Classical Artwork Generation using Generative Adversarial Networks
CS-GY 6953 / ECE-GY 7123 Deep Learning Project Report — Spring 2024

Giorgi Merabishvili[1], Aaftab Mohammad[2], Mohd Faizaan Khan[3]

[1]New York University, Tandon School of Engineering, Department of Electrical and Computer Engineering (ECE)
[2]New York University, Tandon School of Engineering, Department of Electrical and Computer Engineering (ECE)
[3]New York University, Tandon School of Engineering, Department of Computer Science and Engineering (CSE)

Final Project GitHub Repository:
https://github.com/giorgix121/Classical-Artwork-Generation-using-Generative-Adversarial-Networks

Abstract
This paper presents a Generative Adversarial Network (GAN) designed to generate high-quality artwork images based on the "Best Artworks of All Time" dataset. Our GAN model features a generator-discriminator architecture optimized through spectral normalization and dropout techniques to enhance image quality and stability. The generator comprises initial layers focusing on broader features and detail layers refining finer details, while the discriminator incorporates adaptive average pooling and Gaussian noise augmentation to combat overfitting. Over 500 epochs, we iteratively adjusted learning rates based on discriminator performance feedback, achieving notable improvements in the fidelity and diversity of generated images. Experimental results demonstrate the efficacy of our approach in producing realistic and diverse artwork images, advancing the state-of-the-art in GAN-based art generation.

Introduction
Generative Adversarial Networks (GANs) have revolutionized image synthesis, enabling the creation of realistic images across various domains. This paper proposes a GAN architecture to generate artwork images using the "Best Artworks of All Time" dataset. To address common challenges like mode collapse and instability, we incorporate spectral normalization and dropout layers. The generator is designed with initial layers capturing broad features and detail layers refining these features for high-quality images. The discriminator is augmented with Gaussian noise to improve robustness.
We employed a feedback mechanism to dynamically adjust the learning rates of the generator's layers based on discriminator performance. This adaptive strategy enhanced training stability and output quality. Over 500 epochs, our model consistently produced diverse and high-quality artwork images, demonstrating its potential in GAN-based image synthesis in the artistic domain.

Literature Survey
GANs like StyleGAN and BigGAN have pushed boundaries of art generation, producing complex and artistically diverse images. While some studies like Elgammal et al. (2017) have shown how AI can learn to imitate artistic styles, others (Kazemi 2019) have investigated the possibility of using these models to produce completely original works. Building on this foundation, our project focused on classical art to explore historical artistic expressions.

Dataset
The "Best Artworks of All Time" dataset, sourced from Kaggle, serves as the foundation for our GAN-based art generation model. This dataset comprises a diverse collection of 8683 images featuring renowned paintings from various artists and art movements. Each image in the dataset has been resized to 128x128 pixels to standardize input dimensions for our model. We applied data augmentation techniques, including random horizontal flips and rotations, to increase the variability of the training set and improve the model's generalization capabilities. Additionally, we calculated the dataset's mean and standard deviation to normalize the images, ensuring consistent training conditions. This dataset's rich diversity and high-quality images provide an excellent basis for training our GAN to generate realistic and varied artwork images.

Architecture
I – Generator
Architecture:
The generator is designed with a two-stage approach. The initial layers capture broad features using ConvTranspose2d layers with dimensions of 1024 and 512 feature maps, followed by ReLU activations and BatchNorm2d layers for stabilization. The detail layers refine these features using ConvTranspose2d layers with smaller

dimensions (256, 128, 64) and similar activation and normalization layers, concluding with a final ConvTranspose2d layer outputting a 3-channel image with a Tanh activation function.

Reason for Use:

This architectural design allows the generator to progressively build up an image from a low-resolution representation to a high-resolution output, effectively capturing both broad structural features and fine details. The use of BatchNorm2d layers helps stabilize the training process by normalizing intermediate feature maps. The inclusion of adaptive learning rates for the initial and detail layers based on discriminator feedback further enhances the training dynamics.

Advantages:

- High-Quality Image Generation: The progressive refinement approach enables the generation of detailed and high-quality images.
- Stabilized Training: Batch normalization layers help in maintaining stable training dynamics.
- Efficient Feature Learning: The two-stage architecture ensures efficient learning of both global structures and local details.
- Adaptive Training: Adjusting learning rates based on discriminator feedback optimizes training and prevents mode collapse.

```
============================
Total params: 13,245,312
Trainable params: 13,245,312
Non-trainable params: 0
----------------------------
```

Figure 1: Number of parameters of Generator

II - Discriminator

Architecture:

The discriminator employs a series of spectral normalized Conv2d layers, starting with 64 feature maps and progressively increasing to 512. Each Conv2d layer is followed by a LeakyReLU activation and a dropout layer to prevent overfitting. Gaussian noise is added to the input images to increase robustness. The final layers include an adaptive average pooling layer, flattening, and a Sigmoid activation to output a single probability score.

Reason for Use:

Spectral normalization in the Conv2d layers constrains the spectral norm of the weight matrices, ensuring more stable training. Dropout layers provide regularization, reducing the risk of overfitting. Adding Gaussian noise to the input images improves the discriminator's robustness, enabling it to handle variations and noise more effectively.

Advantages:

- Training Stability: Spectral normalization helps maintain stable and balanced training dynamics between the generator and discriminator.
- Regularization: Dropout layers help prevent overfitting, allowing the discriminator to generalize better.
- Enhanced Robustness: Adding Gaussian noise to the input images improves the discriminator's ability to handle variations and noise, leading to more robust performance.
- Improved Feedback: The robust discriminator provides better feedback to the generator, facilitating more realistic image generation.

```
============================
Total params: 2,763,776
Trainable params: 2,763,776
Non-trainable params: 0
----------------------------
```

Figure 2: Number of parameters of Discriminator

Methodology

I - Loss Function

We utilized the Binary Cross-Entropy (BCE) loss for both the generator and discriminator. The discriminator aims to maximize the log-likelihood of correctly classifying real and fake images, while the generator aims to minimize the log-likelihood of the discriminator correctly identifying its outputs as fake. This adversarial loss function ensures that the generator produces increasingly realistic images over time.

Real Images Loss:

$L_{D_{real}} = -\mathbb{E}_{\mathbf{x}\sim p_{data}(\mathbf{x})}[\log D(\mathbf{x})]$

$D(\mathbf{x})$ is the discriminator's output for real images x, and $p_{data}(x)$ is the data distribution.

Fake Images Loss:

$L_{D_{fake}} = -\mathbb{E}_{\mathbf{z}\sim p_{z(\mathbf{z})}}[\log(1-D(G(\mathbf{z})))]$

$G(\mathbf{z})$ is the generator's output for the input noise z, and $p_z(z)$ is the noise distribution.

Total Discriminator Loss:

$L_D = L_{D_{real}} + L_{D_{fake}}$

Generator Loss:

$L_G = -\mathbb{E}_{\mathbf{z}\sim p_{z(\mathbf{z})}}[\log D(G(\mathbf{z}))]$

II - Training Procedure

The training process involves alternating updates between the generator and the discriminator. For each iteration, we perform multiple updates to the discriminator using both real and generated images, followed by an update to the generator. The discriminator's training includes adding Gaussian noise to the real images to enhance robustness, while the generator's training involves backpropagating the adversarial loss to improve image generation quality.

III - Hyperparameters

- The learning rates for the generator's initial and detail layers are set to 0.0002 and 0.00005, respectively.
- The Adam optimizer with beta values of 0.5 and 0.999 is used for both the generator and discriminator.
- A batch size of 64 and a total of 500 epochs are employed.
- The latent vector size for the generator's input is set to 128.

IV - Data Augmentation

To improve the generalization capability of the model, we applied several data augmentation techniques, including random horizontal flips and random rotations up to 5 degrees. These augmentations increase the variability in the training data, helping the model learn more robust features.

V - Learning Rate Schedulers

A dynamic learning rate adjustment strategy was implemented based on the performance feedback of the discriminator. If the discriminator's performance exceeded a predefined threshold, the learning rates for both the generator's initial and detail layers were adjusted to maintain balanced training dynamics. This adaptive learning rate mechanism prevents the discriminator from overpowering the generator or becoming too weak.

VI - Other Training Details

Throughout the training process, we used the Adam optimizer for both the generator and discriminator with different learning rates for the initial and detail layers of the generator (0.0002 and 0.00005 respectively). We employed spectral normalization in the discriminator to stabilize training and prevent exploding gradients. Models were saved at regular intervals to allow for monitoring progress and future fine-tuning. Additionally, we used TensorBoard for visualizing training metrics and generated images to assess the quality and diversity of the outputs over time. A fixed latent vector was used to generate images at the end of each epoch for consistent evaluation and comparison. This comprehensive approach ensures the production of high-quality realistic artwork images showcasing the potential of our GAN architecture.

Results

The results of our GAN-based artwork generation model demonstrate significant improvements in the quality and diversity of the generated images over the training period. The model was trained for 500 epochs, during which we observed that the adaptive learning rate mechanism effectively balanced the training dynamics between the generator and discriminator, preventing issues such as mode collapse.

The generated images exhibited a high level of detail and artistic style closely resembling the artworks in the training dataset. Notable improvements were observed after incorporating spectral normalization and dropout layers in the discriminator, which contributed to more stable training and higher quality outputs. The use of Gaussian noise in the discriminator's input further enhanced the robustness of the model, allowing it to generate more realistic and diverse images.

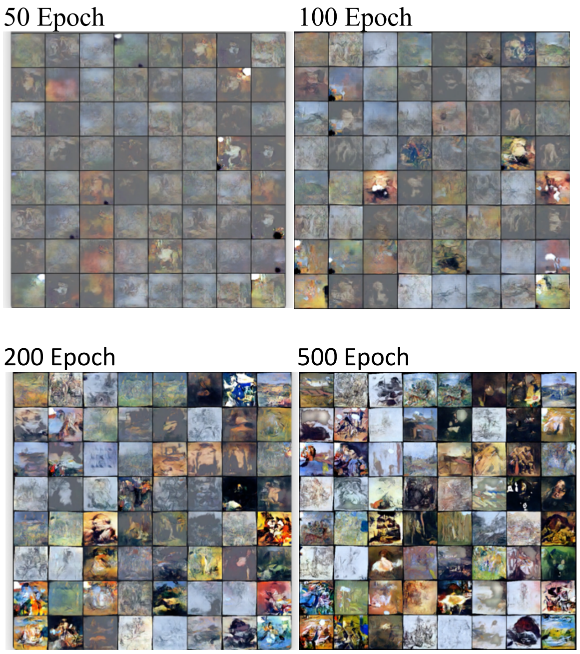

Figure 3: Images generated at different epochs

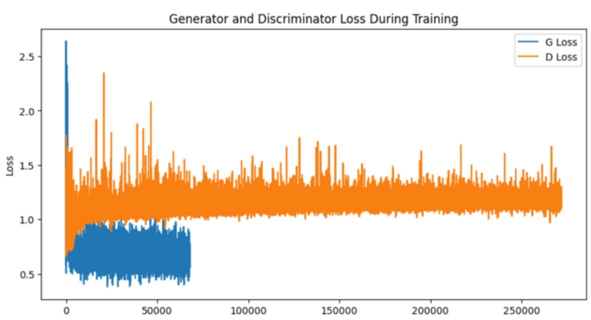

Figure 4: Generator and Discriminator Loss During Training

System Specifications:

```
CPU:  Intel(R) Xeon(R) CPU @ 2.00GHz

GPU: Tesla V100-SXM2-16GB
System Memory: 52217.5 MB
Python Version: 3.10.12 (main, Nov 20 2023, 15:14:05) [GCC
CUDA Version: 12.1
Torch Version: 2.2.1+cu121
```

Figure 5: System Specifications

References:

- Elgammal, A., Liu, B., Elhoseiny, M., & Mazzone, M. (2017). CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms. arXiv preprint arXiv:1706.07068.
- Baker, J. (2023). ARTEMIS: Using GANs with Multiple Discriminators to Generate Art. arXiv. https://arxiv.org/abs/2311.08278
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative Adversarial Nets. Advances in Neural Information Processing Systems, 27.

