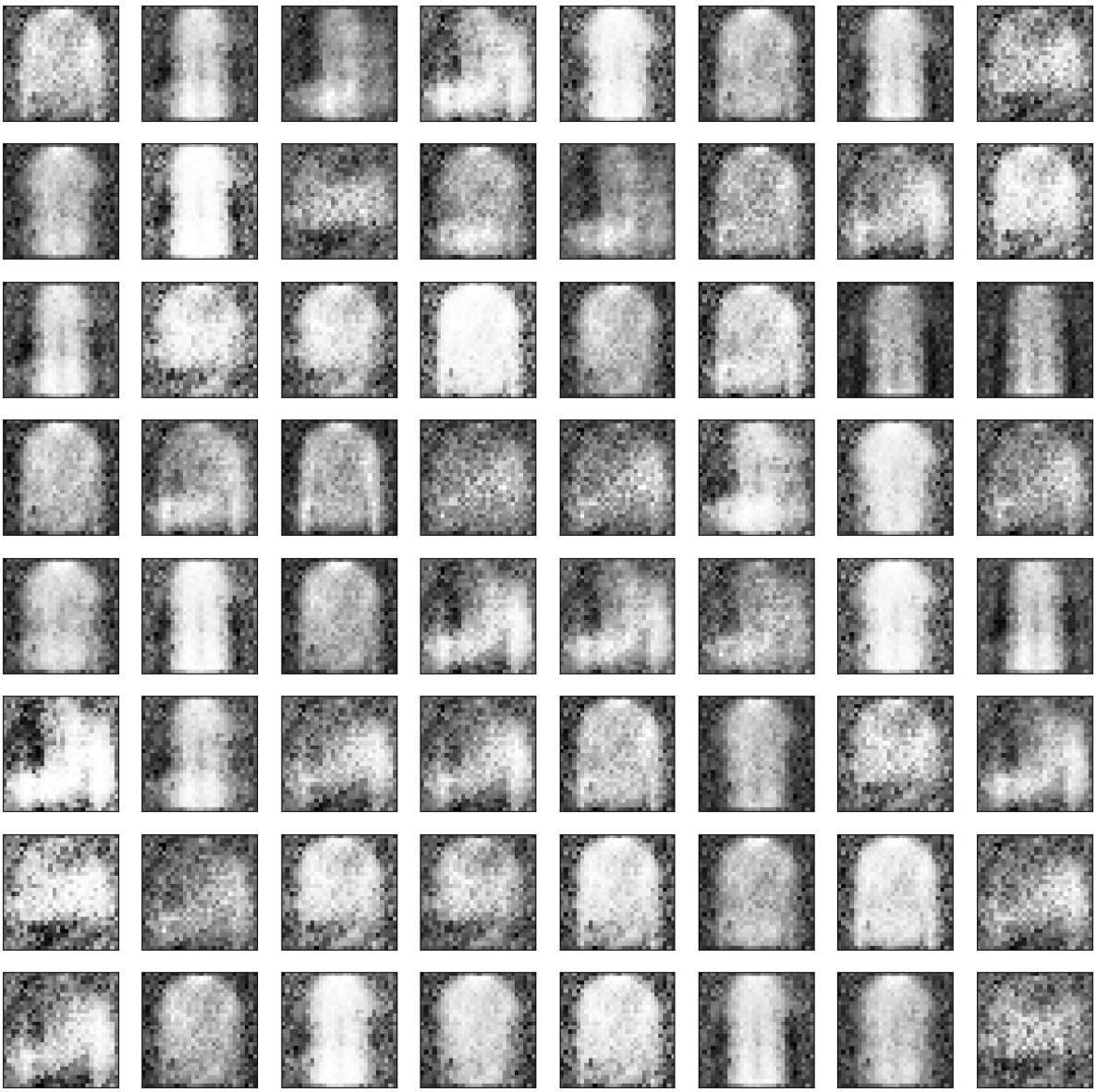
```
Epoch 1: loss_d: 0.9694660305976868, loss_g: 1.8247395753860474
Training Steps Completed:  499
```



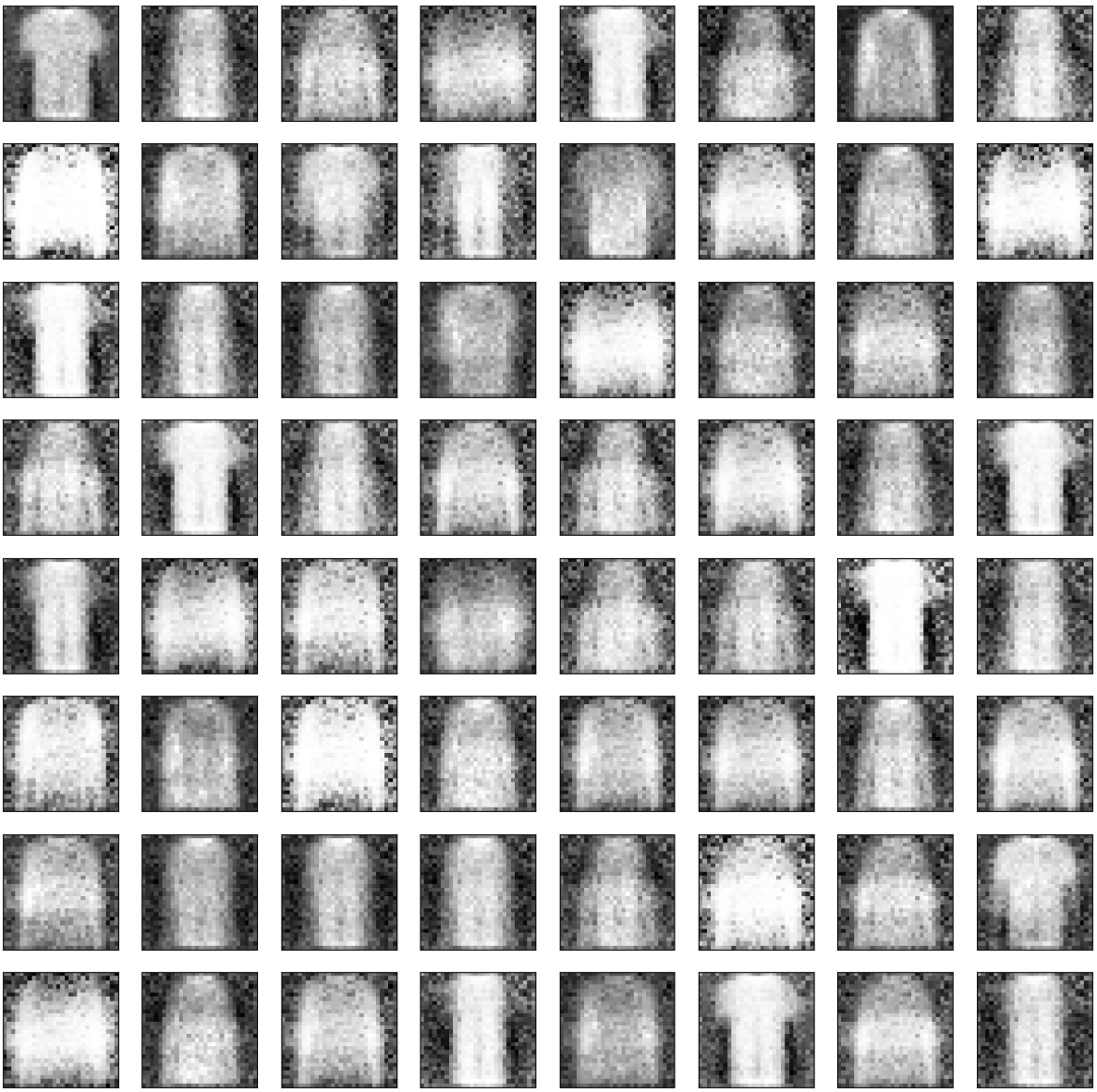
```
Epoch 2: loss_d: 1.1399441957473755, loss_g: 1.3783767223358154
Training Steps Completed:  499
```



```
Epoch 3: loss_d: 0.9844392538070679, loss_g: 1.3892009258270264
