Lab Report – 8

Generative Adversarial Networks (GAN)

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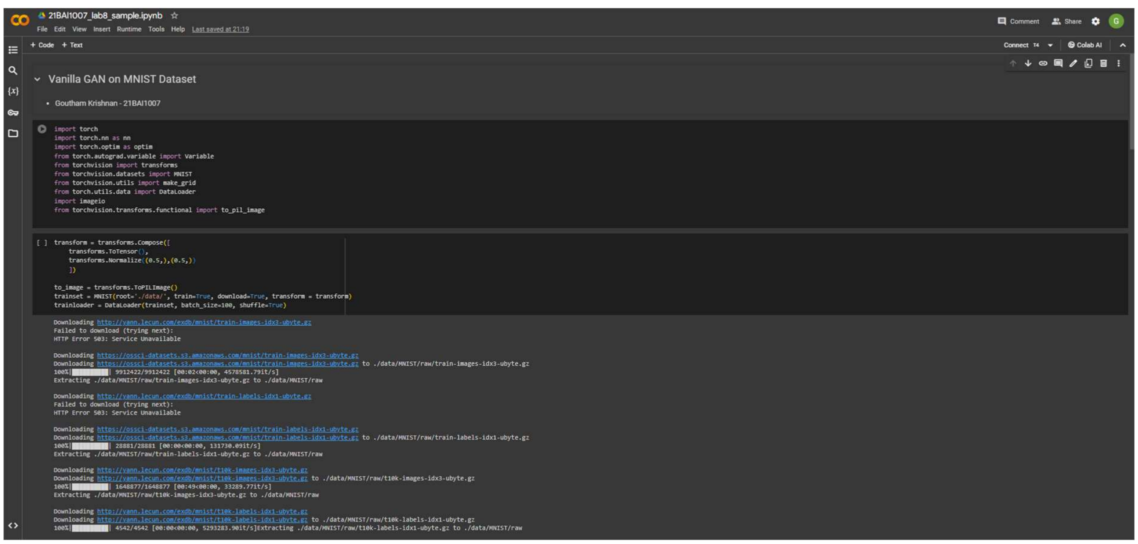
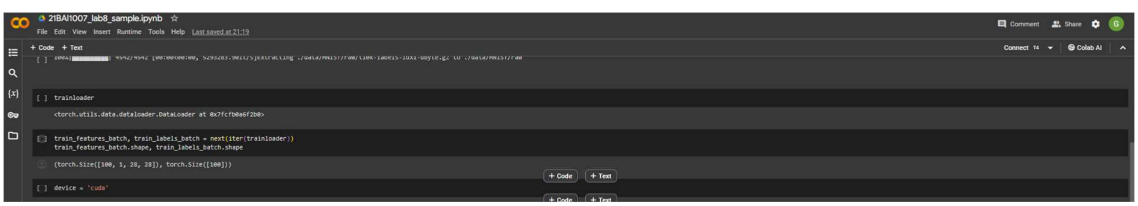
21BAI1007

Aim

1. Implement Vanilla GAN to generate images of the MNIST Handwritten digits dataset.
2. Implement Vanilla GAN to generate images of the CIFAR-10 image dataset.

Code and Output for Aim (i)





