# EXP No: 12 :- Implement a Deep Convolutional GAN to Generate Complex color images

**Aim :-**

To implement a Deep Convolutional Generative Adversarial Network capable of generating realistic color images.

**Objectives :-**

1. To understand the working of GAN's with generator and discriminator networks
2. To build a DCGAN using convolutional and transpose convolutional layers
3. To train the model to generate color images from random noise
4. To visualize and evaluate generated image quality

**Algorithm :-**

1. Import and preprocess color image dataset. (CIFAR-10)
2. Normalize image data to range [-1, 1].
3. Build the Generator.
   → Use Conv2DTranspose layers with BatchNorm & ReLU.
   → output 3-channel (RGB) image using tanh activation
4. Build the Discriminator:
   → Use Conv2D layers with LeakyReLU & Dropout.
   → output binary classification (real/fake)
5. Train both networks adversarially:
   → Discriminator learns to distinguish real/fake
   → Generator learns to fool the discriminator
6. Generate & visualize synthetic images.

## Pseudo Code:-

Load CIFAR-10 dataset

Normalize images to [-1, 1]

Define Generator:

Dense → Reshape → Conv2D Transpose (ReLU)

output: Conv2D Transpose (3, tanh).

Define Discriminator:

Conv2D → LeakyReLU → Dropout

output: Dense(1, sigmoid)

Combine models into DCGAN

Train:

For each epoch:

1. Train discriminator with Real + fake image
2. Train generator via Combined model

Generate and visualize images.