Classical Artwork Generation using Generative Adversarial Networks

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May 14, 2024

[1]:
```
!pip install kaggle
!pip install torchsummary
!pip install imageio
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages
(1.6.12)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-
packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi>=2023.7.22 in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2024.2.2)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2.8.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from kaggle) (2.31.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from kaggle) (4.66.4)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-
packages (from kaggle) (8.0.4)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-
packages (from kaggle) (2.0.7)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages
(from kaggle) (6.1.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-
packages (from bleach->kaggle) (0.5.1)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->kaggle) (3.7)
Requirement already satisfied: torchsummary in /usr/local/lib/python3.10/dist-
packages (1.5.1)
Requirement already satisfied: imageio in /usr/local/lib/python3.10/dist-
packages (2.31.6)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from imageio) (1.25.2)
Requirement already satisfied: pillow<10.1.0,>=8.3.2 in
/usr/local/lib/python3.10/dist-packages (from imageio) (9.4.0)
```

[2]:
```
import os
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision.transforms as tt
from torch.utils.data import DataLoader
from torchvision.datasets import ImageFolder
from torchvision.utils import save_image, make_grid
import matplotlib.pyplot as plt
from tqdm.auto import tqdm
from torch.nn.utils import spectral_norm
from torch.utils.tensorboard import SummaryWriter
import torchvision.utils as vutils
import sys
import subprocess
from torchsummary import summary
import imageio
from IPython.display import Video
from IPython.display import Image
```

[3]:
```
os.environ['KAGGLE_CONFIG_DIR'] = "/content"
!chmod 600 /content/kaggle.json
```

```
chmod: cannot access '/content/kaggle.json': No such file or directory
```

[4]:
```
dataset_path = '/content/dataset'
if not os.path.exists(dataset_path):
    # If the dataset folder doesn't exist, download and unzip the dataset
    !kaggle datasets download -d ikarus777/best-artworks-of-all-time -p␣
  ↪{dataset_path} --unzip
else:
    print("Dataset already downloaded.")
```

```
Dataset already downloaded.
```

[5]:
```
data_dir = '/content/dataset/resized'
image_save_path = '/content/generated_images/'
os.makedirs(image_save_path, exist_ok=True)
```

[6]:
```
def get_mean_std(loader):
    # Vectors to hold image mean and std
    mean = 0.
    std = 0.
    total_images_count = 0
    for images, _ in tqdm(loader, desc="Calculating mean and std"):
        images = images.view(images.size(0), images.size(1), -1)
        mean += images.mean(2).sum(0)
```

```
        std += images.std(2).sum(0)
        total_images_count += images.size(0)

    # Final mean and std
    mean /= total_images_count
    std /= total_images_count
    return mean, std
```

[7]:
```
pre_transforms = tt.Compose([
    tt.Resize((128, 128)),
    tt.ToTensor(),
])
pre_dataset = ImageFolder(data_dir, transform=pre_transforms)
pre_loader = DataLoader(pre_dataset, batch_size=64, shuffle=False,␣
 ↪num_workers=2)

# Calculate mean and std
dataset_mean, dataset_std = get_mean_std(pre_loader)
```

```
/usr/lib/python3.10/multiprocessing/popen_fork.py:66: RuntimeWarning: os.fork()
was called. os.fork() is incompatible with multithreaded code, and JAX is
multithreaded, so this will likely lead to a deadlock.
  self.pid = os.fork()
```

```
Calculating mean and std:   0%|          | 0/136 [00:00<?, ?it/s]
```

[8]:
```
transformations = tt.Compose([

    tt.Resize((128, 128)),
    tt.RandomHorizontalFlip(),
    tt.RandomRotation(5),
    tt.ToTensor(),
    tt.Normalize(dataset_mean.tolist(), dataset_std.tolist())
])

dataset = ImageFolder(data_dir, transform=transformations)
train_dl = DataLoader(dataset, batch_size=64, shuffle=True, num_workers=2,␣
 ↪pin_memory=True)
```

[9]:
```
print(f"Total number of images in dataset: {len(dataset)}")
```

```
Total number of images in dataset: 8683
```

[10]:
```
num_batches = len(train_dl)
print(f"Number of batches per epoch (batch size = 64): {num_batches}")
```

```
Number of batches per epoch (batch size = 64): 136
```

[11]:

```
dataiter = iter(train_dl)
images, labels = next(dataiter)

# Create a grid of images
img_grid = vutils.make_grid(images, nrow=8, normalize=True)

# Display these images
plt.figure(figsize=(10, 10))
plt.imshow(img_grid.permute(1, 2, 0))
plt.axis('off')
plt.show()
```

[12]:
```python
class Generator(nn.Module):
    def __init__(self, latent_size=128):
        super(Generator, self).__init__()

        # Initial layers focus on broader features
        self.initial_layers = nn.Sequential(
            nn.ConvTranspose2d(latent_size, 1024, kernel_size=4, stride=1,␣
↪padding=0, bias=False),
            nn.ReLU(True),
            nn.BatchNorm2d(1024),

            nn.ConvTranspose2d(1024, 512, kernel_size=4, stride=2, padding=1,␣
↪bias=False),
            nn.ReLU(True),
            nn.BatchNorm2d(512),
        )

        # Detail layers focus on finer details
        self.detail_layers = nn.Sequential(
            nn.ConvTranspose2d(512, 256, kernel_size=4, stride=2, padding=1,␣
↪bias=False),
            nn.ReLU(True),
            nn.BatchNorm2d(256),

            nn.ConvTranspose2d(256, 128, kernel_size=4, stride=2, padding=1,␣
↪bias=False),
            nn.ReLU(True),
            nn.BatchNorm2d(128),

            nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2, padding=1,␣
↪bias=False),
            nn.ReLU(True),
            nn.BatchNorm2d(64),

            nn.ConvTranspose2d(64, 3, kernel_size=4, stride=2, padding=1,␣
↪bias=False),
            nn.Tanh(),
        )

    def forward(self, x):
        x = self.initial_layers(x)
        x = self.detail_layers(x)
        return x
```

[13]:
```python
class Discriminator(nn.Module):
    def __init__(self, dropout_rate=0.3):
        super(Discriminator, self).__init__()
```

```
        self.disc = nn.Sequential(
            spectral_norm(nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1,␣
↪bias=False)),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(dropout_rate),

            spectral_norm(nn.Conv2d(64, 128, kernel_size=4, stride=2,␣
↪padding=1, bias=False)),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(dropout_rate),

            spectral_norm(nn.Conv2d(128, 256, kernel_size=4, stride=2,␣
↪padding=1, bias=False)),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(dropout_rate),

            spectral_norm(nn.Conv2d(256, 512, kernel_size=4, stride=2,␣
↪padding=1, bias=False)),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Dropout(dropout_rate),

            spectral_norm(nn.Conv2d(512, 1, kernel_size=4, stride=1, padding=0,␣
↪bias=False)),
            nn.AdaptiveAvgPool2d((1, 1)),
            nn.Flatten(),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.disc(x)
```

[14]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
generator = Generator().to(device)
discriminator = Discriminator().to(device)

opt_d = torch.optim.Adam(discriminator.parameters(), lr=0.0001, betas=(0.5, 0.
↪999))
```

[15]:
```
def adjust_learning_rates(optimizer_initial, optimizer_detail, feedback_signal):

    lr_adjustment_factor = 0.95

    # discriminator is too good
    if feedback_signal > 0.8:
        for param_group in optimizer_initial.param_groups:
```

```
            param_group['lr'] *= lr_adjustment_factor
        for param_group in optimizer_detail.param_groups:
            param_group['lr'] *= lr_adjustment_factor

    # discriminator is too poor
    elif feedback_signal < 0.3:
        for param_group in optimizer_initial.param_groups:
            param_group['lr'] /= lr_adjustment_factor
        for param_group in optimizer_detail.param_groups:
            param_group['lr'] /= lr_adjustment_factor
```

[16]:
```
opt_initial = torch.optim.Adam(generator.initial_layers.parameters(), lr=0.
 ↪0002, betas=(0.5, 0.999))
opt_detail = torch.optim.Adam(generator.detail_layers.parameters(), lr=0.00005,␣
 ↪betas=(0.5, 0.999))
```

[17]:
```
def train_discriminator(real_images):

    # Adding Gaussian noise
    noise = torch.randn_like(real_images) * 0.05
    real_images = real_images + noise

    opt_d.zero_grad()
    real_preds = discriminator(real_images)
    real_targets = torch.full_like(real_preds, 0.9)
    real_loss = F.binary_cross_entropy(real_preds, real_targets)
    real_score = torch.mean(real_preds).item()

    latent = torch.randn(real_images.size(0), 128, 1, 1, device=device)
    fake_images = generator(latent)
    fake_preds = discriminator(fake_images.detach())
    fake_targets = torch.full_like(fake_preds, 0.1)
    fake_loss = F.binary_cross_entropy(fake_preds, fake_targets)
    fake_score = torch.mean(fake_preds).item()

    loss = real_loss + fake_loss
    loss.backward()
    opt_d.step()
    return loss.item(), real_score, fake_score
```

[18]:
```
def train_generator():

    # Zero the gradients for both optimizers
    opt_initial.zero_grad()
    opt_detail.zero_grad()

    latent = torch.randn(64, 128, 1, 1, device=device)
```

```
    fake_images = generator(latent)
    preds = discriminator(fake_images)
    targets = torch.ones_like(preds)
    loss = F.binary_cross_entropy(preds, targets)

    # Perform backpropagation
    loss.backward()

    # Update both parts of the generator
    opt_initial.step()
    opt_detail.step()

    return loss.item()
```

[19]:
```
def save_models(generator, discriminator, epoch, save_directory="/content/
 ↪saved_models"):
    os.makedirs(save_directory, exist_ok=True)
    torch.save(generator.state_dict(), os.path.join(save_directory,␣
 ↪f"generator_epoch_{epoch}.pth"))
    torch.save(discriminator.state_dict(), os.path.join(save_directory,␣
 ↪f"discriminator_epoch_{epoch}.pth"))
    print(f"Saved models to {save_directory} at epoch {epoch}")
```

[20]:
```
num_epochs = 500
save_interval = 100
fixed_latent = torch.randn(64, 128, 1, 1, device=device)
writer = SummaryWriter('runs/gan_experiment')
```

[21]:
```
generator_losses = []
discriminator_losses = []
hyperparams = {
    'g_lr': [], 'd_lr': []
}
```

[22]:
```
for epoch in range(num_epochs):
    epoch_d_loss, epoch_g_loss = 0, 0
    num_batches = len(train_dl)
    discriminator_effectiveness = []

    with tqdm(total=num_batches, desc=f"Epoch {epoch + 1}/{num_epochs}",␣
 ↪unit='batch') as pbar:
        for real_images, _ in train_dl:
            real_images = real_images.to(device)
            generator.train()
            discriminator.train()

            # n_critic iterations
```

```
            for _ in range(4):
                d_loss, real_score, fake_score =␣
↪train_discriminator(real_images)
                discriminator_effectiveness.append((real_score + (1 -␣
↪fake_score)) / 2)
                discriminator_losses.append(d_loss)


            # Generator update
            g_loss = train_generator()
            generator_losses.append(g_loss)

            # Logging
            batch_num = epoch * num_batches + pbar.n
            writer.add_scalar('Loss/Generator', g_loss, batch_num)
            writer.add_scalar('Loss/Discriminator', d_loss, batch_num)

            # Progress update
            pbar.set_postfix_str(f"D Loss: {d_loss:.4f}, G Loss: {g_loss:.4f}")
            pbar.update()

            # Cumulative loss calculation
            epoch_d_loss += d_loss
            epoch_g_loss += g_loss

            # Log current learning rates
            hyperparams['d_lr'].append(opt_d.param_groups[0]['lr'])
            hyperparams['g_lr'].append(opt_initial.param_groups[0]['lr'] +␣
↪opt_detail.param_groups[0]['lr'])


        # Feedback-based learning rate adjustment
        avg_discriminator_effectiveness = sum(discriminator_effectiveness) /␣
↪len(discriminator_effectiveness)
        adjust_learning_rates(opt_initial, opt_detail,␣
↪avg_discriminator_effectiveness)


        # Generate images at the end of each epoch
        with torch.no_grad():
            generated_images = generator(fixed_latent).cpu()
            save_image(generated_images, os.path.join(image_save_path,␣
↪f'generated_images_epoch_{epoch}.png'), normalize=True, nrow=8)

        # Epoch summary
```

```
        print(f"Epoch {epoch + 1}/{num_epochs}: Average D Loss: {epoch_d_loss /
 ↪num_batches:.4f}, Average G Loss: {epoch_g_loss / num_batches:.4f}")

        # Save models at specified interval
        if (epoch + 1) % save_interval == 0 or epoch == num_epochs - 1:
            save_models(generator, discriminator, epoch)

# Cleanup
writer.close()
```

```
Epoch 1/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 1/500: Average D Loss: 0.7533, Average G Loss: 1.9294

Epoch 2/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 2/500: Average D Loss: 0.7841, Average G Loss: 1.7830

Epoch 3/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 3/500: Average D Loss: 0.8142, Average G Loss: 1.6581

Epoch 4/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 4/500: Average D Loss: 0.7937, Average G Loss: 1.6543