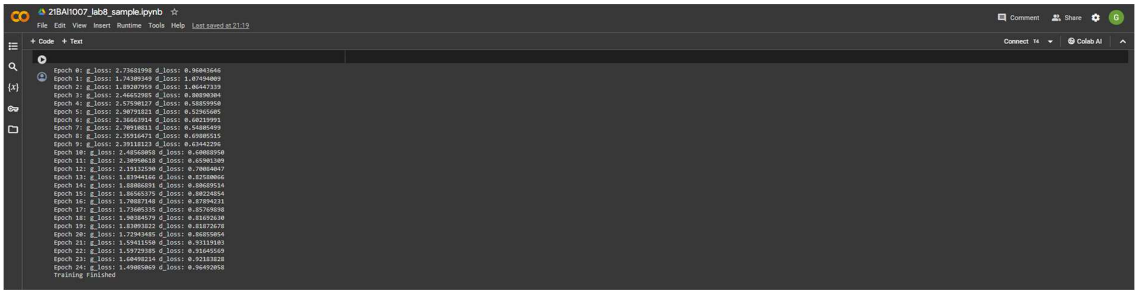
21BAI1007_lab8_sample.ipynb

```python
device = 'cuda'
```

```python
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.n_features = 128
        self.n_out = 784
        self.fc0 = nn.Sequential(
                    nn.Linear(self.n_features, 256),
                    nn.LeakyReLU(0.2)
                    )
        self.fc1 = nn.Sequential(
                    nn.Linear(256, 512),
                    nn.LeakyReLU(0.2)
                    )
        self.fc2 = nn.Sequential(
                    nn.Linear(512, 1024),
                    nn.LeakyReLU(0.2)
                    )
        self.fc3 = nn.Sequential(
                    nn.Linear(1024, self.n_out),
                    nn.Tanh()
                    )
    def forward(self, x):
        x = self.fc0(x)
        x = self.fc1(x)
        x = self.fc2(x)
        x = self.fc3(x)
        x = x.view(-1, 1, 28, 28)
        return x

class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.n_in = 784
        self.n_out = 1
        self.fc0 = nn.Sequential(
                    nn.Linear(self.n_in, 1024),
                    nn.LeakyReLU(0.2),
                    nn.Dropout(0.3)
                    )
        self.fc1 = nn.Sequential(
                    nn.Linear(1024, 512),
                    nn.LeakyReLU(0.2),
                    nn.Dropout(0.3)
                    )
        self.fc2 = nn.Sequential(
                    nn.Linear(512, 256),
                    nn.LeakyReLU(0.2),
                    nn.Dropout(0.3)
                    )
        self.fc3 = nn.Sequential(
                    nn.Linear(256, self.n_out),
                    nn.Sigmoid()
                    )
```

```python
        self.fc3 = nn.Sequential(
                    nn.Linear(256, self.n_out),
                    nn.Sigmoid()
                    )
    def forward(self, x):
        x = x.view(-1, 784)
        x = self.fc0(x)
        x = self.fc1(x)
        x = self.fc2(x)
        x = self.fc3(x)
        return x

generator = Generator()
discriminator = Discriminator()

generator.to(device)
discriminator.to(device)

g_optim = optim.Adam(generator.parameters(), lr=2e-4)
d_optim = optim.Adam(discriminator.parameters(), lr=2e-4)

g_losses = []
d_losses = []
images = []

criterion = nn.BCELoss()

def noise(n, n_features=128):
    return Variable(torch.randn(n, n_features)).to(device)

def make_ones(size):
    data = Variable(torch.ones(size, 1))
    return data.to(device)

def make_zeros(size):
    data = Variable(torch.zeros(size, 1))
    return data.to(device)

def train_discriminator(optimizer, real_data, fake_data):
    n = real_data.size(0)

    optimizer.zero_grad()

    prediction_real = discriminator(real_data)
    error_real = criterion(prediction_real, make_ones(n))
    error_real.backward()

    prediction_fake = discriminator(fake_data)
    error_fake = criterion(prediction_fake, make_zeros(n))

    error_fake.backward()
    optimizer.step()

    return error_real + error_fake
```

```python
    return error_real + error_fake

def train_generator(optimizer, fake_data):
    n = fake_data.size(0)
    optimizer.zero_grad()

    prediction = discriminator(fake_data)
    error = criterion(prediction, make_ones(n))

    error.backward()
    optimizer.step()

    return error

num_epochs = 25
k = 1
test_noise = noise(64)

generator.train()
discriminator.train()
for epoch in range(num_epochs):
    g_error = 0.0
    d_error = 0.0
    for i, data in enumerate(trainloader):
        imgs, _ = data
        n = len(imgs)
        for j in range(k):
            fake_data = generator(noise(n)).detach()
            real_data = imgs.to(device)
            d_error += train_discriminator(d_optim, real_data, fake_data)
        fake_data = generator(noise(n))
        g_error += train_generator(g_optim, fake_data)

    img = generator(test_noise).cpu().detach()
    img = make_grid(img)
    images.append(img)
    g_losses.append(g_error/i)
    d_losses.append(d_error/i)
    print('Epoch {}: g_loss: {:.8f} d_loss: {:.8f}\r'.format(epoch, g_error/i, d_error/i))

print('Training Finished')
torch.save(generator.state_dict(), 'mnist_generator.pth')

def to_image(tensor):
    """Converts a PyTorch tensor to a PIL Image."""
    return to_pil_image(tensor)

import numpy as np
from matplotlib import pyplot as plt
imgs = [np.array(to_image(i)) for i in images]
imageio.mimsave('progress.gif', imgs)
```