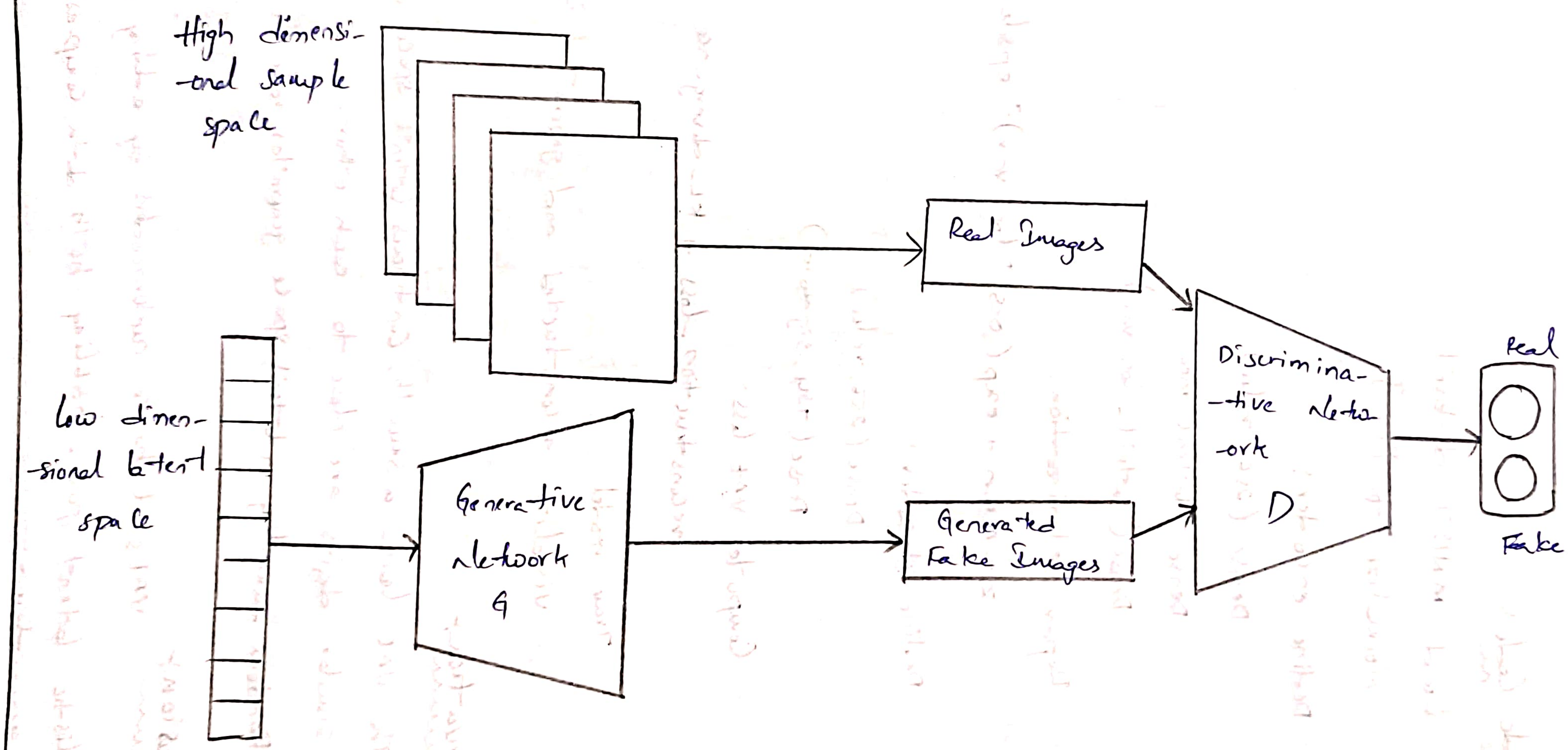
## Observation:-

- The DCGAN learns to produce increasingly realistic color images as training progresses.
- Generated images evolve from random ~~si~~ noise to clear structures.

## Conclusion:-

DCGANs effectively learn to generate Complex, realistic color images using adverstatrial training b/w the generator & discriminator. They demonstrate the power of deep Convolutional networks for unsupervised image generation

# GAN ARCHITECTURE FOR IMAGE



output:-

Epoch [1/10] D loss: 1.0992, G loss: 0.5678

Epoch [2/10] D loss: 0.5060, G loss: 2.7113

Epoch [3/10] D loss: 1.2431, G loss: 3.9827

Epoch [4/10] D loss: 0.4229, G loss: 2.2684

Epoch [5/10] D loss: 1.1486, G loss: 8.1007

Epoch [6/10] D loss: 1.0081, G loss: 6.7625

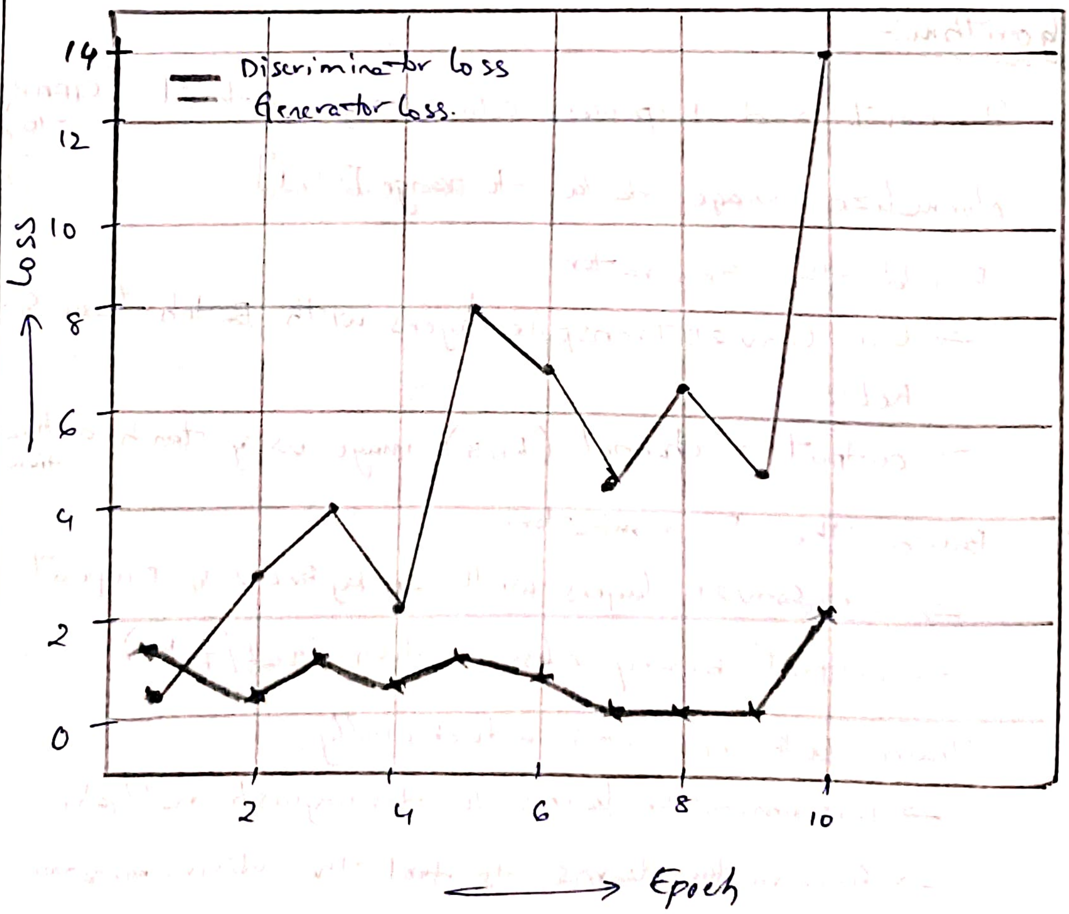
Epoch [7/10] D loss: 0.0252, G loss: 4.5718