Training Steps Completed:  499
```

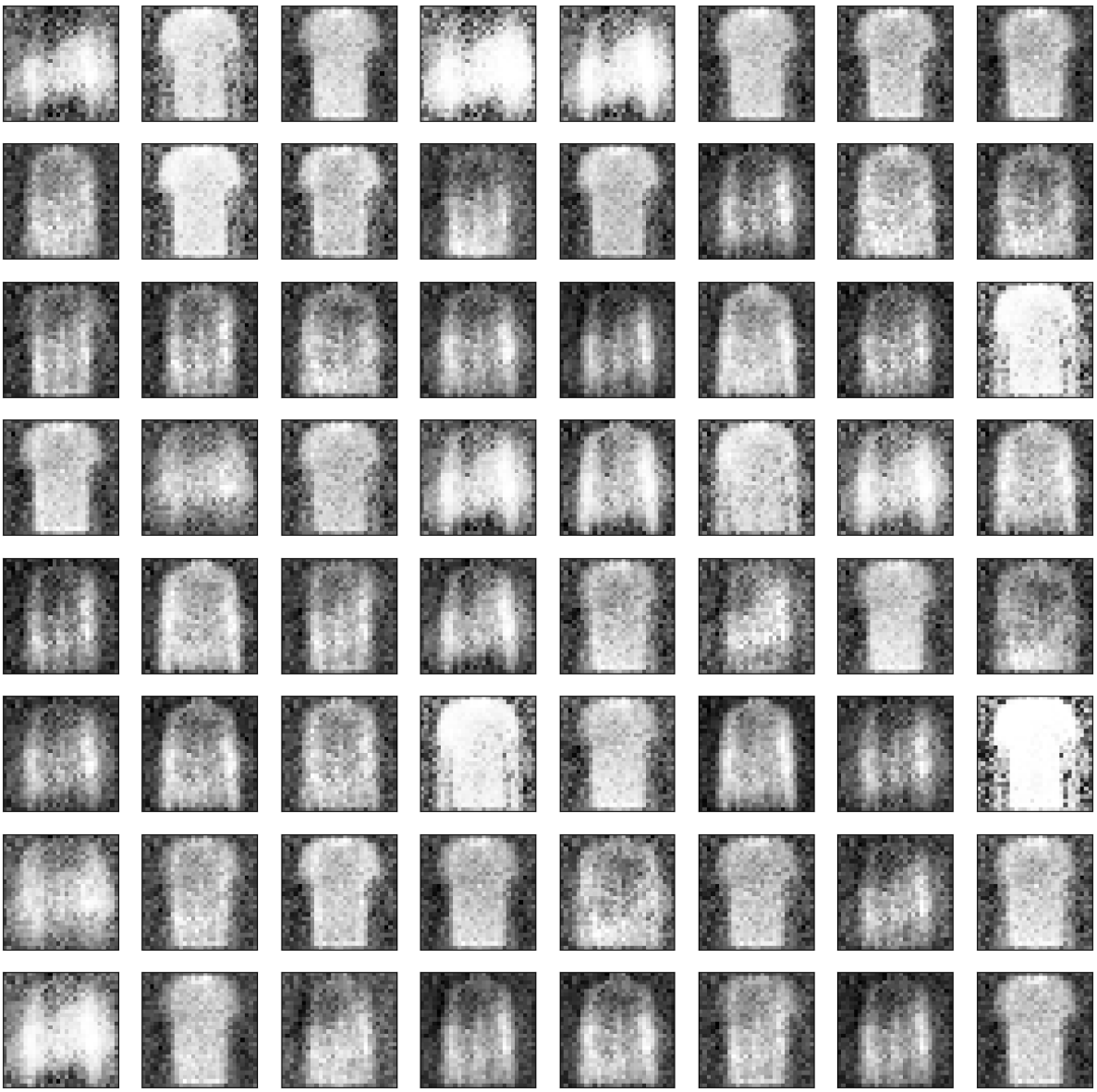


```
Epoch 4: loss_d: 0.9357741475105286, loss_g: 1.586155652999878
Training Steps Completed:  499
```

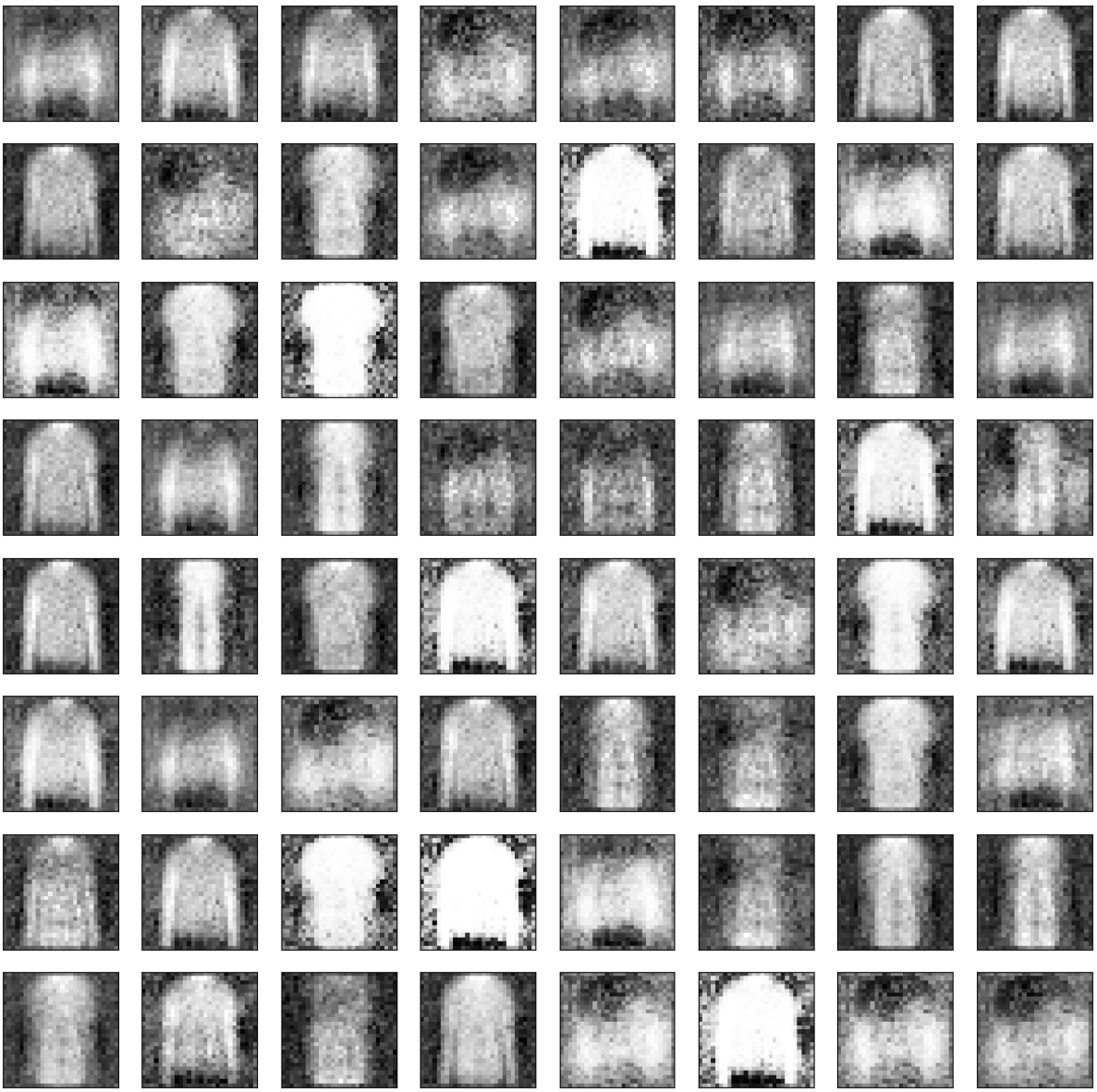


```
Epoch 5: loss_d: 0.9688796997070312, loss_g: 1.4648841619491577
Training Steps Completed:  499
```

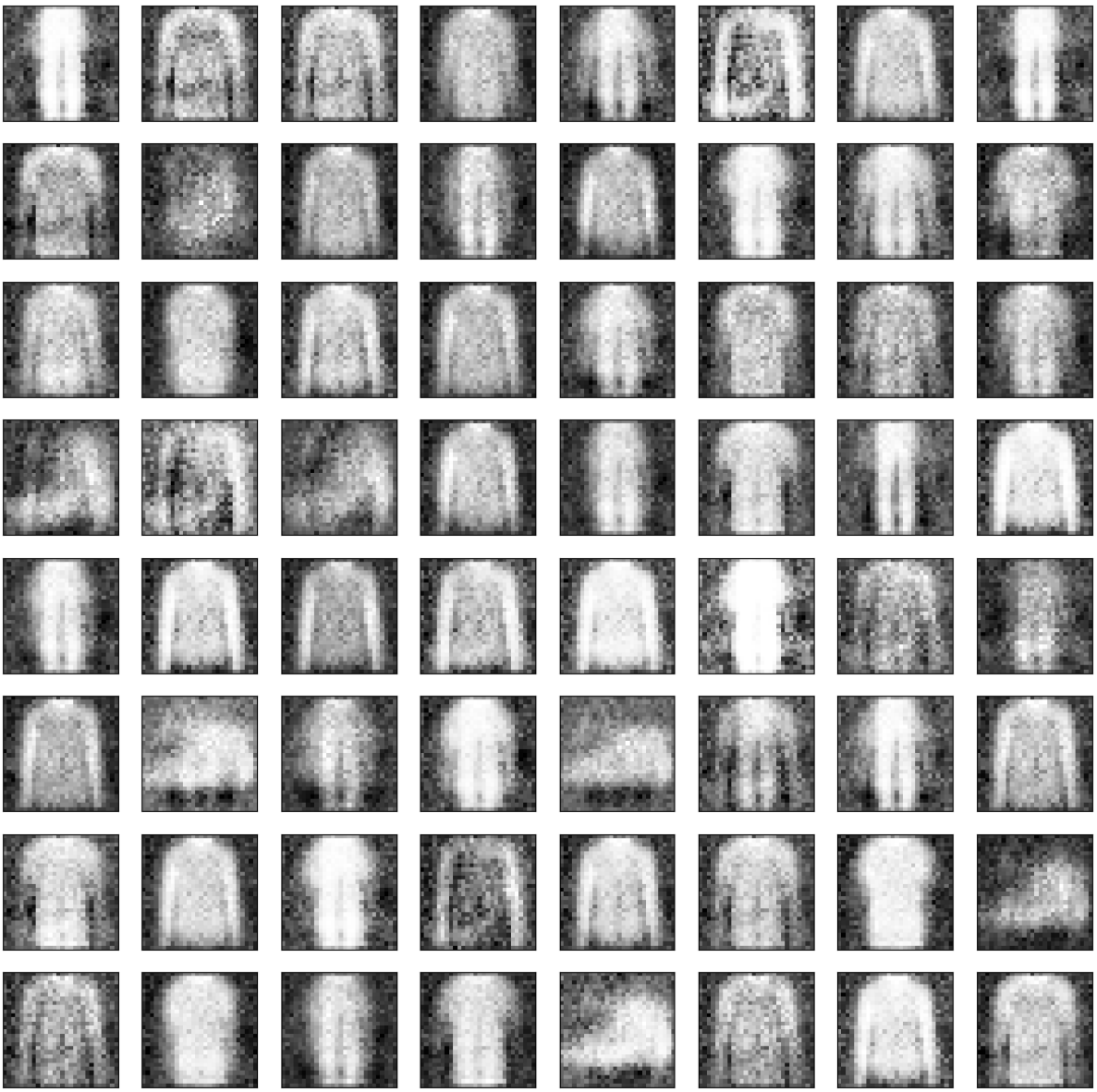
```