Epoch 5/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 5/500: Average D Loss: 0.7825, Average G Loss: 1.6485

Epoch 6/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 6/500: Average D Loss: 0.7953, Average G Loss: 1.5864

Epoch 7/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 7/500: Average D Loss: 0.8143, Average G Loss: 1.4850

Epoch 8/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 8/500: Average D Loss: 0.8592, Average G Loss: 1.2103

Epoch 9/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 9/500: Average D Loss: 0.9089, Average G Loss: 1.0399

Epoch 10/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 10/500: Average D Loss: 0.9422, Average G Loss: 0.9485

Epoch 11/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 11/500: Average D Loss: 0.9498, Average G Loss: 0.9214

Epoch 12/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 12/500: Average D Loss: 0.9640, Average G Loss: 0.8861

Epoch 13/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 13/500: Average D Loss: 0.9702, Average G Loss: 0.8665

Epoch 14/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 14/500: Average D Loss: 0.9799, Average G Loss: 0.8470

Epoch 15/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 15/500: Average D Loss: 0.9840, Average G Loss: 0.8395

Epoch 16/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 16/500: Average D Loss: 0.9910, Average G Loss: 0.8289

Epoch 17/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 17/500: Average D Loss: 0.9984, Average G Loss: 0.8032

Epoch 18/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 18/500: Average D Loss: 1.0089, Average G Loss: 0.7900

Epoch 19/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 19/500: Average D Loss: 1.0109, Average G Loss: 0.7797

Epoch 20/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7b125e54d630>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process

Epoch 20/500: Average D Loss: 1.0179, Average G Loss: 0.7607

Epoch 21/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7b125e54d630>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
```

```
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7b125e54d630>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process

Epoch 21/500: Average D Loss: 1.0182, Average G Loss: 0.7625

Epoch 22/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7b125e54d630>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7b125e54d630>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process

Epoch 22/500: Average D Loss: 1.0232, Average G Loss: 0.7476

Epoch 23/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Exception ignored in: Exception ignored in: <function
_MultiProcessingDataLoaderIter.__del__ at 0x7b125e54d630>
<function _MultiProcessingDataLoaderIter.__del__ at 0x7b125e54d630>Traceback
(most recent call last):
```

```
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
        self._shutdown_workers()self._shutdown_workers()

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
        if w.is_alive():if w.is_alive():

  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
        assert self._parent_pid == os.getpid(), 'can only test a child
process'assert self._parent_pid == os.getpid(), 'can only test a child process'

AssertionErrorAssertionError: : can only test a child process
can only test a child process

Epoch 23/500: Average D Loss: 1.0262, Average G Loss: 0.7454

Epoch 24/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Exception ignored in: Exception ignored in: <function
_MultiProcessingDataLoaderIter.__del__ at 0x7b125e54d630>
<function _MultiProcessingDataLoaderIter.__del__ at 0x7b125e54d630>Traceback
(most recent call last):

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
Traceback (most recent call last):
      File "/usr/local/lib/python3.10/dist-
packages/torch/utils/data/dataloader.py", line 1479, in __del__
self._shutdown_workers()
self._shutdown_workers()  File "/usr/local/lib/python3.10/dist-
packages/torch/utils/data/dataloader.py", line 1462, in _shutdown_workers

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
        if w.is_alive():if w.is_alive():

  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive
        assert self._parent_pid == os.getpid(), 'can only test a child
process'assert self._parent_pid == os.getpid(), 'can only test a child process'
```

```
AssertionErrorAssertionError:
: can only test a child processcan only test a child process
Epoch 24/500: Average D Loss: 1.0249, Average G Loss: 0.7461
Epoch 25/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 25/500: Average D Loss: 1.0273, Average G Loss: 0.7487
Epoch 26/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 26/500: Average D Loss: 1.0370, Average G Loss: 0.7330
Epoch 27/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 27/500: Average D Loss: 1.0256, Average G Loss: 0.7477
Epoch 28/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 28/500: Average D Loss: 1.0294, Average G Loss: 0.7294
Epoch 29/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 29/500: Average D Loss: 1.0366, Average G Loss: 0.7270
Epoch 30/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 30/500: Average D Loss: 1.0333, Average G Loss: 0.7257
Epoch 31/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 31/500: Average D Loss: 1.0553, Average G Loss: 0.7092
Epoch 32/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 32/500: Average D Loss: 1.0357, Average G Loss: 0.7304
Epoch 33/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 33/500: Average D Loss: 1.0387, Average G Loss: 0.7200
Epoch 34/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 34/500: Average D Loss: 1.0371, Average G Loss: 0.7238
Epoch 35/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 35/500: Average D Loss: 1.0304, Average G Loss: 0.7388
Epoch 36/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 36/500: Average D Loss: 1.0453, Average G Loss: 0.7073
Epoch 37/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 37/500: Average D Loss: 1.0483, Average G Loss: 0.7118
Epoch 38/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 38/500: Average D Loss: 1.0444, Average G Loss: 0.7151
Epoch 39/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 39/500: Average D Loss: 1.0640, Average G Loss: 0.7031
Epoch 40/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 40/500: Average D Loss: 1.0455, Average G Loss: 0.7129
Epoch 41/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 41/500: Average D Loss: 1.0526, Average G Loss: 0.7096
Epoch 42/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 42/500: Average D Loss: 1.0563, Average G Loss: 0.7034
Epoch 43/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 43/500: Average D Loss: 1.0492, Average G Loss: 0.7126
Epoch 44/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 44/500: Average D Loss: 1.0516, Average G Loss: 0.7100
Epoch 45/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 45/500: Average D Loss: 1.0520, Average G Loss: 0.7085
Epoch 46/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 46/500: Average D Loss: 1.0491, Average G Loss: 0.7432
Epoch 47/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 47/500: Average D Loss: 1.0363, Average G Loss: 0.7405
Epoch 48/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 48/500: Average D Loss: 1.0403, Average G Loss: 0.7275
Epoch 49/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 49/500: Average D Loss: 1.0522, Average G Loss: 0.7054
Epoch 50/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 50/500: Average D Loss: 1.0474, Average G Loss: 0.7179
Epoch 51/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 51/500: Average D Loss: 1.0452, Average G Loss: 0.7133
Epoch 52/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 52/500: Average D Loss: 1.0476, Average G Loss: 0.7145
Epoch 53/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 53/500: Average D Loss: 1.0503, Average G Loss: 0.7102
Epoch 54/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 54/500: Average D Loss: 1.0549, Average G Loss: 0.7019
Epoch 55/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 55/500: Average D Loss: 1.0505, Average G Loss: 0.7105
Epoch 56/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 56/500: Average D Loss: 1.0546, Average G Loss: 0.7083
Epoch 57/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 57/500: Average D Loss: 1.0563, Average G Loss: 0.7056
Epoch 58/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 58/500: Average D Loss: 1.0467, Average G Loss: 0.7173
Epoch 59/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 59/500: Average D Loss: 1.0545, Average G Loss: 0.7077
Epoch 60/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 60/500: Average D Loss: 1.0634, Average G Loss: 0.6996
Epoch 61/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 61/500: Average D Loss: 1.0573, Average G Loss: 0.7121
Epoch 62/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 62/500: Average D Loss: 1.0545, Average G Loss: 0.7124
Epoch 63/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 63/500: Average D Loss: 1.0545, Average G Loss: 0.7076
Epoch 64/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 64/500: Average D Loss: 1.0661, Average G Loss: 0.6937
Epoch 65/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 65/500: Average D Loss: 1.0590, Average G Loss: 0.7051
Epoch 66/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 66/500: Average D Loss: 1.0580, Average G Loss: 0.7052
Epoch 67/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 67/500: Average D Loss: 1.0583, Average G Loss: 0.7030
Epoch 68/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 68/500: Average D Loss: 1.0607, Average G Loss: 0.7007
Epoch 69/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 69/500: Average D Loss: 1.0621, Average G Loss: 0.7018
Epoch 70/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 70/500: Average D Loss: 1.0609, Average G Loss: 0.7058
Epoch 71/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 71/500: Average D Loss: 1.0537, Average G Loss: 0.7105
Epoch 72/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 72/500: Average D Loss: 1.0662, Average G Loss: 0.7019
Epoch 73/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 73/500: Average D Loss: 1.0658, Average G Loss: 0.7049
Epoch 74/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 74/500: Average D Loss: 1.0589, Average G Loss: 0.7085
Epoch 75/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 75/500: Average D Loss: 1.0627, Average G Loss: 0.7040
Epoch 76/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 76/500: Average D Loss: 1.0654, Average G Loss: 0.6998
Epoch 77/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 77/500: Average D Loss: 1.0616, Average G Loss: 0.7051
Epoch 78/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 78/500: Average D Loss: 1.0809, Average G Loss: 0.6933
Epoch 79/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 79/500: Average D Loss: 1.0598, Average G Loss: 0.7174
Epoch 80/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 80/500: Average D Loss: 1.0631, Average G Loss: 0.7062
Epoch 81/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 81/500: Average D Loss: 1.0733, Average G Loss: 0.7038
Epoch 82/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 82/500: Average D Loss: 1.0724, Average G Loss: 0.7029
Epoch 83/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 83/500: Average D Loss: 1.0702, Average G Loss: 0.7090
Epoch 84/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 84/500: Average D Loss: 1.0777, Average G Loss: 0.7035
Epoch 85/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 85/500: Average D Loss: 1.0691, Average G Loss: 0.7083
Epoch 86/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 86/500: Average D Loss: 1.0841, Average G Loss: 0.6994
Epoch 87/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 87/500: Average D Loss: 1.0730, Average G Loss: 0.7088

Epoch 88/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 88/500: Average D Loss: 1.0669, Average G Loss: 0.7155

Epoch 89/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 89/500: Average D Loss: 1.0769, Average G Loss: 0.7055

Epoch 90/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 90/500: Average D Loss: 1.0741, Average G Loss: 0.7063

Epoch 91/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 91/500: Average D Loss: 1.0821, Average G Loss: 0.7068

Epoch 92/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 92/500: Average D Loss: 1.0784, Average G Loss: 0.7167

Epoch 93/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 93/500: Average D Loss: 1.0806, Average G Loss: 0.7081

Epoch 94/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 94/500: Average D Loss: 1.0802, Average G Loss: 0.7126

Epoch 95/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 95/500: Average D Loss: 1.0728, Average G Loss: 0.7152

Epoch 96/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 96/500: Average D Loss: 1.0673, Average G Loss: 0.7184

Epoch 97/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 97/500: Average D Loss: 1.0837, Average G Loss: 0.7069

Epoch 98/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 98/500: Average D Loss: 1.0778, Average G Loss: 0.7094

Epoch 99/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 99/500: Average D Loss: 1.0815, Average G Loss: 0.7055

Epoch 100/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 100/500: Average D Loss: 1.0846, Average G Loss: 0.7094
Saved models to /content/saved_models at epoch 99

Epoch 101/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 101/500: Average D Loss: 1.0892, Average G Loss: 0.7100

Epoch 102/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 102/500: Average D Loss: 1.0813, Average G Loss: 0.7048
```

```
Epoch 103/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 103/500: Average D Loss: 1.0820, Average G Loss: 0.7050
Epoch 104/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 104/500: Average D Loss: 1.0769, Average G Loss: 0.7167
Epoch 105/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 105/500: Average D Loss: 1.0833, Average G Loss: 0.7112
Epoch 106/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 106/500: Average D Loss: 1.0814, Average G Loss: 0.7134
Epoch 107/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 107/500: Average D Loss: 1.0884, Average G Loss: 0.7115
Epoch 108/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 108/500: Average D Loss: 1.0783, Average G Loss: 0.7144
Epoch 109/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 109/500: Average D Loss: 1.0849, Average G Loss: 0.7055
Epoch 110/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 110/500: Average D Loss: 1.0793, Average G Loss: 0.7148
Epoch 111/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 111/500: Average D Loss: 1.0824, Average G Loss: 0.7144
Epoch 112/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 112/500: Average D Loss: 1.0847, Average G Loss: 0.7087
Epoch 113/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 113/500: Average D Loss: 1.0865, Average G Loss: 0.7093
Epoch 114/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 114/500: Average D Loss: 1.0876, Average G Loss: 0.7054
Epoch 115/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 115/500: Average D Loss: 1.0836, Average G Loss: 0.7083
Epoch 116/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 116/500: Average D Loss: 1.0818, Average G Loss: 0.7172
Epoch 117/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 117/500: Average D Loss: 1.0897, Average G Loss: 0.7068
Epoch 118/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 118/500: Average D Loss: 1.0872, Average G Loss: 0.7131
```