Epoch [8/10] D loss: 0.0043, G loss: 6.3371

Epoch [9/10] D loss: 0.1380, G loss: 4.7357

Epoch [10/10] D loss: 2.3294, G loss: 14.0363

Epoch vs Loss (GAN).



dltlab12.ipynb

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```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import torchvision.utils as vutils
import matplotlib.pyplot as plt
import numpy as np

# 1. Hyperparameters
batch_size = 128
latent_dim = 100
epochs = 10
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# 2. Data loading (CIFAR-10 color images)
transform = transforms.Compose([
    transforms.Resize(64),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])
dataset = datasets.CIFAR10(root='./data', download=True, transform=transform)
dataloader = DataLoader(dataset, batch_size=batch_size, shuffle=True)

# 3. Define Generator
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.ConvTranspose2d(100, 512, 4, 1, 0, bias=False),
            nn.BatchNorm2d(512), nn.ReLU(True),
            nn.ConvTranspose2d(512, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256), nn.ReLU(True),
            nn.ConvTranspose2d(256, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128), nn.ReLU(True),
            nn.ConvTranspose2d(128, 64, 4, 2, 1, bias=False),
            nn.BatchNorm2d(64), nn.ReLU(True),
            nn.ConvTranspose2d(64, 3, 4, 2, 1, bias=False),
            nn.Tanh()
        )
    def forward(self, x):
        return self.model(x)
```

```python
# 4. Define Discriminator
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Conv2d(3, 64, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(64, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128), nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(128, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256), nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(256, 512, 4, 2, 1, bias=False),
            nn.BatchNorm2d(512), nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(512, 1, 4, 1, 0, bias=False),
            nn.Sigmoid()
        )
    def forward(self, x):
        return self.model(x).view(-1, 1)

# 5. Initialize models
netG, netD = Generator().to(device), Discriminator().to(device)
criterion = nn.BCELoss()
optimizerG = optim.Adam(netG.parameters(), lr=0.0002, betas=(0.5, 0.999))
optimizerD = optim.Adam(netD.parameters(), lr=0.0002, betas=(0.5, 0.999))

# Lists to store losses
d_losses = []
g_losses = []

# 6. Training loop
for epoch in range(epochs):
    for i, (real_imgs, _) in enumerate(dataloader):
        real_imgs = real_imgs.to(device)
        batch_size = real_imgs.size(0)

        # Real labels = 1, Fake labels = 0
        real_labels = torch.ones(batch_size, 1, device=device)
        fake_labels = torch.zeros(batch_size, 1, device=device)

        # Train Discriminator
        z = torch.randn(batch_size, latent_dim, 1, 1, device=device)
        fake_imgs = netG(z)
```

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        real_loss = criterion(netD(real_imgs), real_labels)
        fake_loss = criterion(netD(fake_imgs.detach()), fake_labels)
        d_loss = real_loss + fake_loss

        optimizerD.zero_grad()
        d_loss.backward()
        optimizerD.step()

        # Train Generator
        g_loss = criterion(netD(fake_imgs), real_labels)
        optimizerG.zero_grad()
        g_loss.backward()
        optimizerG.step()

    # Store losses
    d_losses.append(d_loss.item())
    g_losses.append(g_loss.item())

    print(f"Epoch [{epoch+1}/{epochs}] D Loss: {d_loss:.4f}, G Loss: {g_loss:.4f}")

# 7. Plot Epoch Graph (Loss vs Epoch)
plt.figure(figsize=(8,5))
plt.plot(range(1, epochs+1), d_losses, label='Discriminator Loss', marker='o')
plt.plot(range(1, epochs+1), g_losses, label='Generator Loss', marker='o')
plt.title("Epoch vs Loss (GAN Training Progress)")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()

# 8. Generate samples
z = torch.randn(64, latent_dim, 1, 1, device=device)
fake_imgs = netG(z)
vutils.save_image(fake_imgs, 'dcgan_generated.png', normalize=True)
plt.figure(figsize=(8,8))
plt.axis("off")
plt.title("Generated Images")
plt.imshow(np.transpose(vutils.make_grid(fake_imgs[:64], padding=2, normalize=True).cpu(), (1,2,0)))
plt.show()
```