Epoch 6: loss_d: 0.9627387523651123, loss_g: 1.4375097751617432
Training Steps Completed:  499
```



```
Epoch 7: loss_d: 0.9848072528839111, loss_g: 1.3207499980926514
Training Steps Completed:  499
```

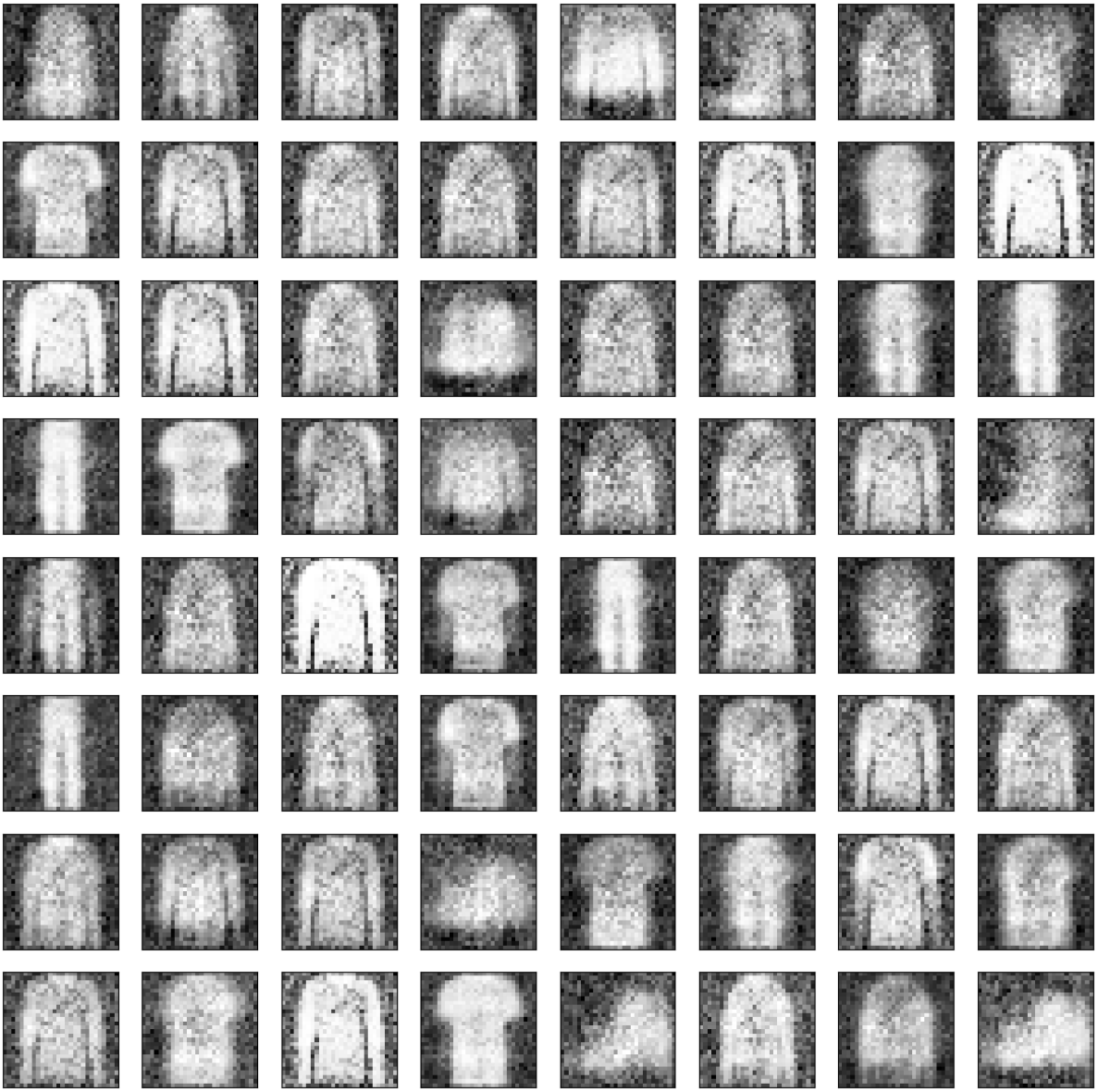


```
Epoch 8: loss_d: 0.9613051414489746, loss_g: 1.4039595127105713
Training Steps Completed:  499
```