```
Epoch 119/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 119/500: Average D Loss: 1.0903, Average G Loss: 0.7083
Epoch 120/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 120/500: Average D Loss: 1.0868, Average G Loss: 0.7226
Epoch 121/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 121/500: Average D Loss: 1.0882, Average G Loss: 0.7057
Epoch 122/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 122/500: Average D Loss: 1.0846, Average G Loss: 0.7178
Epoch 123/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 123/500: Average D Loss: 1.0902, Average G Loss: 0.7068
Epoch 124/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 124/500: Average D Loss: 1.0921, Average G Loss: 0.7020
Epoch 125/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 125/500: Average D Loss: 1.0939, Average G Loss: 0.7087
Epoch 126/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 126/500: Average D Loss: 1.0910, Average G Loss: 0.7067
Epoch 127/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 127/500: Average D Loss: 1.0911, Average G Loss: 0.7139
Epoch 128/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 128/500: Average D Loss: 1.0910, Average G Loss: 0.7087
Epoch 129/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 129/500: Average D Loss: 1.0826, Average G Loss: 0.7220
Epoch 130/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 130/500: Average D Loss: 1.0914, Average G Loss: 0.7082
Epoch 131/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 131/500: Average D Loss: 1.0918, Average G Loss: 0.7096
Epoch 132/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 132/500: Average D Loss: 1.0969, Average G Loss: 0.7049
Epoch 133/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 133/500: Average D Loss: 1.0880, Average G Loss: 0.7149
Epoch 134/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 134/500: Average D Loss: 1.0883, Average G Loss: 0.7084
```

```
Epoch 135/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 135/500: Average D Loss: 1.0957, Average G Loss: 0.7042
Epoch 136/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 136/500: Average D Loss: 1.0920, Average G Loss: 0.7119
Epoch 137/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 137/500: Average D Loss: 1.0941, Average G Loss: 0.7076
Epoch 138/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 138/500: Average D Loss: 1.0981, Average G Loss: 0.7020
Epoch 139/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 139/500: Average D Loss: 1.0941, Average G Loss: 0.7165
Epoch 140/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 140/500: Average D Loss: 1.0940, Average G Loss: 0.7134
Epoch 141/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 141/500: Average D Loss: 1.0914, Average G Loss: 0.7135
Epoch 142/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 142/500: Average D Loss: 1.0993, Average G Loss: 0.7026
Epoch 143/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 143/500: Average D Loss: 1.0905, Average G Loss: 0.7166
Epoch 144/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 144/500: Average D Loss: 1.0951, Average G Loss: 0.7112
Epoch 145/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 145/500: Average D Loss: 1.0975, Average G Loss: 0.7129
Epoch 146/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 146/500: Average D Loss: 1.0948, Average G Loss: 0.7150
Epoch 147/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 147/500: Average D Loss: 1.0943, Average G Loss: 0.7074
Epoch 148/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 148/500: Average D Loss: 1.0964, Average G Loss: 0.7117
Epoch 149/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 149/500: Average D Loss: 1.0938, Average G Loss: 0.7101
Epoch 150/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 150/500: Average D Loss: 1.0972, Average G Loss: 0.7147
```

```
Epoch 151/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 151/500: Average D Loss: 1.0970, Average G Loss: 0.7111
Epoch 152/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 152/500: Average D Loss: 1.0966, Average G Loss: 0.7146
Epoch 153/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 153/500: Average D Loss: 1.1010, Average G Loss: 0.7057
Epoch 154/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 154/500: Average D Loss: 1.0961, Average G Loss: 0.7102
Epoch 155/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 155/500: Average D Loss: 1.0954, Average G Loss: 0.7126
Epoch 156/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 156/500: Average D Loss: 1.0980, Average G Loss: 0.7096
Epoch 157/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 157/500: Average D Loss: 1.1016, Average G Loss: 0.6991
Epoch 158/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 158/500: Average D Loss: 1.1016, Average G Loss: 0.7052
Epoch 159/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 159/500: Average D Loss: 1.1012, Average G Loss: 0.7100
Epoch 160/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 160/500: Average D Loss: 1.1035, Average G Loss: 0.7014
Epoch 161/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 161/500: Average D Loss: 1.1053, Average G Loss: 0.7049
Epoch 162/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 162/500: Average D Loss: 1.0978, Average G Loss: 0.7126
Epoch 163/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 163/500: Average D Loss: 1.1043, Average G Loss: 0.7060
Epoch 164/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 164/500: Average D Loss: 1.1035, Average G Loss: 0.7039
Epoch 165/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 165/500: Average D Loss: 1.1061, Average G Loss: 0.7071
Epoch 166/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 166/500: Average D Loss: 1.1097, Average G Loss: 0.7001
```

```
Epoch 167/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 167/500: Average D Loss: 1.1008, Average G Loss: 0.7099
Epoch 168/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 168/500: Average D Loss: 1.1070, Average G Loss: 0.7078
Epoch 169/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 169/500: Average D Loss: 1.1039, Average G Loss: 0.7138
Epoch 170/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 170/500: Average D Loss: 1.1060, Average G Loss: 0.7104
Epoch 171/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 171/500: Average D Loss: 1.1034, Average G Loss: 0.7064
Epoch 172/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 172/500: Average D Loss: 1.1054, Average G Loss: 0.7056
Epoch 173/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 173/500: Average D Loss: 1.1101, Average G Loss: 0.6990
Epoch 174/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 174/500: Average D Loss: 1.1070, Average G Loss: 0.7040
Epoch 175/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 175/500: Average D Loss: 1.1082, Average G Loss: 0.7005
Epoch 176/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 176/500: Average D Loss: 1.1117, Average G Loss: 0.7003
Epoch 177/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 177/500: Average D Loss: 1.1067, Average G Loss: 0.7000
Epoch 178/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 178/500: Average D Loss: 1.1079, Average G Loss: 0.7085
Epoch 179/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 179/500: Average D Loss: 1.1068, Average G Loss: 0.7093
Epoch 180/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 180/500: Average D Loss: 1.1073, Average G Loss: 0.7058
Epoch 181/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 181/500: Average D Loss: 1.1133, Average G Loss: 0.7000
Epoch 182/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 182/500: Average D Loss: 1.1107, Average G Loss: 0.7020
```

```
Epoch 183/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 183/500: Average D Loss: 1.1046, Average G Loss: 0.7194
Epoch 184/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 184/500: Average D Loss: 1.1145, Average G Loss: 0.6956
Epoch 185/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 185/500: Average D Loss: 1.1114, Average G Loss: 0.7069
Epoch 186/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 186/500: Average D Loss: 1.1072, Average G Loss: 0.7114
Epoch 187/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 187/500: Average D Loss: 1.1094, Average G Loss: 0.7064
Epoch 188/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 188/500: Average D Loss: 1.1154, Average G Loss: 0.6939
Epoch 189/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 189/500: Average D Loss: 1.1145, Average G Loss: 0.7025
Epoch 190/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 190/500: Average D Loss: 1.1143, Average G Loss: 0.7018
Epoch 191/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 191/500: Average D Loss: 1.1091, Average G Loss: 0.7131
Epoch 192/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 192/500: Average D Loss: 1.1122, Average G Loss: 0.6981
Epoch 193/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 193/500: Average D Loss: 1.1127, Average G Loss: 0.7063
Epoch 194/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 194/500: Average D Loss: 1.1137, Average G Loss: 0.7015
Epoch 195/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 195/500: Average D Loss: 1.1141, Average G Loss: 0.7026
Epoch 196/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 196/500: Average D Loss: 1.1135, Average G Loss: 0.7068
Epoch 197/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 197/500: Average D Loss: 1.1129, Average G Loss: 0.7074
Epoch 198/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 198/500: Average D Loss: 1.1138, Average G Loss: 0.6998
```

```
Epoch 199/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 199/500: Average D Loss: 1.1157, Average G Loss: 0.7023

Epoch 200/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 200/500: Average D Loss: 1.1157, Average G Loss: 0.7028
Saved models to /content/saved_models at epoch 199

Epoch 201/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 201/500: Average D Loss: 1.1178, Average G Loss: 0.6947

Epoch 202/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 202/500: Average D Loss: 1.1137, Average G Loss: 0.6989

Epoch 203/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 203/500: Average D Loss: 1.1136, Average G Loss: 0.7032

Epoch 204/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 204/500: Average D Loss: 1.1124, Average G Loss: 0.7033

Epoch 205/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 205/500: Average D Loss: 1.1114, Average G Loss: 0.7101

Epoch 206/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 206/500: Average D Loss: 1.1126, Average G Loss: 0.7059

Epoch 207/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 207/500: Average D Loss: 1.1110, Average G Loss: 0.7010

Epoch 208/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 208/500: Average D Loss: 1.1159, Average G Loss: 0.6973

Epoch 209/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 209/500: Average D Loss: 1.1139, Average G Loss: 0.7044

Epoch 210/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 210/500: Average D Loss: 1.1193, Average G Loss: 0.7016

Epoch 211/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 211/500: Average D Loss: 1.1133, Average G Loss: 0.7085

Epoch 212/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 212/500: Average D Loss: 1.1190, Average G Loss: 0.7001

Epoch 213/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 213/500: Average D Loss: 1.1221, Average G Loss: 0.6937