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Epoch [1/10] D Loss: 1.0992, G Loss: 0.5678
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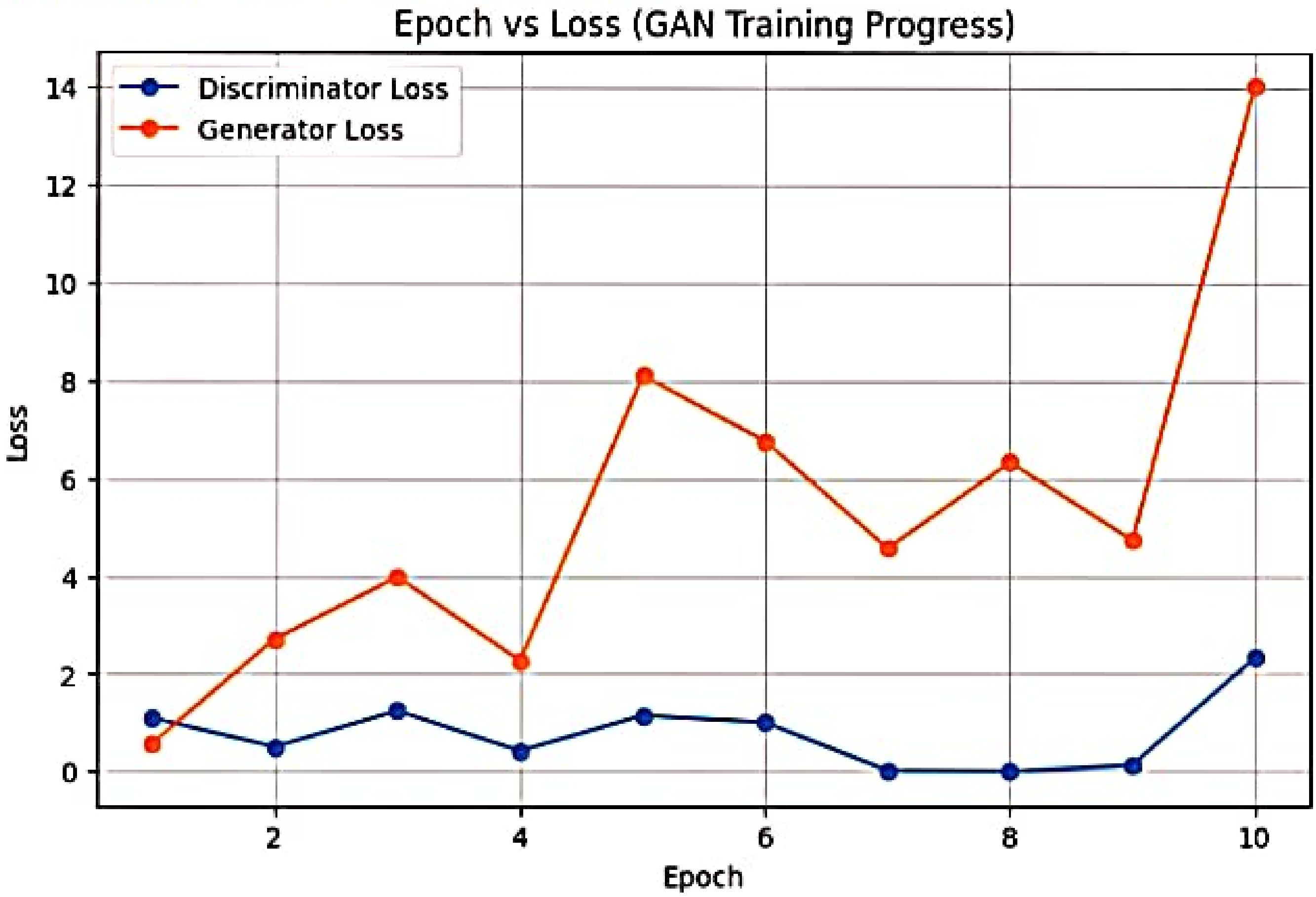

