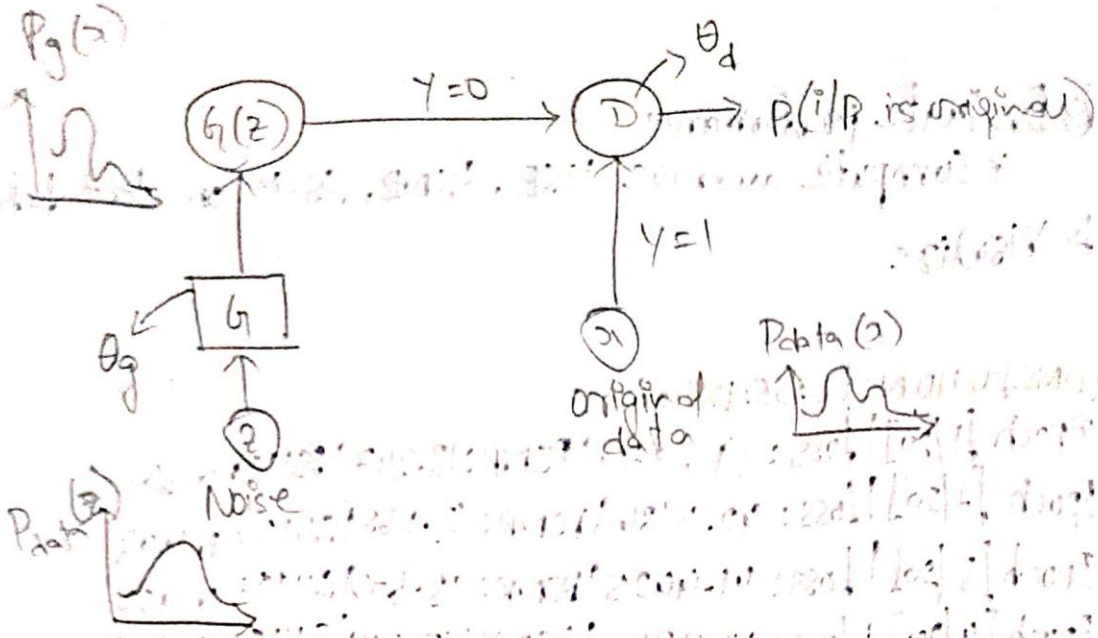


$$\min_G \max_D V(G,D) = \mathbb{E}_{x\sim P_{data}}[\ln(D(x))] + \mathbb{E}_{x\sim P_z}[\ln(1-D(G(z)))]$$

$$V(G,D) \text{ max if } \frac{P_{data}(D)}{P_{data}(x)+P_g(x)}$$

$$\min_G V = \mathbb{E}_{x\sim P_{data}} \ln\left(\frac{P_{data}(D)}{P_{data}(x)+P_g(x)}\right) + \mathbb{E}_{x\sim P_g}\left(1 - \frac{P_{data}(D)}{P_{data}(x)+P_g(x)}\right)$$

Jensan-Shannon divergence

$$JS(P_1\|P_2)\ \frac{1}{2}\mathbb{E}_{x\sim p_1}\ln\left(\frac{P_1}{\frac{P_1+P_2}{2}}\right) + \frac{1}{2}\mathbb{E}_{x\sim P_2}\left(\frac{P_2}{\frac{P_1+P_2}{2}}\right)$$

$$\min_G V = 2JS(P_{data}\|P_g) - 2\log 2$$

~~When will~~ $JS(P_{data}\|P_g) = 0$

if $P_{data} = P_g \approx$ Goal

if that's the case.

$$\min_G V = -2\log 2$$

Exp. 12

IMPLEMENT A DEEP CONVOLUTIONAL GAN TO GENERATE COMPLEX COLOUR IMAGES

AIM

To Implement and train Deep Convolutional Generative Adversarial Network (DCGAN) to generate relistic Color images resembling the CIFAR-10 Dataset.

OBJECTIVE:

* Understand the GAN architecture : Generator Discrimina
* Implement a DCGAN using convolutional layers for image generation.
* Train the GAN on the CIFAR-10 dataset (colour images, 32×3 pixels, 10 classes
* Visualize loss curves and generated images during training
* Evaluate generator performance through visual inspection and sample image grids.

PSEUDOCODE

↳ Import necessary libraries

↳ Prepare CIFAR-10 dataset

 * Resize images to 64×64 for DCGAN

 * Normalize images to [-1, 1]

↳ Define the Generator network

 Input : random latent vector z

 - Use ConvTranspose 2d + BatchNorm + ReLU Layers.