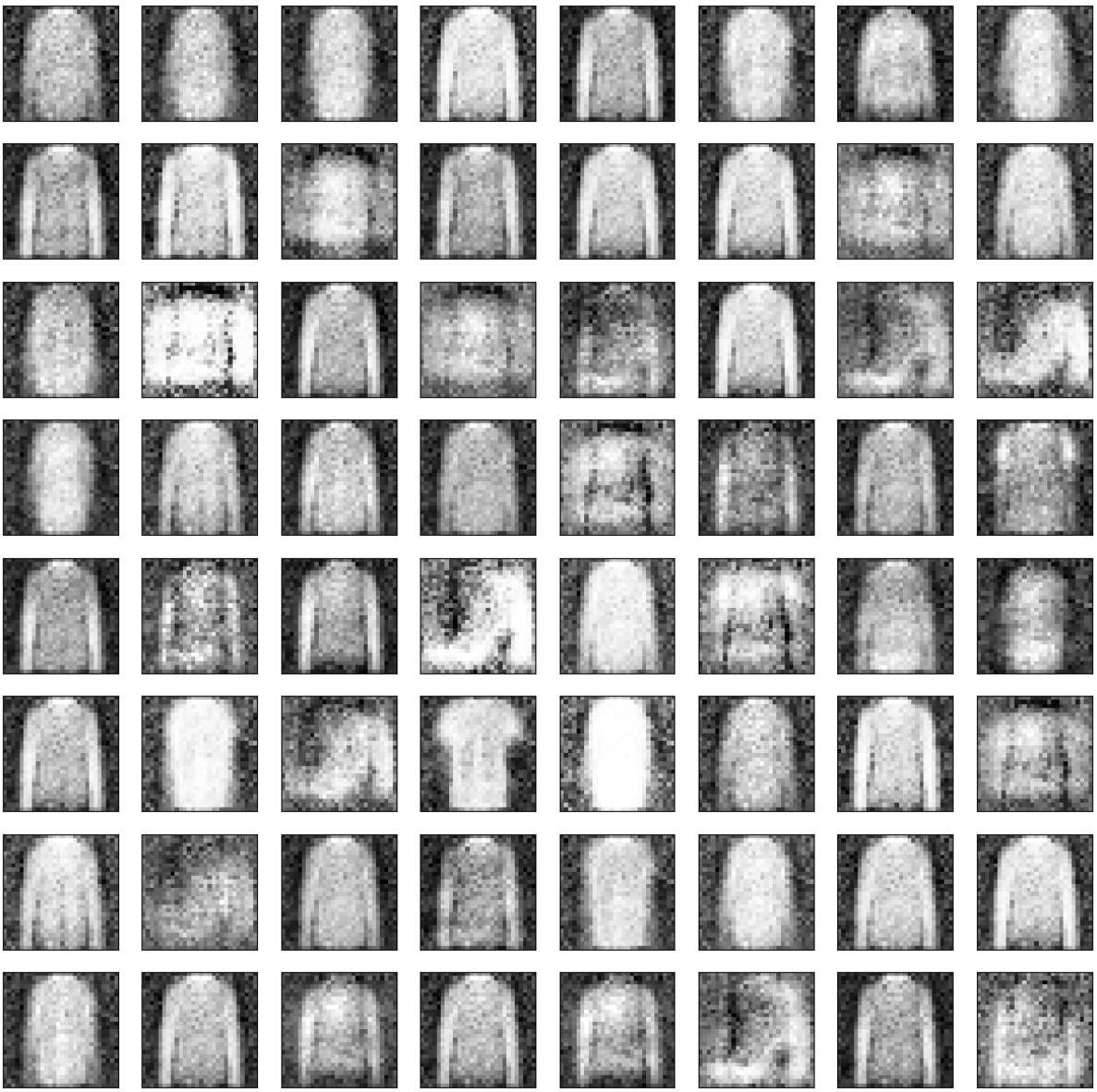
```
Epoch 9: loss_d: 0.9866572618484497, loss_g: 1.3418234586715698
Training Steps Completed:  499
```

```
Epoch 10: loss_d: 0.9602514505386353, loss_g: 1.6135871410369873
Training Steps Completed:  499
```

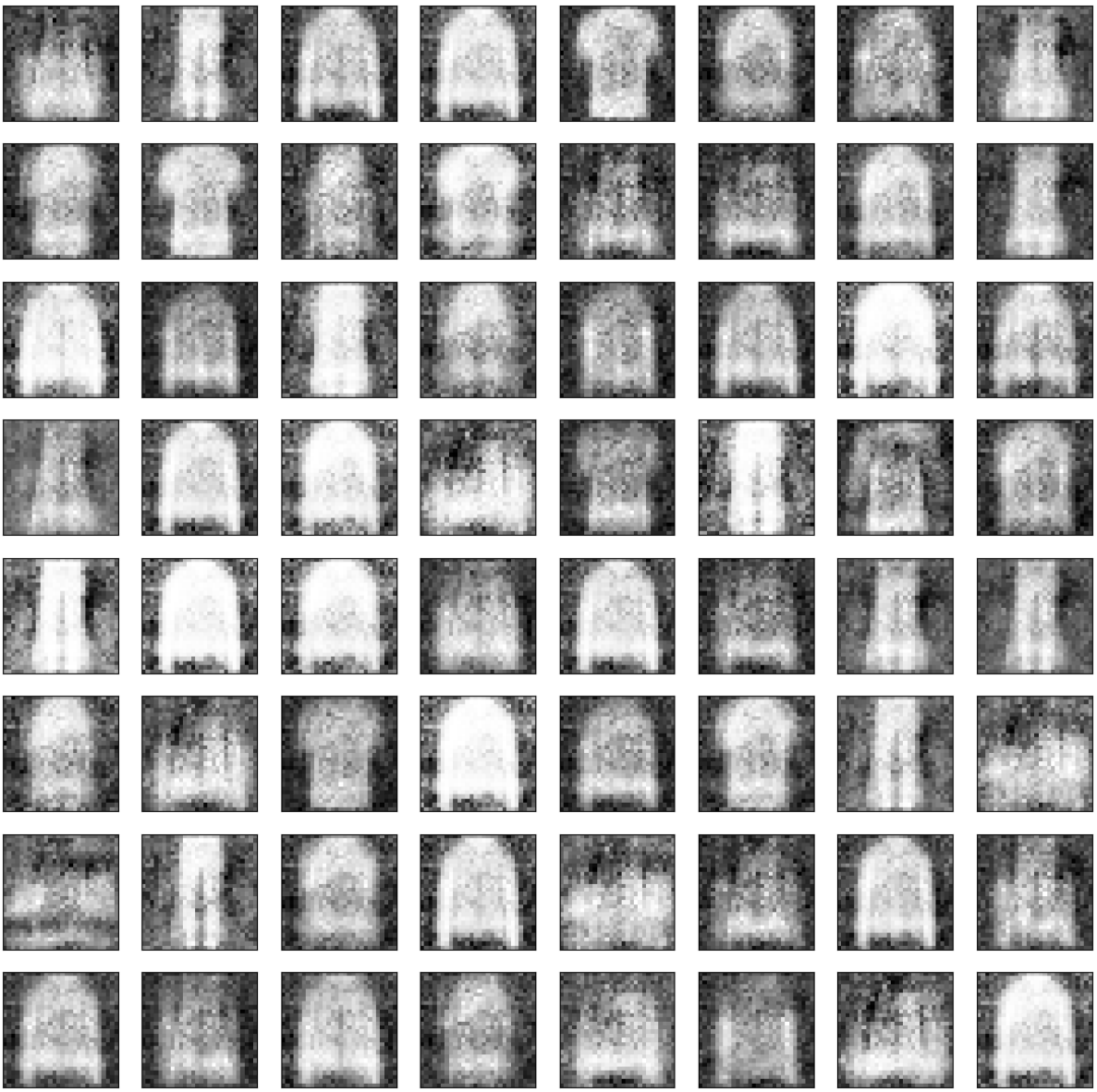


```
Epoch 11: loss_d: 0.9789851903915405, loss_g: 1.3583877086639404
Training Steps Completed:  499