Epoch 214/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 214/500: Average D Loss: 1.1234, Average G Loss: 0.6999
Epoch 215/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 215/500: Average D Loss: 1.1175, Average G Loss: 0.6993
Epoch 216/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 216/500: Average D Loss: 1.1216, Average G Loss: 0.6923
Epoch 217/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 217/500: Average D Loss: 1.1171, Average G Loss: 0.6973
Epoch 218/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 218/500: Average D Loss: 1.1199, Average G Loss: 0.7012
Epoch 219/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 219/500: Average D Loss: 1.1207, Average G Loss: 0.6914
Epoch 220/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 220/500: Average D Loss: 1.1227, Average G Loss: 0.7020
Epoch 221/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 221/500: Average D Loss: 1.1186, Average G Loss: 0.6996
Epoch 222/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 222/500: Average D Loss: 1.1183, Average G Loss: 0.7012
Epoch 223/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 223/500: Average D Loss: 1.1210, Average G Loss: 0.6965
Epoch 224/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 224/500: Average D Loss: 1.1213, Average G Loss: 0.6973
Epoch 225/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 225/500: Average D Loss: 1.1196, Average G Loss: 0.7020
Epoch 226/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 226/500: Average D Loss: 1.1182, Average G Loss: 0.6981
Epoch 227/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 227/500: Average D Loss: 1.1169, Average G Loss: 0.6969
Epoch 228/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 228/500: Average D Loss: 1.1179, Average G Loss: 0.6962
Epoch 229/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 229/500: Average D Loss: 1.1188, Average G Loss: 0.6996
Epoch 230/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 230/500: Average D Loss: 1.1231, Average G Loss: 0.6943
Epoch 231/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 231/500: Average D Loss: 1.1214, Average G Loss: 0.6940
Epoch 232/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 232/500: Average D Loss: 1.1205, Average G Loss: 0.6988
Epoch 233/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 233/500: Average D Loss: 1.1219, Average G Loss: 0.6987
Epoch 234/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 234/500: Average D Loss: 1.1208, Average G Loss: 0.6977
Epoch 235/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 235/500: Average D Loss: 1.1195, Average G Loss: 0.7027
Epoch 236/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 236/500: Average D Loss: 1.1340, Average G Loss: 0.6879
Epoch 237/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 237/500: Average D Loss: 1.1256, Average G Loss: 0.6933
Epoch 238/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 238/500: Average D Loss: 1.1231, Average G Loss: 0.7017
Epoch 239/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 239/500: Average D Loss: 1.1193, Average G Loss: 0.7000
Epoch 240/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 240/500: Average D Loss: 1.1273, Average G Loss: 0.6942
Epoch 241/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 241/500: Average D Loss: 1.1257, Average G Loss: 0.6887
Epoch 242/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 242/500: Average D Loss: 1.1236, Average G Loss: 0.6985
Epoch 243/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 243/500: Average D Loss: 1.1283, Average G Loss: 0.6930
Epoch 244/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 244/500: Average D Loss: 1.1323, Average G Loss: 0.6835
Epoch 245/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 245/500: Average D Loss: 1.1245, Average G Loss: 0.6964
Epoch 246/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 246/500: Average D Loss: 1.1227, Average G Loss: 0.6960
Epoch 247/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 247/500: Average D Loss: 1.1272, Average G Loss: 0.6968
Epoch 248/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 248/500: Average D Loss: 1.1237, Average G Loss: 0.6969
Epoch 249/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 249/500: Average D Loss: 1.1258, Average G Loss: 0.6944
Epoch 250/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 250/500: Average D Loss: 1.1317, Average G Loss: 0.6859
Epoch 251/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 251/500: Average D Loss: 1.1270, Average G Loss: 0.6917
Epoch 252/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 252/500: Average D Loss: 1.1214, Average G Loss: 0.7007
Epoch 253/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 253/500: Average D Loss: 1.1270, Average G Loss: 0.6937
Epoch 254/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 254/500: Average D Loss: 1.1283, Average G Loss: 0.6910
Epoch 255/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 255/500: Average D Loss: 1.1307, Average G Loss: 0.6922
Epoch 256/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 256/500: Average D Loss: 1.1263, Average G Loss: 0.6925
Epoch 257/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 257/500: Average D Loss: 1.1328, Average G Loss: 0.6859
Epoch 258/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 258/500: Average D Loss: 1.1266, Average G Loss: 0.7007
Epoch 259/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 259/500: Average D Loss: 1.1305, Average G Loss: 0.6870
Epoch 260/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 260/500: Average D Loss: 1.1330, Average G Loss: 0.6925
Epoch 261/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 261/500: Average D Loss: 1.1298, Average G Loss: 0.6946
Epoch 262/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 262/500: Average D Loss: 1.1298, Average G Loss: 0.6928
Epoch 263/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 263/500: Average D Loss: 1.1301, Average G Loss: 0.6897
Epoch 264/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 264/500: Average D Loss: 1.1280, Average G Loss: 0.6965
Epoch 265/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 265/500: Average D Loss: 1.1300, Average G Loss: 0.6904
Epoch 266/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 266/500: Average D Loss: 1.1307, Average G Loss: 0.6865
Epoch 267/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 267/500: Average D Loss: 1.1323, Average G Loss: 0.6898
Epoch 268/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 268/500: Average D Loss: 1.1320, Average G Loss: 0.6895
Epoch 269/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 269/500: Average D Loss: 1.1346, Average G Loss: 0.6808
Epoch 270/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 270/500: Average D Loss: 1.1287, Average G Loss: 0.7023
Epoch 271/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 271/500: Average D Loss: 1.1252, Average G Loss: 0.6964
Epoch 272/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 272/500: Average D Loss: 1.1317, Average G Loss: 0.6897
Epoch 273/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 273/500: Average D Loss: 1.1288, Average G Loss: 0.6977
Epoch 274/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 274/500: Average D Loss: 1.1306, Average G Loss: 0.6910
Epoch 275/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 275/500: Average D Loss: 1.1283, Average G Loss: 0.6882
Epoch 276/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 276/500: Average D Loss: 1.1322, Average G Loss: 0.6943
Epoch 277/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 277/500: Average D Loss: 1.1313, Average G Loss: 0.6908
Epoch 278/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 278/500: Average D Loss: 1.1247, Average G Loss: 0.6931
Epoch 279/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 279/500: Average D Loss: 1.1298, Average G Loss: 0.6963
Epoch 280/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 280/500: Average D Loss: 1.1327, Average G Loss: 0.6881
Epoch 281/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 281/500: Average D Loss: 1.1360, Average G Loss: 0.6897
Epoch 282/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 282/500: Average D Loss: 1.1333, Average G Loss: 0.6936
Epoch 283/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 283/500: Average D Loss: 1.1310, Average G Loss: 0.6879
Epoch 284/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 284/500: Average D Loss: 1.1333, Average G Loss: 0.6910
Epoch 285/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 285/500: Average D Loss: 1.1363, Average G Loss: 0.6869
Epoch 286/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 286/500: Average D Loss: 1.1339, Average G Loss: 0.6948
Epoch 287/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 287/500: Average D Loss: 1.1323, Average G Loss: 0.6922
Epoch 288/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 288/500: Average D Loss: 1.1335, Average G Loss: 0.6930
Epoch 289/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 289/500: Average D Loss: 1.1330, Average G Loss: 0.6933
Epoch 290/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 290/500: Average D Loss: 1.1334, Average G Loss: 0.6965
Epoch 291/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 291/500: Average D Loss: 1.1344, Average G Loss: 0.6952
Epoch 292/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 292/500: Average D Loss: 1.1372, Average G Loss: 0.6907
Epoch 293/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 293/500: Average D Loss: 1.1386, Average G Loss: 0.6886
Epoch 294/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 294/500: Average D Loss: 1.1347, Average G Loss: 0.6899
Epoch 295/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 295/500: Average D Loss: 1.1388, Average G Loss: 0.6868
Epoch 296/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 296/500: Average D Loss: 1.1369, Average G Loss: 0.6976
Epoch 297/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 297/500: Average D Loss: 1.1405, Average G Loss: 0.6925
Epoch 298/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 298/500: Average D Loss: 1.1404, Average G Loss: 0.6940
Epoch 299/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 299/500: Average D Loss: 1.1387, Average G Loss: 0.6964
Epoch 300/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 300/500: Average D Loss: 1.1380, Average G Loss: 0.6892
Saved models to /content/saved_models at epoch 299
Epoch 301/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 301/500: Average D Loss: 1.1397, Average G Loss: 0.6897
Epoch 302/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 302/500: Average D Loss: 1.1393, Average G Loss: 0.6833
Epoch 303/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 303/500: Average D Loss: 1.1380, Average G Loss: 0.6936
Epoch 304/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 304/500: Average D Loss: 1.1370, Average G Loss: 0.6936
Epoch 305/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 305/500: Average D Loss: 1.1396, Average G Loss: 0.6882
Epoch 306/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 306/500: Average D Loss: 1.1388, Average G Loss: 0.6897
Epoch 307/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 307/500: Average D Loss: 1.1376, Average G Loss: 0.6921
Epoch 308/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 308/500: Average D Loss: 1.1373, Average G Loss: 0.6882
Epoch 309/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 309/500: Average D Loss: 1.1417, Average G Loss: 0.6852
```

```
Epoch 310/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 310/500: Average D Loss: 1.1393, Average G Loss: 0.6906
Epoch 311/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 311/500: Average D Loss: 1.1378, Average G Loss: 0.6866
Epoch 312/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 312/500: Average D Loss: 1.1361, Average G Loss: 0.6880
Epoch 313/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 313/500: Average D Loss: 1.1415, Average G Loss: 0.6832
Epoch 314/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 314/500: Average D Loss: 1.1416, Average G Loss: 0.6869
Epoch 315/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 315/500: Average D Loss: 1.1415, Average G Loss: 0.6830
Epoch 316/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 316/500: Average D Loss: 1.1431, Average G Loss: 0.6866
Epoch 317/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 317/500: Average D Loss: 1.1398, Average G Loss: 0.6891
Epoch 318/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 318/500: Average D Loss: 1.1422, Average G Loss: 0.6838
Epoch 319/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 319/500: Average D Loss: 1.1405, Average G Loss: 0.6876
Epoch 320/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 320/500: Average D Loss: 1.1367, Average G Loss: 0.6919
Epoch 321/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 321/500: Average D Loss: 1.1407, Average G Loss: 0.6863
Epoch 322/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 322/500: Average D Loss: 1.1387, Average G Loss: 0.6909
Epoch 323/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 323/500: Average D Loss: 1.1424, Average G Loss: 0.6881
Epoch 324/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 324/500: Average D Loss: 1.1412, Average G Loss: 0.6879
Epoch 325/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 325/500: Average D Loss: 1.1422, Average G Loss: 0.6821
```

```
Epoch 326/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 326/500: Average D Loss: 1.1421, Average G Loss: 0.6851
Epoch 327/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 327/500: Average D Loss: 1.1455, Average G Loss: 0.6862
Epoch 328/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 328/500: Average D Loss: 1.1374, Average G Loss: 0.6933
Epoch 329/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 329/500: Average D Loss: 1.1397, Average G Loss: 0.6871
Epoch 330/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 330/500: Average D Loss: 1.1443, Average G Loss: 0.6792
Epoch 331/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 331/500: Average D Loss: 1.1488, Average G Loss: 0.6766
Epoch 332/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 332/500: Average D Loss: 1.1428, Average G Loss: 0.6813
Epoch 333/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 333/500: Average D Loss: 1.1435, Average G Loss: 0.6836
Epoch 334/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 334/500: Average D Loss: 1.1437, Average G Loss: 0.6849
Epoch 335/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 335/500: Average D Loss: 1.1452, Average G Loss: 0.6745
Epoch 336/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 336/500: Average D Loss: 1.1468, Average G Loss: 0.6864
Epoch 337/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 337/500: Average D Loss: 1.1428, Average G Loss: 0.6834
Epoch 338/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 338/500: Average D Loss: 1.1434, Average G Loss: 0.6845
Epoch 339/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 339/500: Average D Loss: 1.1427, Average G Loss: 0.6800
Epoch 340/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 340/500: Average D Loss: 1.1481, Average G Loss: 0.6806
Epoch 341/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 341/500: Average D Loss: 1.1455, Average G Loss: 0.6914
```

```
Epoch 342/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 342/500: Average D Loss: 1.1436, Average G Loss: 0.6812
Epoch 343/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 343/500: Average D Loss: 1.1444, Average G Loss: 0.6919
Epoch 344/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 344/500: Average D Loss: 1.1501, Average G Loss: 0.6772
Epoch 345/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 345/500: Average D Loss: 1.1470, Average G Loss: 0.6790
Epoch 346/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 346/500: Average D Loss: 1.1472, Average G Loss: 0.6838
Epoch 347/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 347/500: Average D Loss: 1.1407, Average G Loss: 0.6923
Epoch 348/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 348/500: Average D Loss: 1.1437, Average G Loss: 0.6956
Epoch 349/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 349/500: Average D Loss: 1.1413, Average G Loss: 0.6886
Epoch 350/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 350/500: Average D Loss: 1.1460, Average G Loss: 0.6857
Epoch 351/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 351/500: Average D Loss: 1.1474, Average G Loss: 0.6744
Epoch 352/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 352/500: Average D Loss: 1.1447, Average G Loss: 0.6815
Epoch 353/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 353/500: Average D Loss: 1.1451, Average G Loss: 0.6837
Epoch 354/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 354/500: Average D Loss: 1.1491, Average G Loss: 0.6772
Epoch 355/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 355/500: Average D Loss: 1.1466, Average G Loss: 0.6791
Epoch 356/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 356/500: Average D Loss: 1.1423, Average G Loss: 0.6937
Epoch 357/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 357/500: Average D Loss: 1.1430, Average G Loss: 0.6806
```

```
Epoch 358/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 358/500: Average D Loss: 1.1473, Average G Loss: 0.6857
Epoch 359/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 359/500: Average D Loss: 1.1464, Average G Loss: 0.6827
Epoch 360/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 360/500: Average D Loss: 1.1467, Average G Loss: 0.6800
Epoch 361/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 361/500: Average D Loss: 1.1498, Average G Loss: 0.6796
Epoch 362/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 362/500: Average D Loss: 1.1452, Average G Loss: 0.6892
Epoch 363/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 363/500: Average D Loss: 1.1477, Average G Loss: 0.6837
Epoch 364/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 364/500: Average D Loss: 1.1490, Average G Loss: 0.6776
Epoch 365/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 365/500: Average D Loss: 1.1502, Average G Loss: 0.6807
Epoch 366/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 366/500: Average D Loss: 1.1458, Average G Loss: 0.6852
Epoch 367/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 367/500: Average D Loss: 1.1474, Average G Loss: 0.6810
Epoch 368/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 368/500: Average D Loss: 1.1456, Average G Loss: 0.6762
Epoch 369/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 369/500: Average D Loss: 1.1491, Average G Loss: 0.6849
Epoch 370/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 370/500: Average D Loss: 1.1480, Average G Loss: 0.6830
Epoch 371/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 371/500: Average D Loss: 1.1459, Average G Loss: 0.6892
Epoch 372/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 372/500: Average D Loss: 1.1476, Average G Loss: 0.6785
Epoch 373/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 373/500: Average D Loss: 1.1432, Average G Loss: 0.6931
```

```
Epoch 374/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 374/500: Average D Loss: 1.1466, Average G Loss: 0.6829
Epoch 375/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 375/500: Average D Loss: 1.1479, Average G Loss: 0.6819
Epoch 376/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 376/500: Average D Loss: 1.1505, Average G Loss: 0.6818
Epoch 377/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 377/500: Average D Loss: 1.1506, Average G Loss: 0.6826
Epoch 378/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 378/500: Average D Loss: 1.1520, Average G Loss: 0.6829
Epoch 379/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 379/500: Average D Loss: 1.1527, Average G Loss: 0.6823
Epoch 380/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 380/500: Average D Loss: 1.1505, Average G Loss: 0.6808
Epoch 381/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 381/500: Average D Loss: 1.1465, Average G Loss: 0.6766
Epoch 382/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 382/500: Average D Loss: 1.1463, Average G Loss: 0.6816
Epoch 383/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 383/500: Average D Loss: 1.1469, Average G Loss: 0.6820
Epoch 384/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 384/500: Average D Loss: 1.1483, Average G Loss: 0.6853
Epoch 385/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 385/500: Average D Loss: 1.1521, Average G Loss: 0.6810
Epoch 386/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 386/500: Average D Loss: 1.1486, Average G Loss: 0.6846
Epoch 387/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 387/500: Average D Loss: 1.1449, Average G Loss: 0.6855
Epoch 388/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 388/500: Average D Loss: 1.1509, Average G Loss: 0.6806
Epoch 389/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 389/500: Average D Loss: 1.1477, Average G Loss: 0.6877
```