21BAI1007_lab8_sample.ipynb

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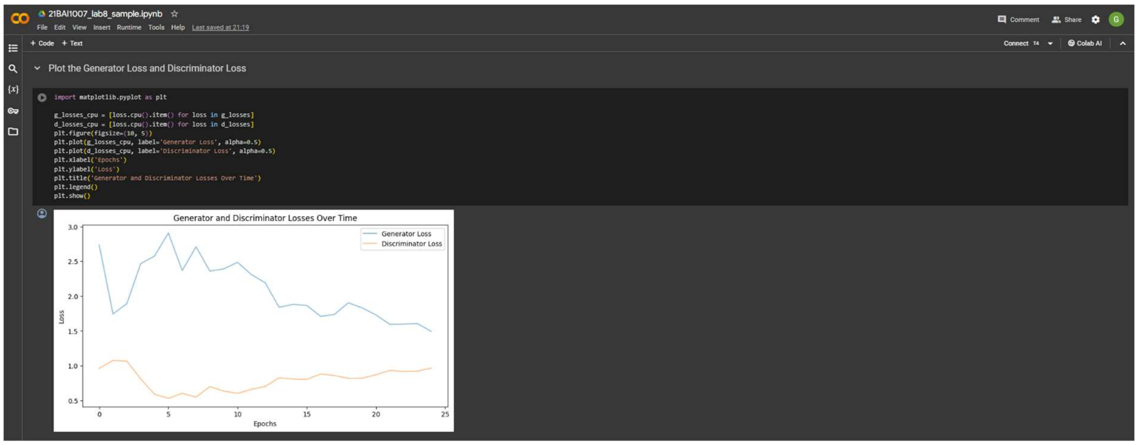
```
Epoch 0: g_loss: 2.73681998 d_loss: 0.96043646
Epoch 1: g_loss: 1.74309349 d_loss: 1.07494009
Epoch 2: g_loss: 1.89207959 d_loss: 1.06447339
Epoch 3: g_loss: 2.46652985 d_loss: 0.80890304
Epoch 4: g_loss: 2.57590127 d_loss: 0.58859950
Epoch 5: g_loss: 2.90791821 d_loss: 0.52965605
Epoch 6: g_loss: 2.36663914 d_loss: 0.60219991
Epoch 7: g_loss: 2.70910811 d_loss: 0.54805499
Epoch 8: g_loss: 2.35916471 d_loss: 0.69805515
Epoch 9: g_loss: 2.39118123 d_loss: 0.63442296
Epoch 10: g_loss: 2.48568058 d_loss: 0.60088950
Epoch 11: g_loss: 2.30950618 d_loss: 0.65901309
Epoch 12: g_loss: 2.19132590 d_loss: 0.70084047
Epoch 13: g_loss: 1.83944166 d_loss: 0.82580066
Epoch 14: g_loss: 1.88086891 d_loss: 0.80689514
Epoch 15: g_loss: 1.86565375 d_loss: 0.80224854
Epoch 16: g_loss: 1.70887148 d_loss: 0.87894231
Epoch 17: g_loss: 1.73605335 d_loss: 0.85769898
Epoch 18: g_loss: 1.90384579 d_loss: 0.81692630
Epoch 19: g_loss: 1.83093822 d_loss: 0.81872678
Epoch 20: g_loss: 1.72943485 d_loss: 0.86855054
Epoch 21: g_loss: 1.59411550 d_loss: 0.93119103
Epoch 22: g_loss: 1.59729385 d_loss: 0.91645569
Epoch 23: g_loss: 1.60498214 d_loss: 0.92183828
Epoch 24: g_loss: 1.49085069 d_loss: 0.96492058
Training Finished
```