```

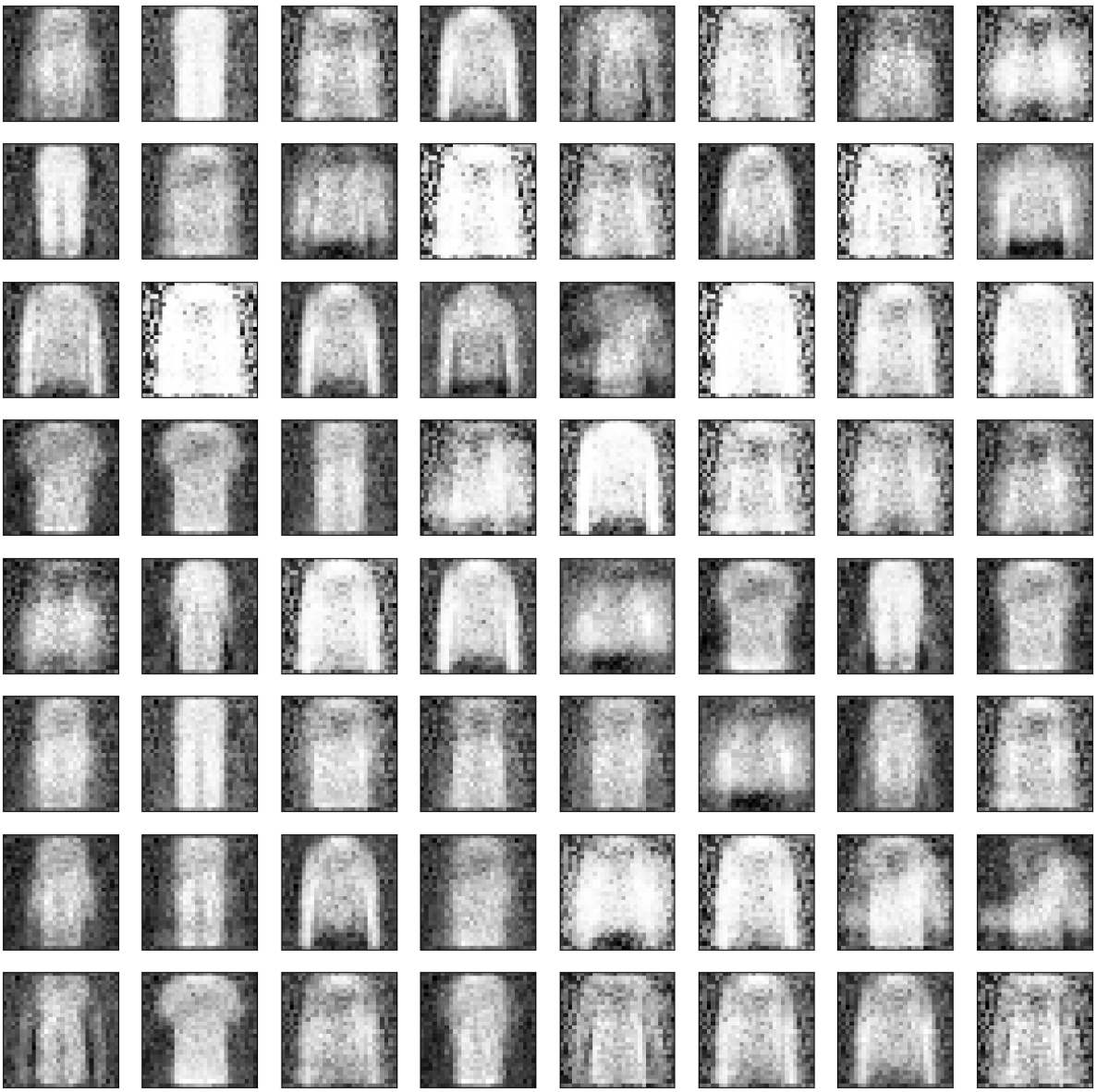
```
Epoch 12: loss_d: 0.9949526786804199, loss_g: 1.2763011455535889
Training Steps Completed:  499
```



```
Epoch 13: loss_d: 1.007961392402649, loss_g: 1.3118679523468018
Training Steps Completed:  499
```



```
Epoch 14: loss_d: 0.9944226145744324, loss_g: 1.4150930643081665
Training Steps Completed:  499
```