 Output : 3×64×64 RGB image (Tanh activation)

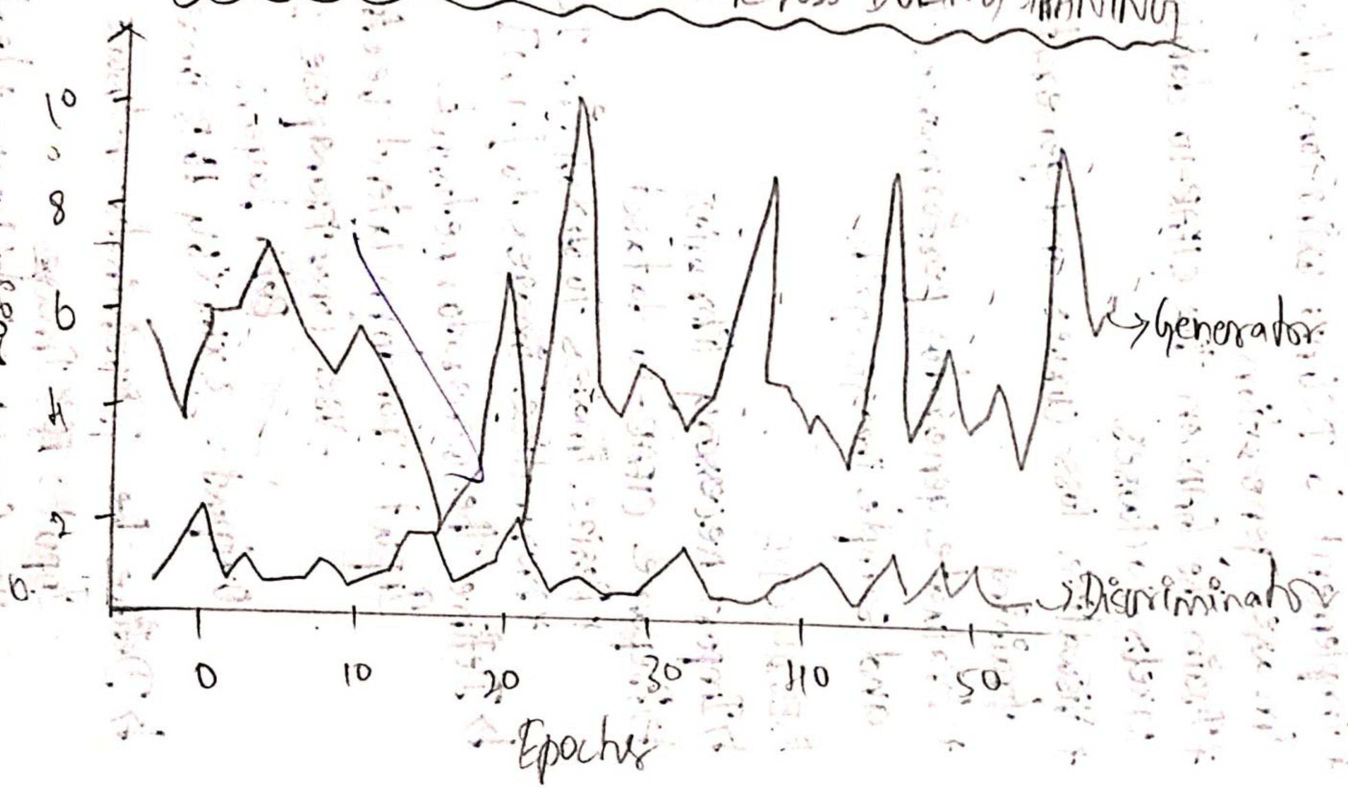
↳ Define the Discriminator network

 - Input : RGB Image.

 - Use Conv2d + BatchNorm + LeakyReLU layers.

 - Output : 3×64×64 RGB Image (Tanh activation)

GENERATOR AND DISCRIMINATOR LOSS DURING TRAINING



↳ Training loop : for each epoch train
↳ Visualize :

OBSERVATION :

Epoch 1/50 | D loss : 0.8317 | G loss : 5.2526
Epoch 2/50 | D loss : 0.6497 | G loss : 3.2739
Epoch 3/50 | D loss : 1.7764 | G loss : 5.9727
Epoch 4/50 | D loss : 0.1891 | G loss : 5.9591
Epoch 5/50 | D loss : 0.5729 | G loss : 7.0114.
⋮

Epoch 49/50 | D loss : 0.0240 | G loss : 5.6246
Epoch 50/50 | D loss : 0.0264 | G loss : 5.6373.

RESULT:

We have Implemented Deep convolutional GAN sucessfully for Multicolour Images.

