



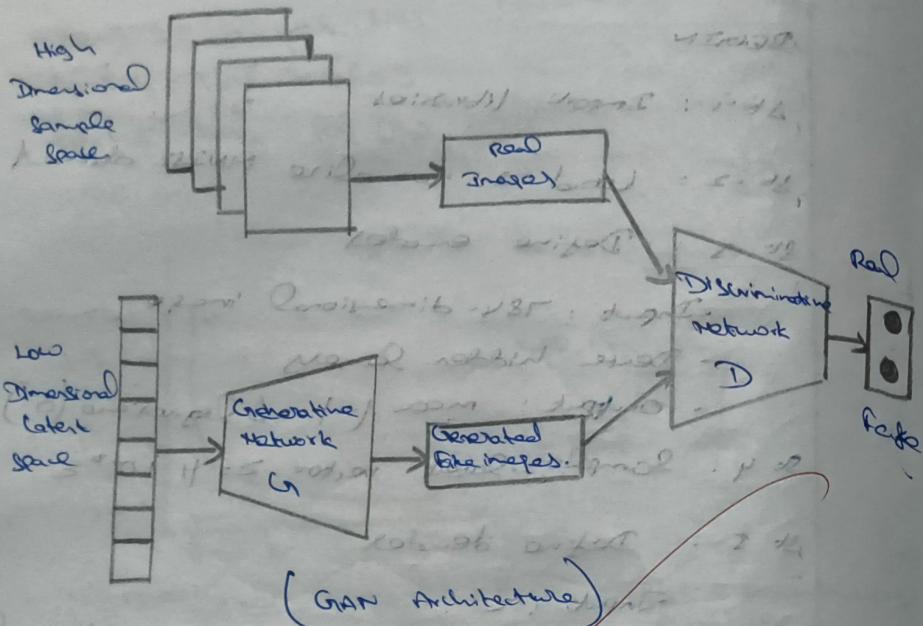
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Name: Vishwan. S
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2	31/7/25	Implement a classifier using open source dataset		
3	7/8/25	Study the classifier with respect to: Statistical parameters.		✓, 100%
4	14/8/25	Build a simple feed forward neural network to Recognize Handwritten characters.		✓, 100% (12/2/25)
5	22/8/25	Study of Activation functions & their role.		✓, 100% (27/9/25)
6	9/9/25	Implement Convolutional Network & Backpropagation in Deep neural Network		✓, 100% (1/10/25)
7	16/9/25	Build a CNN model to classify cat > dog image.		✓, 100% (1/10/25)
8	20/9/25	Build a RNN Network.	8	✓, 100% (30/9)
9	9/10/25	Experiment using LSTM		✓, 100% (30/9)
10	9/10/25	Autoencoder		✓, 100% (30/9)
11	9/10/25	VARIATIONAL Autoencoder		✓, 100% (30/9)
12	17/10/25	Deep convolutional GAN		✓, 100% (30/9)



17/10/25

Implement a Deep convolutional
Lab 12: GAN to generate complex color image

Aim:

To implement a deep convolutional Generative Adversarial Network to generate complex color images from random noise.

Objectives:

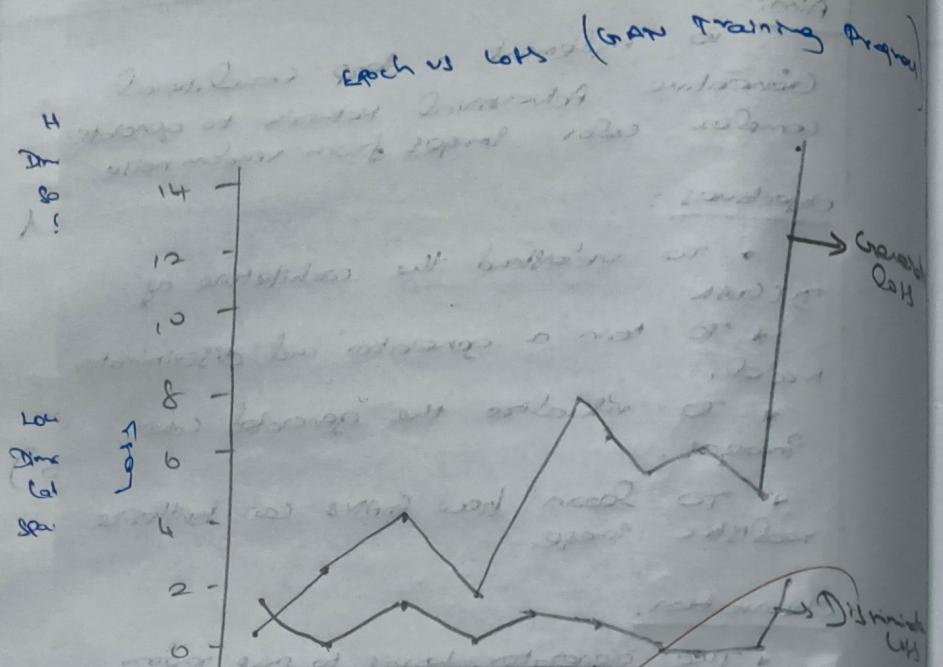
- To understand the architecture of DCGAN.
- To train a generator and discriminator model.
- To visualize the generated color images.
- To learn how GANs can synthesize realistic images.