21BAI1007_lab8_sample.ipynb

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Plot the Generator Loss and Discriminator Loss

```python
import matplotlib.pyplot as plt

g_losses_cpu = [loss.cpu().item() for loss in g_losses]
d_losses_cpu = [loss.cpu().item() for loss in d_losses]
plt.figure(figsize=(10, 5))
plt.plot(g_losses_cpu, label='Generator Loss', alpha=0.5)
plt.plot(d_losses_cpu, label='Discriminator Loss', alpha=0.5)
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Generator and Discriminator Losses Over Time')
plt.legend()
plt.show()
```


Code and Output for Aim (ii)

21bai1007-cifar10-gan.ipynb

Vanilla GAN on CIFAR-10 Dataset

- Goutham Krishnan - 21BAI1007

```python
import torch
import torch.nn as nn
import torch.optim as optim
from torch.autograd.variable import Variable
from torchvision import transforms
from torchvision.datasets import CIFAR10
from torchvision.utils import make_grid
from torch.utils.data import DataLoader
import imageio
from torchvision.transforms.functional import to_pil_image
```

```python
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

trainset = CIFAR10(root='./data/', train=True, download=True, transform = transform)
trainloader = DataLoader(trainset, batch_size=100, shuffle=True)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/cifar-10-python.tar.gz
100%|██████████| 170498071/170498071 [00:02<00:00, 76135866.18it/s]
Extracting ./data/cifar-10-python.tar.gz to ./data/
```

```python
train_features_batch, train_labels_batch = next(iter(trainloader))
train_features_batch.shape, train_labels_batch.shape
```

```
(torch.Size([100, 3, 32, 32]), torch.Size([100]))
```

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

```python
device
```

```
device(type='cuda')
```

21bai1007-cifar10-gan.ipynb

```python
device
```

```
device(type='cuda')
```

```python
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.n_features = 128
        self.n_out = 3072
        self.fc0 = nn.Sequential(
                    nn.Linear(self.n_features, 256),
                    nn.LeakyReLU(0.2)
                    )
        self.fc1 = nn.Sequential(
                    nn.Linear(256, 512),
                    nn.LeakyReLU(0.2)
                    )
        self.fc2 = nn.Sequential(
                    nn.Linear(512, 1024),
                    nn.LeakyReLU(0.2)
                    )
        self.fc3 = nn.Sequential(
                    nn.Linear(1024, self.n_out),
                    nn.Tanh()
                    )
    def forward(self, x):
        x = self.fc0(x)
        x = self.fc1(x)
        x = self.fc2(x)
        x = self.fc3(x)
        x = x.view(-1, 3, 32, 32)
        return x
```

21bai1007-cifar10-gan.ipynb

```python
        return x

class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.n_in = 3072
        self.n_out = 1
        self.fc0 = nn.Sequential(
                    nn.Linear(self.n_in, 1024),
                    nn.LeakyReLU(0.2),
                    #nn.Dropout(0.3)
                    )
        self.fc1 = nn.Sequential(
                    nn.Linear(1024, 512),
                    nn.LeakyReLU(0.2),
                    nn.Dropout(0.3)
                    )
        self.fc2 = nn.Sequential(
                    nn.Linear(512, 256),
                    nn.LeakyReLU(0.2),
                    #nn.Dropout(0.3)
                    )
        self.fc3 = nn.Sequential(
                    nn.Linear(256, self.n_out),
                    nn.Sigmoid()
                    )
    def forward(self, x):
        x = x.view(-1, 3072)
        x = self.fc0(x)
        x = self.fc1(x)
        x = self.fc2(x)
        x = self.fc3(x)
        return x

generator = Generator()
discriminator = Discriminator()

generator.to(device)
discriminator.to(device)

g_optim = optim.Adam(generator.parameters(), lr=2e-4)
d_optim = optim.Adam(discriminator.parameters(), lr=2e-4)

g_losses = []
d_losses = []
images = []

criterion = nn.BCELoss()
```