LAB_12

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Lab 12: DCGAN on CIFAR-10 via KaggleHub

```python
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms, utils
import matplotlib.pyplot as plt
import numpy as np
from tqdm import tqdm
import kagglehub
import os
```

Device setup

```python
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Device:", device)
```

```
Device: cuda
```

Download CIFAR-10 Dataset from KaggleHub


```
Device: cuda
```

Download CIFAR-10 Dataset from KaggleHub


```python
import torchvision.transforms as transforms
import torchvision.datasets as datasets
from torch.utils.data import DataLoader

transform = transforms.Compose([
    transforms.Resize(64),            # For DCGAN input
    transforms.CenterCrop(64),
    transforms.ToTensor(),
    transforms.Normalize([0.5]*3, [0.5]*3)
])

train_dataset = datasets.CIFAR10(root='~/.keras/datasets', train=True, download=True, transform=transform)
train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True, num_workers=2)

print("✅ CIFAR-10 PyTorch DataLoader ready.")
print("Number of training samples:", len(train_dataset))
```

```
100%|██████████| 170M/170M [00:04<00:00, 42.2MB/s]
✅ CIFAR-10 PyTorch DataLoader ready.
Number of training samples: 50000
```

Define Generator

Number of training samples: 50000

Define Generator

```
class Generator(nn.Module):
    def __init__(self, latent_dim=100):
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.ConvTranspose2d(latent_dim, 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, z):
```

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, img):
        return self.model(img)
```

Initialize models, loss, and optimizers

```
latent_dim = 100
generator = Generator(latent_dim).to(device)
discriminator = Discriminator().to(device)

criterion = nn.BCELoss()
optimizer_G = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.999))
optimizer_D = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5, 0.999))
```

Training Loop

```
epochs = 50
fixed_noise = torch.randn(64, latent_dim, 1, 1, device=device)
G_losses, D_losses = [], []

for epoch in range(epochs):
    for imgs, _ in tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs}"):
        real_imgs = imgs.to(device)
        batch_size = real_imgs.size(0)

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

        # --- Train Discriminator ---
```

Training Loop

```
epochs = 50
fixed_noise = torch.randn(64, latent_dim, 1, 1, device=device)
G_losses, D_losses = [], []

for epoch in range(epochs):
    for imgs, _ in tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs}"):
        real_imgs = imgs.to(device)
        batch_size = real_imgs.size(0)

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

        # --- Train Discriminator ---
```

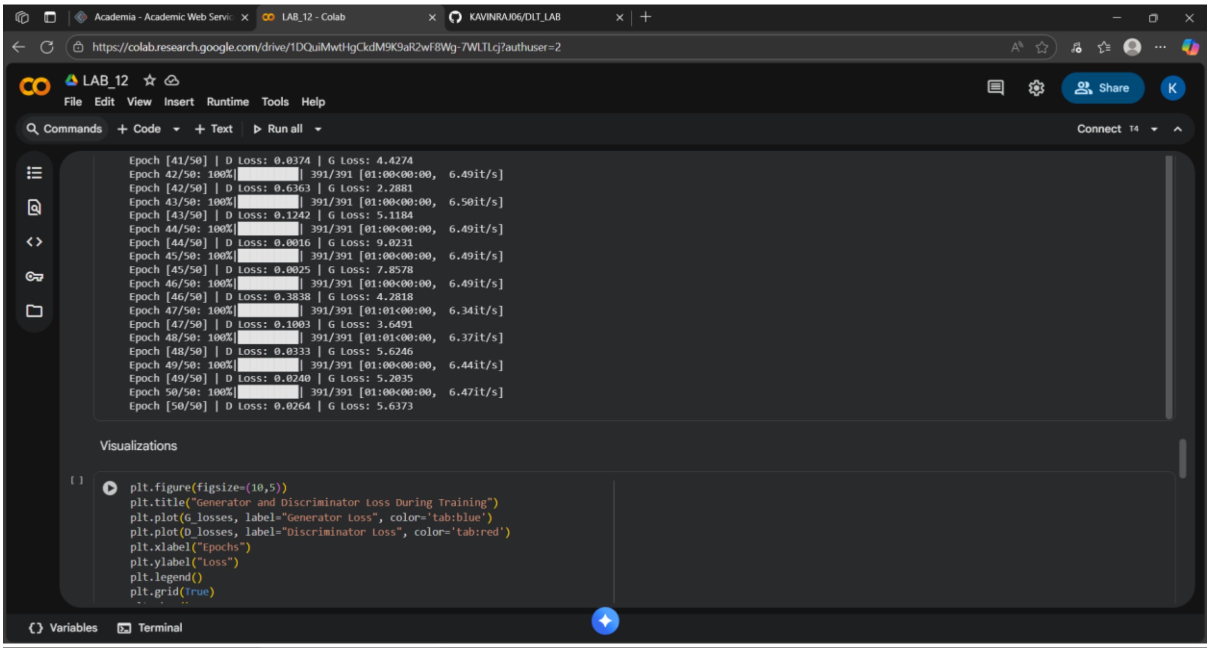

```
        z = torch.randn(batch_size, latent_dim, 1, 1, device=device)
        fake_imgs = generator(z)