```
Epoch 390/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 390/500: Average D Loss: 1.1435, Average G Loss: 0.6867

Epoch 391/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 391/500: Average D Loss: 1.1493, Average G Loss: 0.6822

Epoch 392/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 392/500: Average D Loss: 1.1457, Average G Loss: 0.6821

Epoch 393/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 393/500: Average D Loss: 1.1456, Average G Loss: 0.6844

Epoch 394/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 394/500: Average D Loss: 1.1496, Average G Loss: 0.6737

Epoch 395/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 395/500: Average D Loss: 1.1497, Average G Loss: 0.6752

Epoch 396/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 396/500: Average D Loss: 1.1516, Average G Loss: 0.6783

Epoch 397/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 397/500: Average D Loss: 1.1516, Average G Loss: 0.6727

Epoch 398/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 398/500: Average D Loss: 1.1528, Average G Loss: 0.6766

Epoch 399/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 399/500: Average D Loss: 1.1476, Average G Loss: 0.6829

Epoch 400/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 400/500: Average D Loss: 1.1502, Average G Loss: 0.6836
Saved models to /content/saved_models at epoch 399

Epoch 401/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 401/500: Average D Loss: 1.1538, Average G Loss: 0.6715

Epoch 402/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 402/500: Average D Loss: 1.1557, Average G Loss: 0.6795

Epoch 403/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 403/500: Average D Loss: 1.1531, Average G Loss: 0.6742

Epoch 404/500:   0%|          | 0/136 [00:00<?, ?batch/s]

Epoch 404/500: Average D Loss: 1.1562, Average G Loss: 0.6802

Epoch 405/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 405/500: Average D Loss: 1.1516, Average G Loss: 0.6695
Epoch 406/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 406/500: Average D Loss: 1.1545, Average G Loss: 0.6766
Epoch 407/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 407/500: Average D Loss: 1.1466, Average G Loss: 0.6803
Epoch 408/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 408/500: Average D Loss: 1.1535, Average G Loss: 0.6765
Epoch 409/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 409/500: Average D Loss: 1.1529, Average G Loss: 0.6810
Epoch 410/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 410/500: Average D Loss: 1.1513, Average G Loss: 0.6735
Epoch 411/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 411/500: Average D Loss: 1.1522, Average G Loss: 0.6780
Epoch 412/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 412/500: Average D Loss: 1.1516, Average G Loss: 0.6778
Epoch 413/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 413/500: Average D Loss: 1.1548, Average G Loss: 0.6792
Epoch 414/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 414/500: Average D Loss: 1.1534, Average G Loss: 0.6784
Epoch 415/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 415/500: Average D Loss: 1.1549, Average G Loss: 0.6749
Epoch 416/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 416/500: Average D Loss: 1.1553, Average G Loss: 0.6711
Epoch 417/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 417/500: Average D Loss: 1.1538, Average G Loss: 0.6824
Epoch 418/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 418/500: Average D Loss: 1.1540, Average G Loss: 0.6768
Epoch 419/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 419/500: Average D Loss: 1.1520, Average G Loss: 0.6758
Epoch 420/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 420/500: Average D Loss: 1.1545, Average G Loss: 0.6783
Epoch 421/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 421/500: Average D Loss: 1.1525, Average G Loss: 0.6760
Epoch 422/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 422/500: Average D Loss: 1.1505, Average G Loss: 0.6738
Epoch 423/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 423/500: Average D Loss: 1.1501, Average G Loss: 0.6777
Epoch 424/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 424/500: Average D Loss: 1.1534, Average G Loss: 0.6762
Epoch 425/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 425/500: Average D Loss: 1.1497, Average G Loss: 0.6802
Epoch 426/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 426/500: Average D Loss: 1.1514, Average G Loss: 0.6705
Epoch 427/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 427/500: Average D Loss: 1.1527, Average G Loss: 0.6800
Epoch 428/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 428/500: Average D Loss: 1.1566, Average G Loss: 0.6742
Epoch 429/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 429/500: Average D Loss: 1.1553, Average G Loss: 0.6743
Epoch 430/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 430/500: Average D Loss: 1.1514, Average G Loss: 0.6795
Epoch 431/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 431/500: Average D Loss: 1.1513, Average G Loss: 0.6725
Epoch 432/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 432/500: Average D Loss: 1.1525, Average G Loss: 0.6827
Epoch 433/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 433/500: Average D Loss: 1.1541, Average G Loss: 0.6772
Epoch 434/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 434/500: Average D Loss: 1.1583, Average G Loss: 0.6709
Epoch 435/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 435/500: Average D Loss: 1.1543, Average G Loss: 0.6691
Epoch 436/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 436/500: Average D Loss: 1.1550, Average G Loss: 0.6721
Epoch 437/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 437/500: Average D Loss: 1.1509, Average G Loss: 0.6785
Epoch 438/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 438/500: Average D Loss: 1.1547, Average G Loss: 0.6774
Epoch 439/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 439/500: Average D Loss: 1.1532, Average G Loss: 0.6747
Epoch 440/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 440/500: Average D Loss: 1.1559, Average G Loss: 0.6710
Epoch 441/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 441/500: Average D Loss: 1.1566, Average G Loss: 0.6719
Epoch 442/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 442/500: Average D Loss: 1.1525, Average G Loss: 0.6702
Epoch 443/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 443/500: Average D Loss: 1.1526, Average G Loss: 0.6758
Epoch 444/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 444/500: Average D Loss: 1.1546, Average G Loss: 0.6742
Epoch 445/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 445/500: Average D Loss: 1.1550, Average G Loss: 0.6718
Epoch 446/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 446/500: Average D Loss: 1.1521, Average G Loss: 0.6773
Epoch 447/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 447/500: Average D Loss: 1.1523, Average G Loss: 0.6754
Epoch 448/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 448/500: Average D Loss: 1.1551, Average G Loss: 0.6776
Epoch 449/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 449/500: Average D Loss: 1.1591, Average G Loss: 0.6743
Epoch 450/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 450/500: Average D Loss: 1.1578, Average G Loss: 0.6722
Epoch 451/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 451/500: Average D Loss: 1.1565, Average G Loss: 0.6688
Epoch 452/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 452/500: Average D Loss: 1.1534, Average G Loss: 0.6747
Epoch 453/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 453/500: Average D Loss: 1.1533, Average G Loss: 0.6740
Epoch 454/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 454/500: Average D Loss: 1.1570, Average G Loss: 0.6727
Epoch 455/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 455/500: Average D Loss: 1.1564, Average G Loss: 0.6686
Epoch 456/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 456/500: Average D Loss: 1.1591, Average G Loss: 0.6724
Epoch 457/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 457/500: Average D Loss: 1.1561, Average G Loss: 0.6751
Epoch 458/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 458/500: Average D Loss: 1.1535, Average G Loss: 0.6769
Epoch 459/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 459/500: Average D Loss: 1.1545, Average G Loss: 0.6781
Epoch 460/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 460/500: Average D Loss: 1.1571, Average G Loss: 0.6733
Epoch 461/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 461/500: Average D Loss: 1.1582, Average G Loss: 0.6662
Epoch 462/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 462/500: Average D Loss: 1.1556, Average G Loss: 0.6726
Epoch 463/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 463/500: Average D Loss: 1.1573, Average G Loss: 0.6667
Epoch 464/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 464/500: Average D Loss: 1.1579, Average G Loss: 0.6655
Epoch 465/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 465/500: Average D Loss: 1.1612, Average G Loss: 0.6743
Epoch 466/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 466/500: Average D Loss: 1.1520, Average G Loss: 0.6755
Epoch 467/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 467/500: Average D Loss: 1.1546, Average G Loss: 0.6835
Epoch 468/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 468/500: Average D Loss: 1.1579, Average G Loss: 0.6740
Epoch 469/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

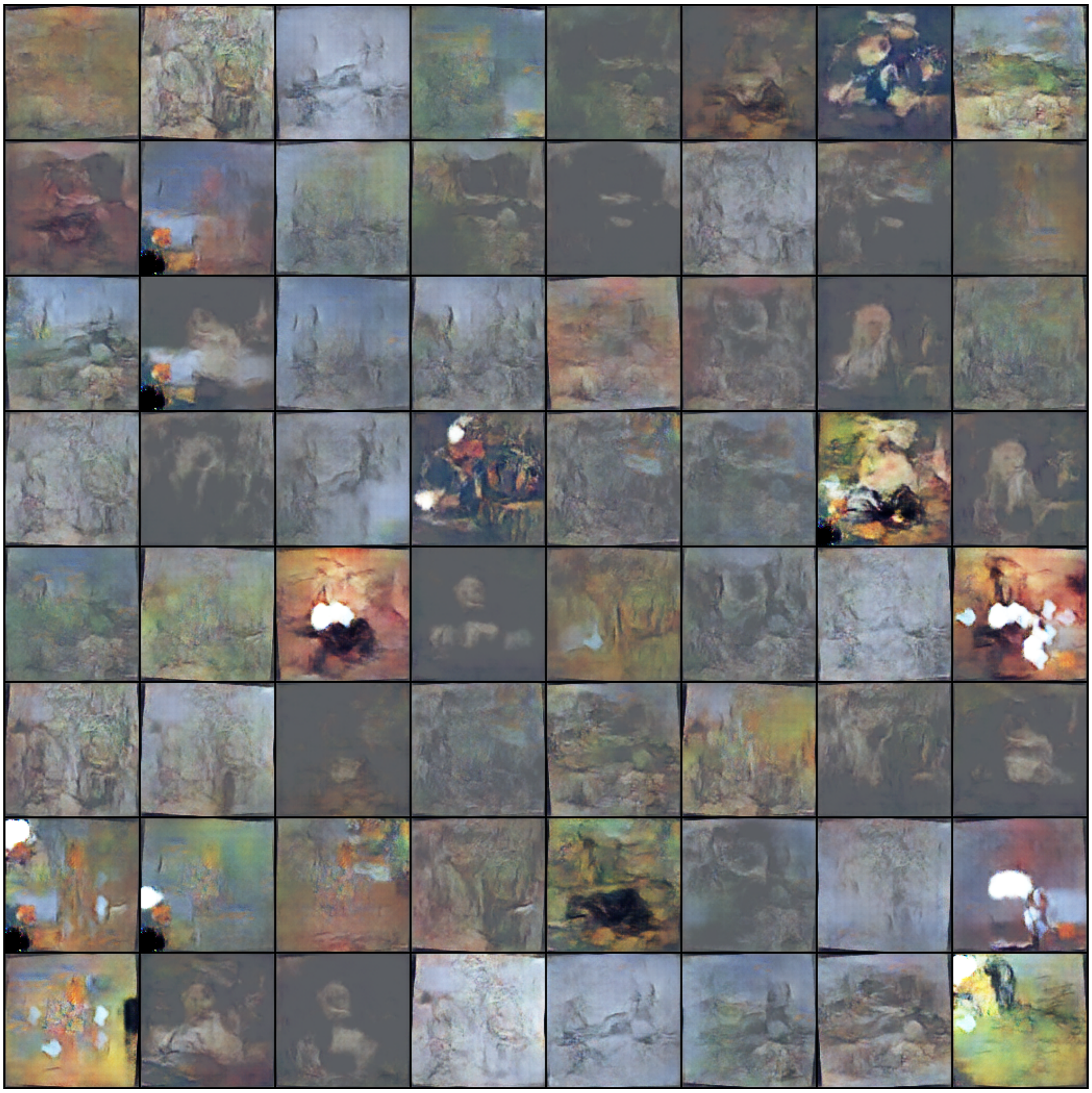
```
Epoch 469/500: Average D Loss: 1.1555, Average G Loss: 0.6746
Epoch 470/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 470/500: Average D Loss: 1.1560, Average G Loss: 0.6743
Epoch 471/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 471/500: Average D Loss: 1.1547, Average G Loss: 0.6719
Epoch 472/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 472/500: Average D Loss: 1.1588, Average G Loss: 0.6669
Epoch 473/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 473/500: Average D Loss: 1.1551, Average G Loss: 0.6744
Epoch 474/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 474/500: Average D Loss: 1.1572, Average G Loss: 0.6699
Epoch 475/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 475/500: Average D Loss: 1.1550, Average G Loss: 0.6731
Epoch 476/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 476/500: Average D Loss: 1.1565, Average G Loss: 0.6719
Epoch 477/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 477/500: Average D Loss: 1.1570, Average G Loss: 0.6709
Epoch 478/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 478/500: Average D Loss: 1.1553, Average G Loss: 0.6724
Epoch 479/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 479/500: Average D Loss: 1.1595, Average G Loss: 0.6719
Epoch 480/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 480/500: Average D Loss: 1.1573, Average G Loss: 0.6712
Epoch 481/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 481/500: Average D Loss: 1.1582, Average G Loss: 0.6668
Epoch 482/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 482/500: Average D Loss: 1.1553, Average G Loss: 0.6714
Epoch 483/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 483/500: Average D Loss: 1.1593, Average G Loss: 0.6718
Epoch 484/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 484/500: Average D Loss: 1.1541, Average G Loss: 0.6770
Epoch 485/500:   0%|          | 0/136 [00:00<?, ?batch/s]
```

```
Epoch 485/500: Average D Loss: 1.1626, Average G Loss: 0.6640
Epoch 486/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 486/500: Average D Loss: 1.1566, Average G Loss: 0.6684
Epoch 487/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 487/500: Average D Loss: 1.1548, Average G Loss: 0.6674
Epoch 488/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 488/500: Average D Loss: 1.1610, Average G Loss: 0.6744
Epoch 489/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 489/500: Average D Loss: 1.1550, Average G Loss: 0.6765
Epoch 490/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 490/500: Average D Loss: 1.1604, Average G Loss: 0.6716
Epoch 491/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 491/500: Average D Loss: 1.1563, Average G Loss: 0.6701
Epoch 492/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 492/500: Average D Loss: 1.1587, Average G Loss: 0.6671
Epoch 493/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 493/500: Average D Loss: 1.1576, Average G Loss: 0.6737
Epoch 494/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 494/500: Average D Loss: 1.1590, Average G Loss: 0.6691
Epoch 495/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 495/500: Average D Loss: 1.1559, Average G Loss: 0.6722
Epoch 496/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 496/500: Average D Loss: 1.1559, Average G Loss: 0.6721
Epoch 497/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 497/500: Average D Loss: 1.1601, Average G Loss: 0.6689
Epoch 498/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 498/500: Average D Loss: 1.1574, Average G Loss: 0.6676
Epoch 499/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 499/500: Average D Loss: 1.1594, Average G Loss: 0.6719
Epoch 500/500:   0%|          | 0/136 [00:00<?, ?batch/s]
Epoch 500/500: Average D Loss: 1.1574, Average G Loss: 0.6784
Saved models to /content/saved_models at epoch 499
```

