EX 10 IMAGE GENERATION USING GENERATIVE ADVERSARIAL

DATE:

Problem Statement:

Train a Generative Adversarial Network (GAN) to generate new images from a dataset. Evaluate the quality of generated images using both visual inspection and a quantitative metric such as Inception Score (IS) or Fréchet Inception Distance (FID).

Suggested Dataset: LSUN Dataset

Objectives:

1. Understand the architecture of GANs and their adversarial training process.
2. Use StyleGAN2-ADA, a state-of-the-art GAN, for high-quality image generation.
3. Evaluate generated images using IS and FID metrics.
4. Compare generated outputs with real samples and assess realism.

Scope:

GANs are powerful generative models used in image synthesis, super-resolution, style transfer, and more. This experiment familiarizes students with modern GAN architectures and helps develop understanding in both visual and metric-based evaluation of generative quality.

Tools and Libraries Used:

1. Python 3.x
2. PyTorch
3. torchvision
4. StyleGAN2-ADA
5. torchmetrics
6. FID & Inception Score libraries
7. CelebA Dataset

Implementation Steps:

Step 1: Clone StyleGAN2-ADA Repository

```
REPO = 'stylegan2-ada-pytorch'
REPO_URL = 'https://github.com/NVlabs/stylegan2-ada-pytorch.git'
```

```
def clone_repo():     if not
os.path.exists(REPO):
subprocess.run(['git', 'clone',
REPO_URL])
sys.path.append(os.path.abspath(RE
PO))
```

Step 2: Download Pretrained Generator

```
MODEL_URL      =         'https://nvlabs-fi-cdn.nvidia.com/stylegan2-
adapytorch/pretrained/ffhq.pkl'
MODEL_PATH = 'ffhq.pkl'

def download_model():     if
not
os.path.exists(MODEL_PAT
H):
        import urllib.request
        urllib.request.urlretrieve(MODEL_URL, MODEL_PATH)
```

Step 3: Generate Synthetic Images

```
def generate_images():
    import
legacy
import
dnnlib
    G = legacy.load_network_pkl(open(MODEL_PATH,
'rb'))['G_ema'].to(device)     os.makedirs('generated_images',
exist_ok=True)     imgs = []
    for i in range(1):  # NUM_IMAGES = 1
z = torch.randn([1, G.z_dim],
device=device)         label = torch.zeros([1,
G.c_dim], device=device)
        img = (G(z, label, truncation_psi=0.5,
noise_mode='const') + 1) * 0.5         save_image(img,
f'generated_images/fake_{i}.png')
imgs.append(img.cpu())     return torch.cat(imgs)
```

Step 4: Calculate Inception Score

```
from torchmetrics.image.inception import InceptionScore

def calculate_inception_score(imgs):     loader =
DataLoader(TensorDataset((imgs * 255).clamp(0, 255).to(torch.uint8)),
batch_size=32)     is_metric = InceptionScore()     for batch in loader:
is_metric.update(batch[0])     mean, std = is_metric.compute()
    print(f"Inception Score: {mean:.2f} ± {std:.2f}")
```

Step 5: Prepare Real Images from CelebA

```
def prepare_real_images():
   dataset = dsets.CelebA(root='./data', split='train',
       transform=transforms.Compose([
transforms.Resize(512),
transforms.CenterCrop(512),
transforms.ToTensor()
       ]),
       download=True)
   loader = DataLoader(dataset, batch_size=1,
shuffle=True)     os.makedirs('real_images',
exist_ok=True)     for i, (img, _) in
enumerate(loader):
       if i >= 1: break
       save_image(img, f"real_images/real_{i}.png")
```