Observation:

- The generator learns to map random noise vectors into synthetic color images.
- The discriminator learns to distinguish between real and fake images.
- During training, the generator gradually improves its output quality while the discriminator's accuracy decreases, indicating effective learning.

Pseudocode:

- 1) Import necessary libraries
- 2) Load dataset
- 3) Normalize images to $[-1, 1]$
- 4) Define the Generator network:
Transposed Conv layers + Batch Norm + ReLU



Discriminator loss initially decreases as the generator's generated images become more realistic. After a few epochs, the discriminator's loss plateaus, indicating that the generator has learned to produce images that are difficult to distinguish from real ones.

After epoch 5, the generator's loss continues to decrease, while the discriminator's loss remains relatively stable around 0.1, indicating that the generator is successfully generating images that are indistinguishable from real ones.

- 5) Define the Discriminator network:
-conv layers + leaky Relu + Dropout
- 6) Define loss function (Binary Cross Entropy)
- 7) Train the model:
for each epoch:
 - a. Train Discriminator with real ad fake images
 - b. Train Generator to fool discriminator
 - c. Display generated images every few epochs.
- 8) Save the final generated color images

Output:

Epoch 1	D loss: 0.7148	G loss: 2.9591
Epoch 2	D loss: 0.5373	G loss: 3.1537
Epoch 3	D loss: 0.6066	G loss: 1.5696
Epoch 4	D loss: 0.6092	G loss: 2.1970
Epoch 5	D loss: 0.7699	G loss: 1.9037
Epoch 6	D loss: 0.3328	G loss: 7.1927
Epoch 7	D loss: 0.1849	G loss: 5.0234
Epoch 8	D loss: 0.5666	G loss: 04.7413
Epoch 9	D loss: 0.0875	G loss: 6.0503
Epoch 10	D loss: 0.0141	G loss: 5.8257

Result:

~~By~~ Successfully implemented the GAN to generate the color image.

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pip install torch torchvision matplotlib

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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")
```

```
# 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)

# 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)
```

dtlab12.ipynb

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```
# 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)
        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()
```

dltlab12.ipynb

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```

print(f"Epoch [{epoch+1}/{epochs}] D Loss: {d_loss}, 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)
utils.save_image(fake_imgs, 'fake_imgs.png', normalize=True)
plt.figure(figsize=(8,5))
plt.axis('off')
plt.title("Generated Images")
plt.imshow(np.transpose(utils.make_grid(fake_imgs[:64], padding=2, normalize=True).cpu(), (1,2,0)))
plt.show()

```

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Epoch	D Loss	G Loss
1/10	1.0022	0.0078
2/10	0.5000	0.0000
3/10	0.4031	3.4827
4/10	0.2026	7.7124
5/10	0.1013	2.0824
6/10	0.1026	1.3480
7/10	0.0081	6.7625
8/10	0.0052	4.5718
9/10	0.0045	6.3371
10/10	0.1280	4.7327
Epoch [10/10]	2.3251	24.8363

Epoch vs Loss (GAN Training Progress)

Epoch	Discriminator Loss	Generator Loss
1	1.0022	0.0078
2	0.5000	0.0000
3	0.4031	3.4827
4	0.2026	7.7124
5	0.1013	2.0824
6	0.1026	1.3480
7	0.0081	6.7625
8	0.0052	4.5718
9	0.0045	6.3371
10	2.3251	14.0000

Generated Images

Variables Terminal