```
Epoch 15: loss_d: 0.9656962752342224, loss_g: 1.4043164253234863
Training Steps Completed:  499
```

```
Epoch 16: loss_d: 0.9760198593139648, loss_g: 1.3481272459030151
Training Steps Completed:  499
```

```
Epoch 17: loss_d: 0.9081671833992004, loss_g: 1.4236488342285156
Training Steps Completed:  499
```

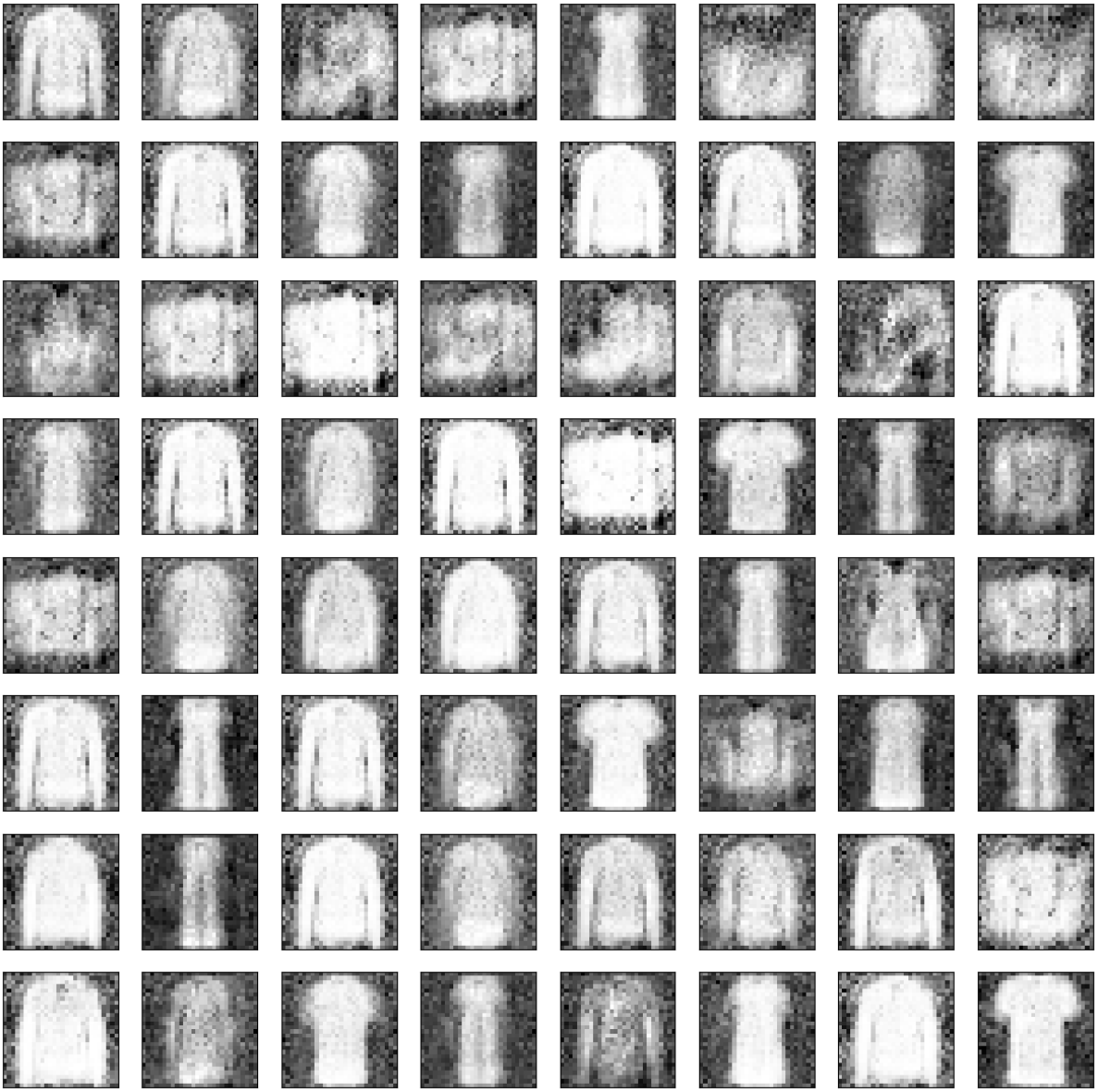
```
Epoch 18: loss_d: 0.9437633156776428, loss_g: 1.291171908378601
Training Steps Completed:  499
```

```
Epoch 19: loss_d: 0.9344487190246582, loss_g: 1.3899822235107422
Training Steps Completed:  499
```

```
Epoch 20: loss_d: 0.9814656376838684, loss_g: 1.3209909200668335
Training Steps Completed:  499
```

```
Epoch 21: loss_d: 0.9480006098747253, loss_g: 1.3294214010238647
Training Steps Completed:  499
```

```
Epoch 22: loss_d: 0.9748787879943848, loss_g: 1.3365697860717773
Training Steps Completed:  499
```



```
Epoch 23: loss_d: 0.9892889857292175, loss_g: 1.280814528465271
```

In [ ]:
```
#save the model
torch.save(generator.state_dict(), 'generator_cond.pth')
torch.save(discriminator.state_dict(), 'discriminator_cond.pth')
```