Step 6: Compute FID Between Real and Generated Images

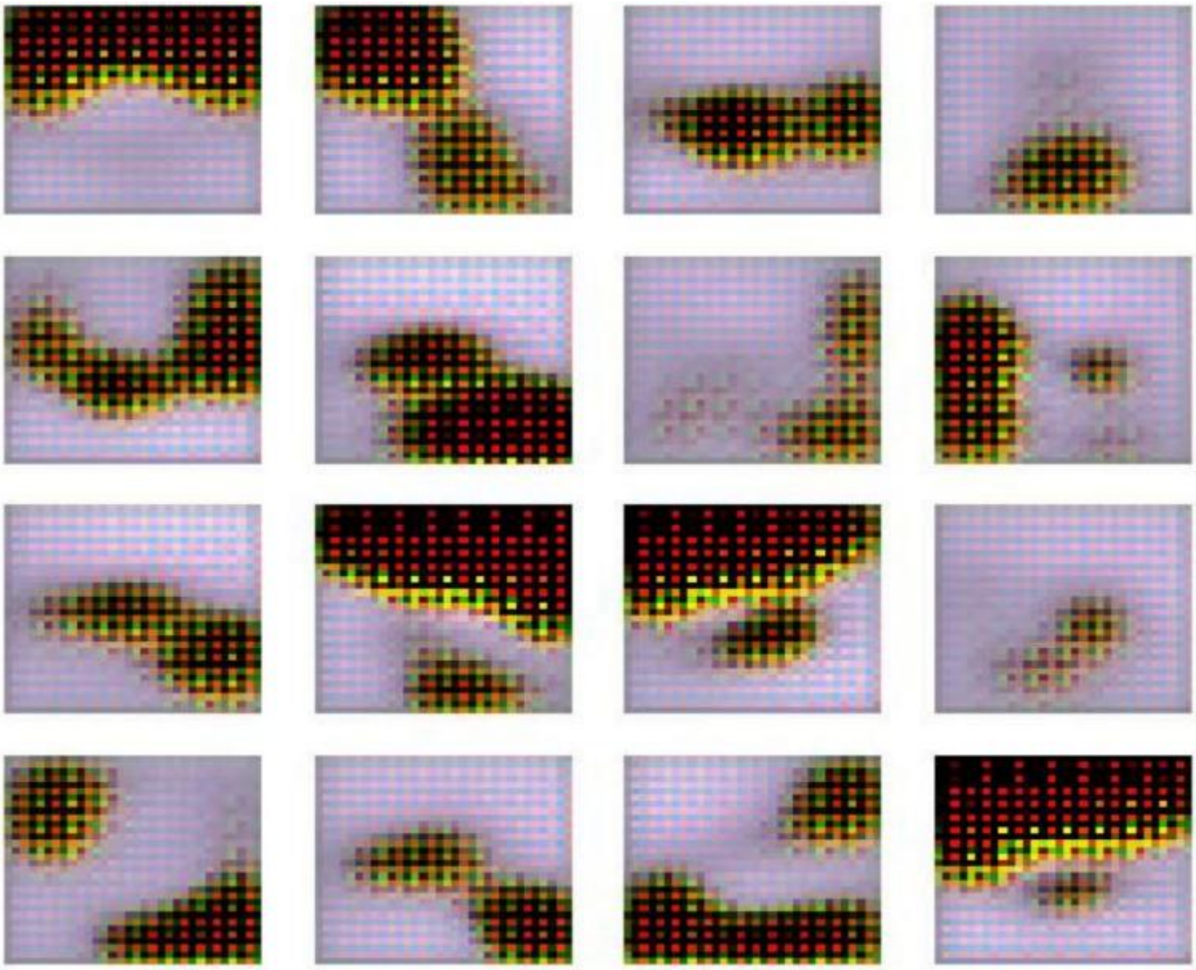
```
def calculate_fid():
   subprocess.run(["python", "-m", "pytorch_fid", "real_images",
"generated_images"])
```

Step 7: Run Entire Workflow

```
def main():
   clone_repo()
download_model()
imgs =
generate_images()
calculate_inception_sco
re(imgs)
prepare_real_images()
   calculate_fid()

if __name__ == "__main__":
   main()
```

OUTPUT:



Conclusion:

This experiment highlights the capabilities of advanced GANs like StyleGAN2 in generating photorealistic images. The use of Inception Score and FID provides quantitative support to visual assessments. GANs remain a cornerstone in generative deep learning research, with wide applications in media, design, and beyond.