21bai1007-cifar10-gan.ipynb

```python
criterion = nn.BCELoss()

def noise(n, n_features=128):
    return Variable(torch.randn(n, n_features)).to(device)

def make_ones(size):
    data = Variable(torch.ones(size, 1))
    return data.to(device)

def make_zeros(size):
    data = Variable(torch.zeros(size, 1))
    return data.to(device)

def train_discriminator(optimizer, real_data, fake_data):
    n = real_data.size(0)

    optimizer.zero_grad()

    prediction_real = discriminator(real_data)
    error_real = criterion(prediction_real, make_ones(n))
    error_real.backward()

    prediction_fake = discriminator(fake_data)
    error_fake = criterion(prediction_fake, make_zeros(n))

    error_fake.backward()
    optimizer.step()

    return error_real + error_fake

def train_generator(optimizer, fake_data):
    n = fake_data.size(0)
    optimizer.zero_grad()

    prediction = discriminator(fake_data)
    error = criterion(prediction, make_ones(n))

    error.backward()
    optimizer.step()

    return error

num_epochs = 30
k = 1
test_noise = noise(64)
```

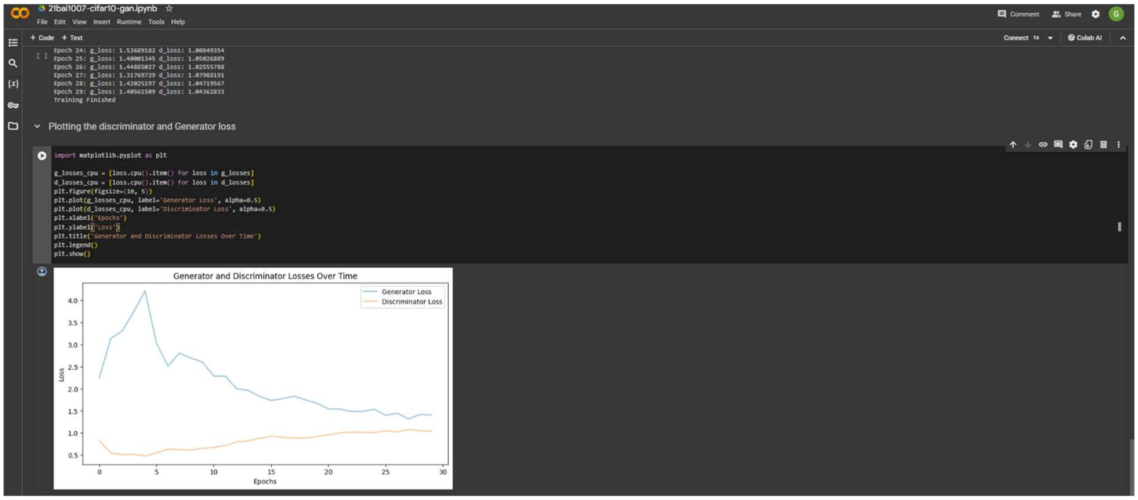
21bai1007-cifar10-gan.ipynb

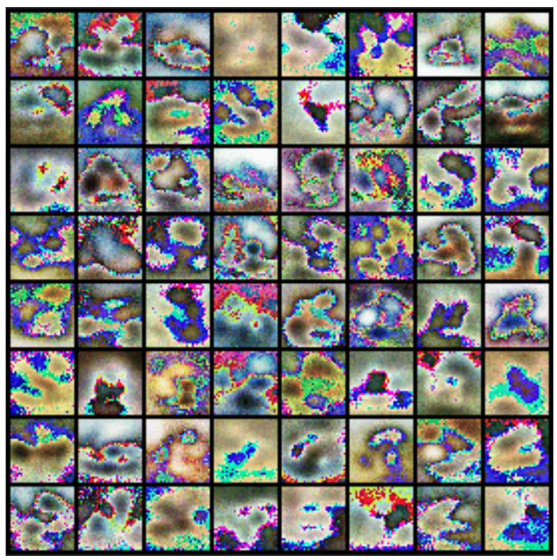
```python
        optimizer.step()

        return error

num_epochs = 30
k = 1
test_noise = noise(64)

generator.train()
discriminator.train()
for epoch in range(num_epochs):
    g_error = 0.0
    d_error = 0.0
    for i, data in enumerate(trainloader):
        imgs, _ = data
        n = len(imgs)
        for j in range(k):
            fake_data = generator(noise(n)).detach()
            real_data = imgs.to(device)
            d_error += train_discriminator(d_optim, real_data, fake_data)
        fake_data = generator(noise(n))
        g_error += train_generator(g_optim, fake_data)

    img = generator(test_noise).cpu().detach()
    img = make_grid(img)
    images.append(img)
    g_losses.append(g_error/i)
    d_losses.append(d_error/i)
    print('Epoch {}: g_loss: {:.8f} d_loss: {:.8f}\r'.format(epoch, g_error/i, d_error/i))

print('Training Finished')
torch.save(generator.state_dict(), 'mnist_generator.pth')

def to_image(tensor):
    """Converts a PyTorch tensor to a PIL Image."""
    return to_pil_image(tensor)

import numpy as np