[23]:

```
Image('./generated_images/generated_images_epoch_100.png')
```

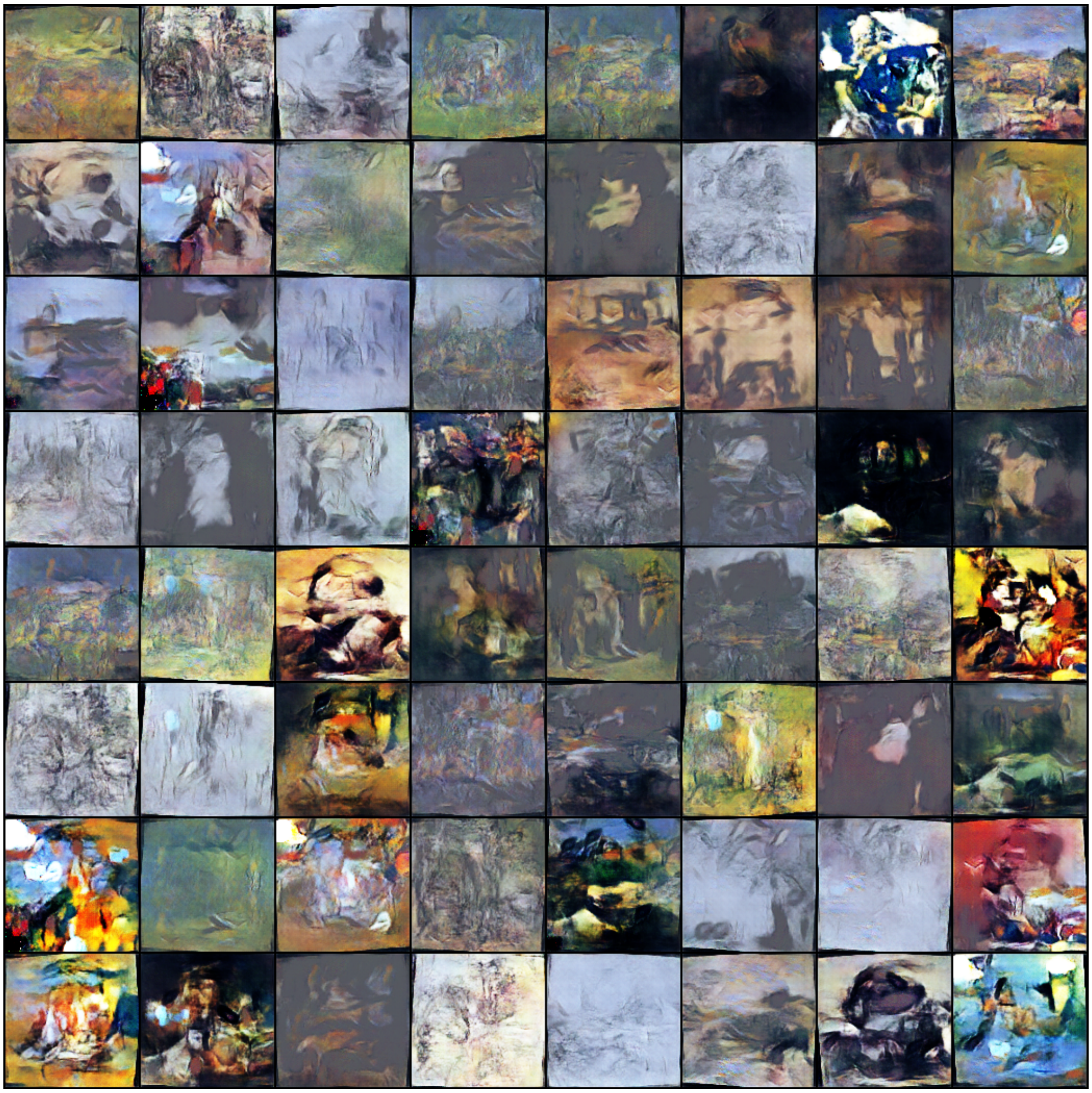
[23]:



[24]:

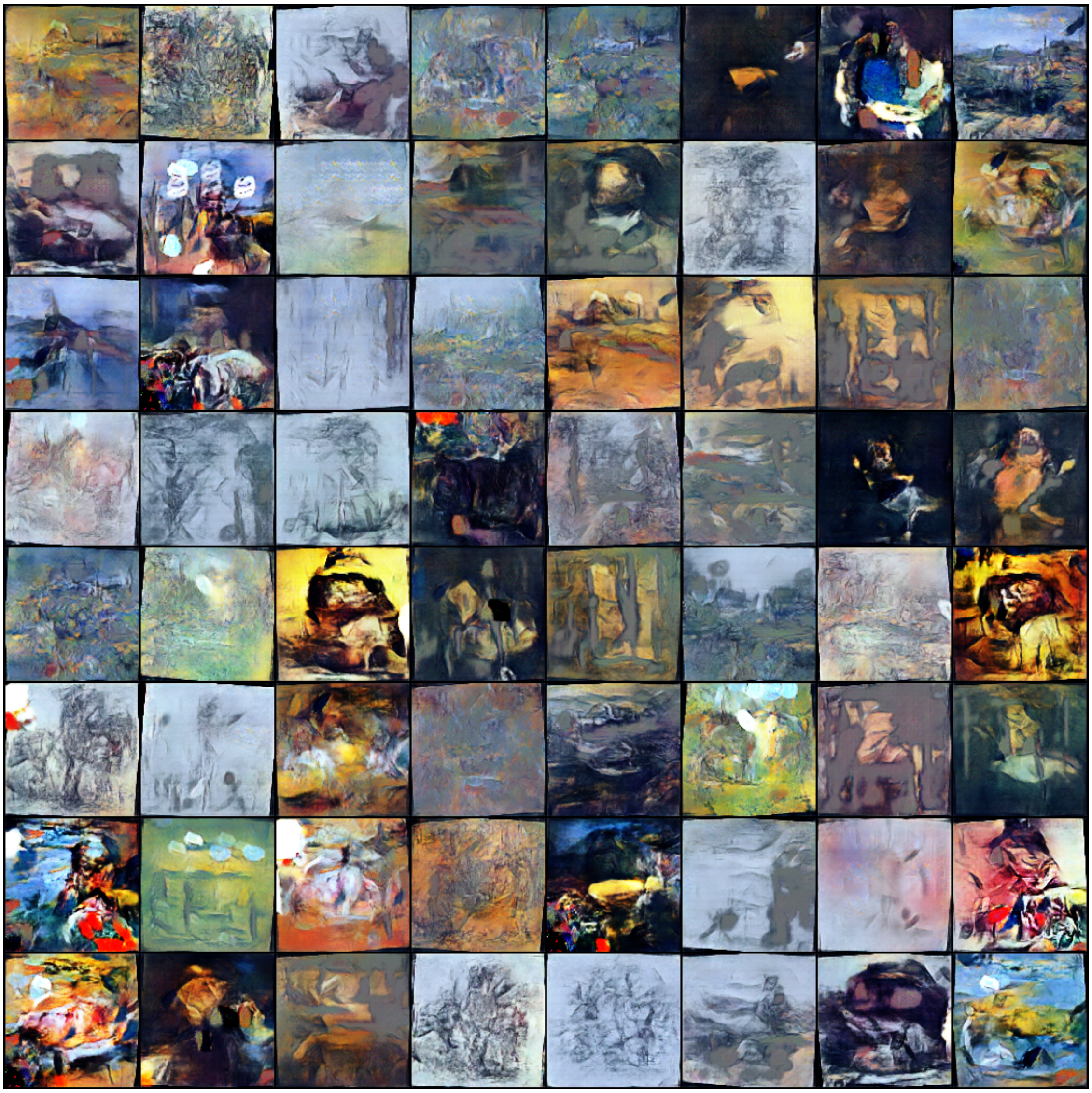
```
Image('./generated_images/generated_images_epoch_200.png')
```

[24]:



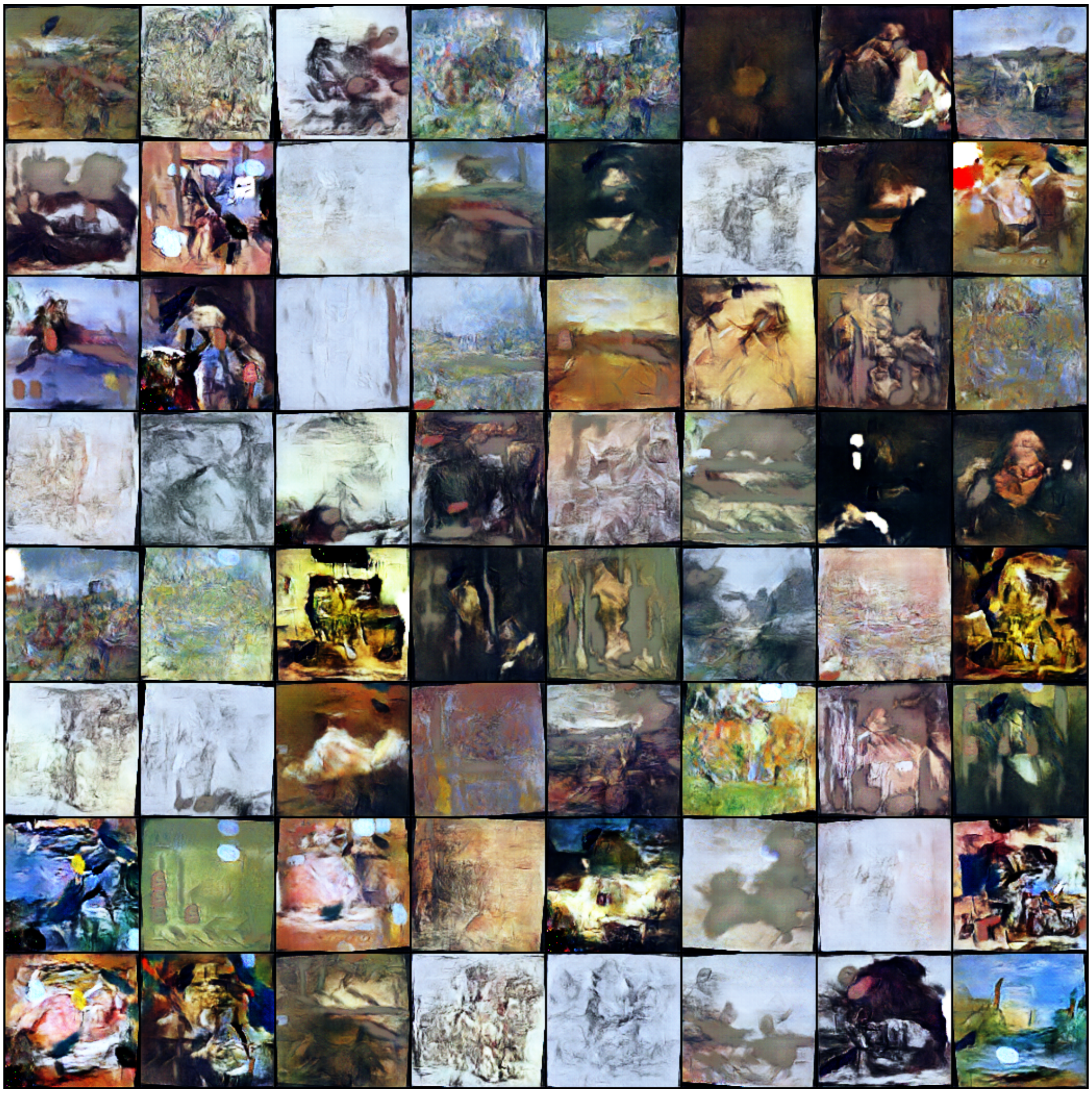
[25]:
```
Image('./generated_images/generated_images_epoch_300.png')
```