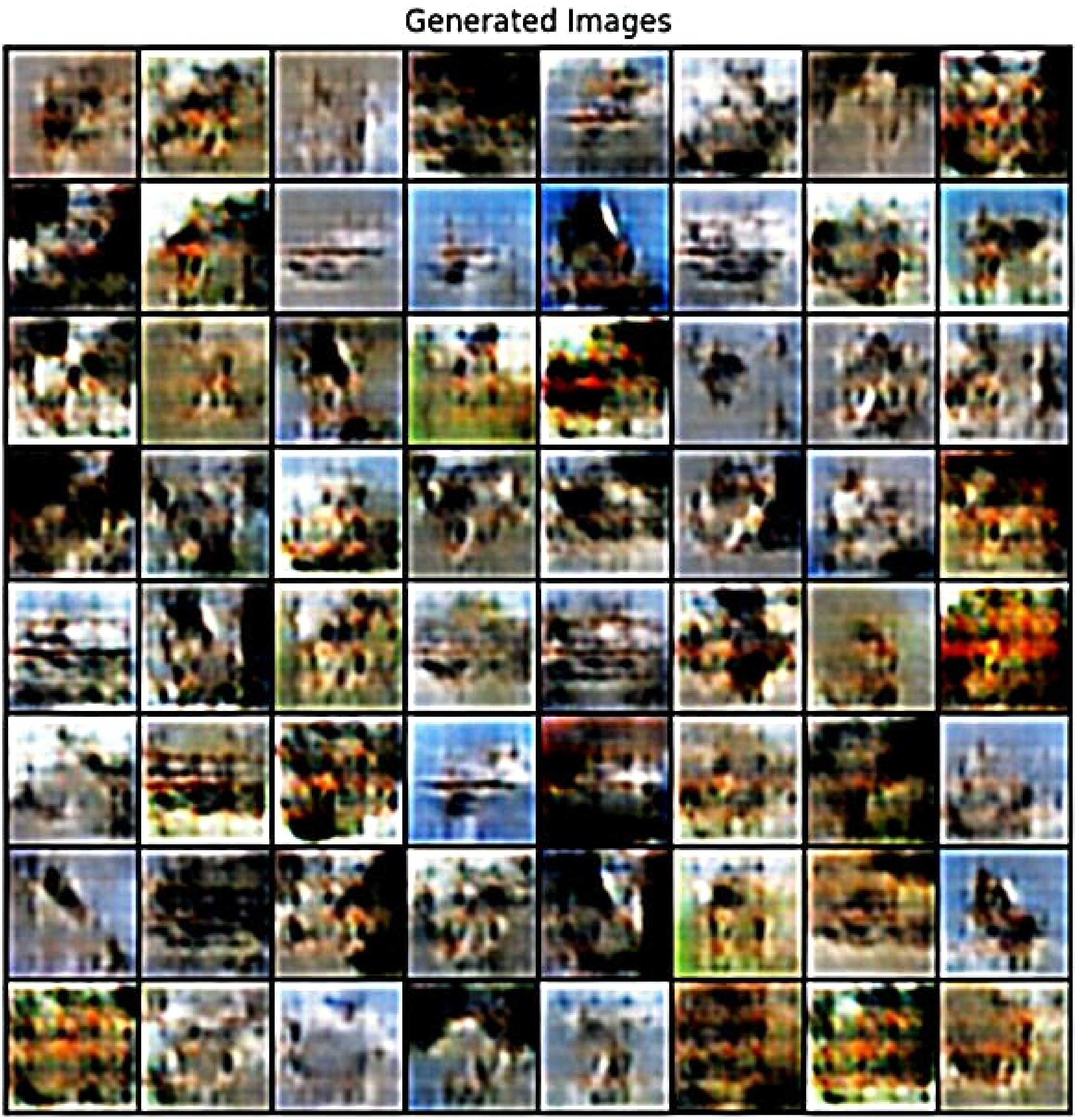
Generated Images