from matplotlib import pyplot as plt
imgs = [np.array(to_image(i)) for i in images]
imageio.mimsave('progress.gif', imgs)
```

21bai1007-cifar10-gan.ipynb

```python
imageio.mimsave('progress.gif', imgs)
```

```
Epoch 0: g_loss: 2.23442745 d_loss: 0.82479674
Epoch 1: g_loss: 3.13400316 d_loss: 0.55228484
Epoch 2: g_loss: 3.30379939 d_loss: 0.51121032
Epoch 3: g_loss: 3.73324966 d_loss: 0.52094626
Epoch 4: g_loss: 4.21040583 d_loss: 0.47892100
Epoch 5: g_loss: 3.02885246 d_loss: 0.55072361
Epoch 6: g_loss: 2.50914526 d_loss: 0.63632798
Epoch 7: g_loss: 2.80670810 d_loss: 0.62263358
Epoch 8: g_loss: 2.69110155 d_loss: 0.61790401
Epoch 9: g_loss: 2.60561609 d_loss: 0.65220708
Epoch 10: g_loss: 2.28687501 d_loss: 0.67567670
Epoch 11: g_loss: 2.28377676 d_loss: 0.71969235
Epoch 12: g_loss: 1.99844444 d_loss: 0.79921025
Epoch 13: g_loss: 1.96393502 d_loss: 0.82091039
Epoch 14: g_loss: 1.82680023 d_loss: 0.88273793
Epoch 15: g_loss: 1.73634279 d_loss: 0.92560983
Epoch 16: g_loss: 1.77444279 d_loss: 0.90220356
Epoch 17: g_loss: 1.83142126 d_loss: 0.88866836
Epoch 18: g_loss: 1.74795461 d_loss: 0.88514179
Epoch 19: g_loss: 1.67497253 d_loss: 0.91695046
Epoch 20: g_loss: 1.54414332 d_loss: 0.95897782
Epoch 21: g_loss: 1.54042912 d_loss: 1.00502944
Epoch 22: g_loss: 1.48579228 d_loss: 1.01907742
Epoch 23: g_loss: 1.48867989 d_loss: 1.01492870
Epoch 24: g_loss: 1.53689182 d_loss: 1.00849354
Epoch 25: g_loss: 1.40001345 d_loss: 1.05026889
Epoch 26: g_loss: 1.44885027 d_loss: 1.02555788
Epoch 27: g_loss: 1.31769729 d_loss: 1.07988191
Epoch 28: g_loss: 1.42025197 d_loss: 1.04719567
Epoch 29: g_loss: 1.40561509 d_loss: 1.04362833
Training Finished
```





Results

Successfully generated images of MNIST Handwritten digits dataset with a generator loss of 1.49 and discriminator loss of 0.96. The generated image is clear and distinguishable as digits.

For the CIFAR-10 image dataset, Vanilla GAN did not turn out to be effective since only dense layers are being used to generate and discriminate images. The generated image after 30 epochs is pixelated and cannot be recognized as specific images. A DCGAN using convolution layers will be more effective for three dimensional and complex image datasets like CIFAR.