[25]:



```
[26]: Image('./generated_images/generated_images_epoch_400.png')
```

[26]:



[27]:
```
Image('./generated_images/generated_images_epoch_499.png')
```

[27]:

[28]:
```python
# Specify the directory where images are saved
image_folder = '/content/generated_images/'
video_path = '/content/generation_animation.mp4'

# Gather sorted list of images by epoch number
image_files = [f for f in os.listdir(image_folder) if f.
 ↪startswith('generated_images_epoch_')]
image_files.sort(key=lambda x: int(x.split('_')[-1].split('.')[0]))

# Load images and append to the list
images = []
for filename in image_files:
    img_path = os.path.join(image_folder, filename)
```

```
    images.append(imageio.imread(img_path))

# Create a video from images
imageio.mimsave(video_path, images, fps=5)
print(f"Video saved at {video_path}")
```

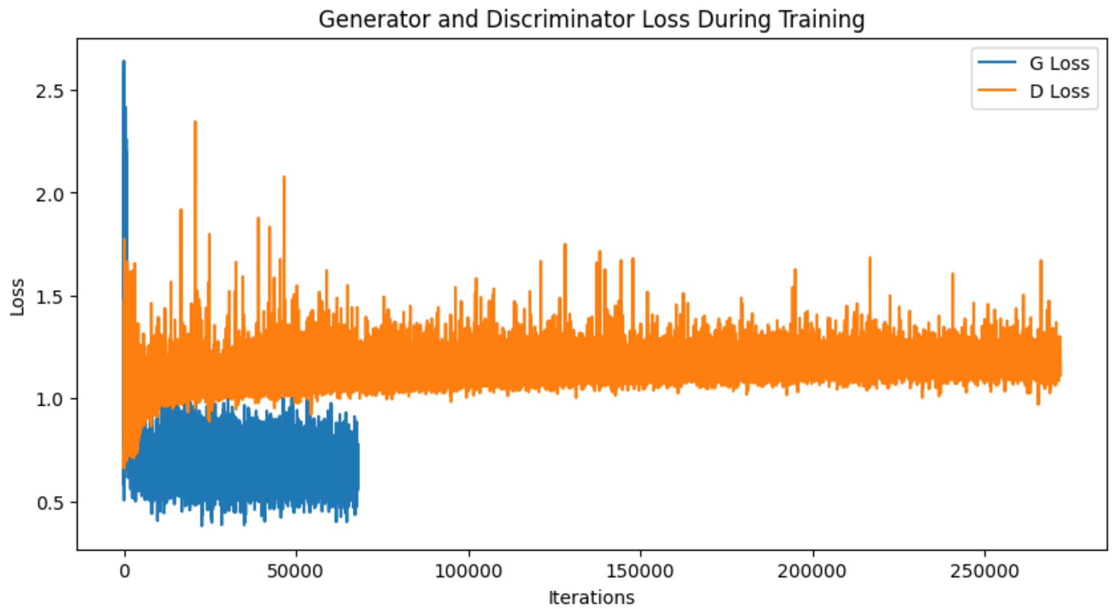
```
<ipython-input-28-75320fa08ed8>:13: DeprecationWarning: Starting with ImageIO v3
the behavior of this function will switch to that of iio.v3.imread. To keep the
current behavior (and make this warning disappear) use `import imageio.v2 as
imageio` or call `imageio.v2.imread` directly.
  images.append(imageio.imread(img_path))
WARNING:imageio_ffmpeg:IMAGEIO FFMPEG_WRITER WARNING: input image is not
divisible by macro_block_size=16, resizing from (1042, 1042) to (1056, 1056) to
ensure video compatibility with most codecs and players. To prevent resizing,
make your input image divisible by the macro_block_size or set the
macro_block_size to 1 (risking incompatibility).
/usr/lib/python3.10/subprocess.py:1796: RuntimeWarning: os.fork() was called.
os.fork() is incompatible with multithreaded code, and JAX is multithreaded, so
this will likely lead to a deadlock.
  self.pid = _posixsubprocess.fork_exec(
```

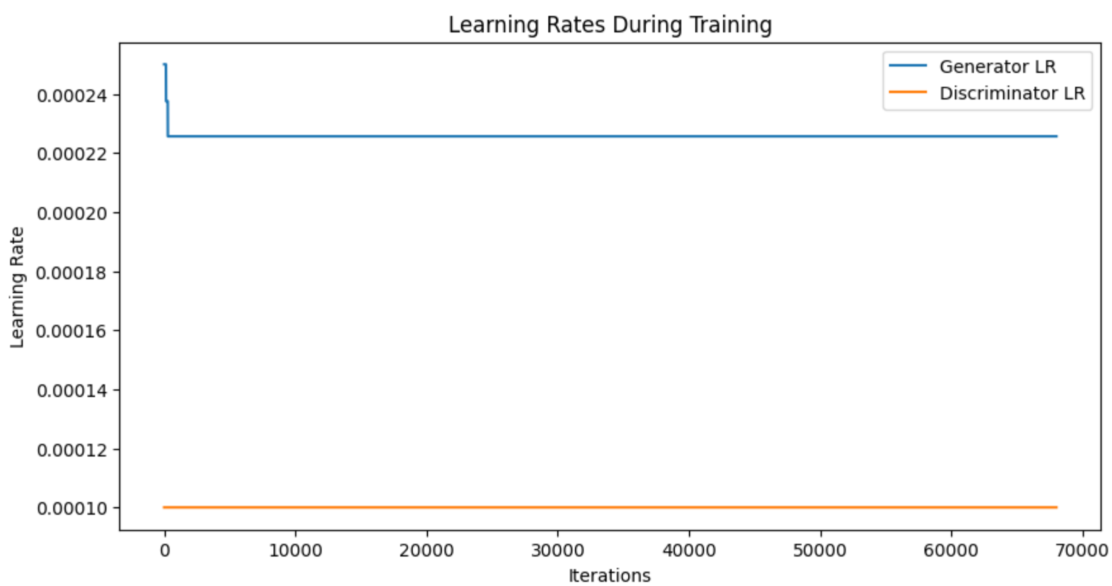
```
Video saved at /content/generation_animation.mp4
```

[29]:

```
# Plotting Losses
plt.figure(figsize=(10, 5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(generator_losses, label="G Loss")
plt.plot(discriminator_losses, label="D Loss")
plt.xlabel("Iterations")
plt.ylabel("Loss")
plt.legend()
plt.show()

# Plotting Learning Rates
plt.figure(figsize=(10, 5))
plt.title("Learning Rates During Training")
plt.plot(hyperparams['g_lr'], label="Generator LR")
plt.plot(hyperparams['d_lr'], label="Discriminator LR")
plt.xlabel("Iterations")
plt.ylabel("Learning Rate")
plt.legend()
plt.show()
```





[30]:
```
# Assuming generator and discriminator are already instantiated
print("Generator Summary:")
print(summary(generator, (128, 1, 1)))  # Latent vector size as input

print("Discriminator Summary:")
print(summary(discriminator, (3, 128, 128)))  # Image size as input
```

```
Generator Summary:
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
   ConvTranspose2d-1          [-1, 1024, 4, 4]       2,097,152
              ReLU-2          [-1, 1024, 4, 4]               0
       BatchNorm2d-3          [-1, 1024, 4, 4]           2,048
   ConvTranspose2d-4           [-1, 512, 8, 8]       8,388,608
              ReLU-5           [-1, 512, 8, 8]               0
       BatchNorm2d-6           [-1, 512, 8, 8]           1,024
   ConvTranspose2d-7         [-1, 256, 16, 16]       2,097,152
              ReLU-8         [-1, 256, 16, 16]               0
       BatchNorm2d-9         [-1, 256, 16, 16]             512
  ConvTranspose2d-10         [-1, 128, 32, 32]         524,288
             ReLU-11         [-1, 128, 32, 32]               0
      BatchNorm2d-12         [-1, 128, 32, 32]             256
  ConvTranspose2d-13          [-1, 64, 64, 64]         131,072
             ReLU-14          [-1, 64, 64, 64]               0
      BatchNorm2d-15          [-1, 64, 64, 64]             128
  ConvTranspose2d-16         [-1, 3, 128, 128]           3,072
             Tanh-17         [-1, 3, 128, 128]               0
================================================================
Total params: 13,245,312
Trainable params: 13,245,312
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 12.38
Params size (MB): 50.53
Estimated Total Size (MB): 62.90
----------------------------------------------------------------
None
Discriminator Summary:
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1          [-1, 64, 64, 64]           3,072
         LeakyReLU-2          [-1, 64, 64, 64]               0
           Dropout-3          [-1, 64, 64, 64]               0
            Conv2d-4         [-1, 128, 32, 32]         131,072
         LeakyReLU-5         [-1, 128, 32, 32]               0
           Dropout-6         [-1, 128, 32, 32]               0
            Conv2d-7         [-1, 256, 16, 16]         524,288
         LeakyReLU-8         [-1, 256, 16, 16]               0
           Dropout-9         [-1, 256, 16, 16]               0
           Conv2d-10           [-1, 512, 8, 8]       2,097,152
        LeakyReLU-11           [-1, 512, 8, 8]               0
          Dropout-12           [-1, 512, 8, 8]               0
           Conv2d-13             [-1, 1, 5, 5]           8,192
```

```
AdaptiveAvgPool2d-14              [-1, 1, 1, 1]               0
         Flatten-15                    [-1, 1]               0
         Sigmoid-16                    [-1, 1]               0
================================================================
Total params: 2,763,776
Trainable params: 2,763,776
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.19
Forward/backward pass size (MB): 11.25
Params size (MB): 10.54
Estimated Total Size (MB): 21.98
----------------------------------------------------------------
None
```

[31]:

```python
# Function to execute shell commands
def shell_cmd(command):
    try:
        return subprocess.check_output(command, shell=True, text=True)
    except subprocess.CalledProcessError:
        return "Unavailable"

# Print CPU Information
print("CPU:", shell_cmd("cat /proc/cpuinfo | grep 'model name' | uniq | awk -F:␣
↪'{print $2}'"))

# Print GPU Information
gpu_info = shell_cmd("nvidia-smi --query-gpu=gpu_name --format=csv,noheader")
print("GPU:", gpu_info.strip() if gpu_info else "No GPU detected")

# Print System Memory Information
mem_info = shell_cmd("cat /proc/meminfo | grep 'MemTotal' | awk '{print $2/1024␣
↪\" MB\"}'")
print("System Memory:", mem_info.strip() if mem_info else "Memory info␣
↪unavailable")

# Python and PyTorch details
print("Python Version:", sys.version)
print("CUDA Version:", torch.version.cuda if torch.cuda.is_available() else␣
↪"CUDA not available")
print("Torch Version:", torch.__version__)
```

```
CPU:  Intel(R) Xeon(R) CPU @ 2.00GHz

GPU: Tesla V100-SXM2-16GB
System Memory: 52217.5 MB
Python Version: 3.10.12 (main, Nov 20 2023, 15:14:05) [GCC 11.4.0]
```

```
CUDA Version: 12.1
Torch Version: 2.2.1+cu121
```