        real_loss = criterion(discriminator(real_imgs), real_labels)
        fake_loss = criterion(discriminator(fake_imgs.detach()), fake_labels)
        D_loss = real_loss + fake_loss

        optimizer_D.zero_grad()
        D_loss.backward()
        optimizer_D.step()

        # --- Train Generator ---
        G_loss = criterion(discriminator(fake_imgs), real_labels)
```

```python
        # --- Train Generator ---
        G_loss = criterion(discriminator(fake_imgs), real_labels)
        optimizer_G.zero_grad()
        G_loss.backward()
        optimizer_G.step()

    G_losses.append(G_loss.item())
    D_losses.append(D_loss.item())

    print(f"Epoch [{epoch+1}/{epochs}] | D Loss: {D_loss.item():.4f} | G Loss: {G_loss.item():.4f}")

    # Save generated images every 10 epochs
    if (epoch + 1) % 10 == 0:
        with torch.no_grad():
            fake = generator(fixed_noise).detach().cpu()
        utils.save_image(fake, f"generated_epoch_{epoch+1}.png", normalize=True, nrow=8)
```

```
Epoch 1/50: 100%|██████████| 391/391 [00:56<00:00,  6.92it/s]
Epoch [1/50] | D Loss: 0.3317 | G Loss: 5.2526
Epoch 2/50: 100%|██████████| 391/391 [00:59<00:00,  6.61it/s]
Epoch [2/50] | D Loss: 0.6499 | G Loss: 3.2739
Epoch 3/50: 100%|██████████| 391/391 [01:02<00:00,  6.29it/s]
Epoch [3/50] | D Loss: 1.7764 | G Loss: 5.9727
Epoch 4/50: 100%|██████████| 391/391 [01:01<00:00,  6.36it/s]
Epoch [4/50] | D Loss: 0.1891 | G Loss: 5.9591
Epoch 5/50: 100%|██████████| 391/391 [01:01<00:00,  6.36it/s]
Epoch [5/50] | D Loss: 0.5739 | G Loss: 7.0114
Epoch 6/50: 100%|██████████| 391/391 [01:01<00:00,  6.34it/s]
Epoch [6/50] | D Loss: 0.0195 | G Loss: 5.3233
Epoch 7/50: 100%|██████████| 391/391 [01:01<00:00,  6.32it/s]
```

```python
        utils.save_image(fake, f"generated_epoch_{epoch+1}.png", normalize=True, nrow=8)
```

```
Epoch [10/50] | D Loss: 0.3229 | G Loss: 3.6671
Epoch 11/50: 100%|██████████| 391/391 [01:01<00:00,  6.34it/s]
Epoch [11/50] | D Loss: 0.0601 | G Loss: 4.5126
Epoch 12/50: 100%|██████████| 391/391 [01:01<00:00,  6.33it/s]
Epoch [12/50] | D Loss: 0.3105 | G Loss: 2.8844
Epoch 13/50: 100%|██████████| 391/391 [01:01<00:00,  6.33it/s]
Epoch [13/50] | D Loss: 0.6866 | G Loss: 0.6030
Epoch 14/50: 100%|██████████| 391/391 [01:01<00:00,  6.33it/s]
Epoch [14/50] | D Loss: 0.5665 | G Loss: 2.1178
Epoch 15/50: 100%|██████████| 391/391 [01:01<00:00,  6.34it/s]
Epoch [15/50] | D Loss: 0.0081 | G Loss: 6.2439
Epoch 16/50: 100%|██████████| 391/391 [01:01<00:00,  6.33it/s]
Epoch [16/50] | D Loss: 0.1634 | G Loss: 3.9746
Epoch 17/50: 100%|██████████| 391/391 [01:01<00:00,  6.34it/s]
Epoch [17/50] | D Loss: 1.0819 | G Loss: 1.1342
Epoch 18/50: 100%|██████████| 391/391 [01:01<00:00,  6.34it/s]
Epoch [18/50] | D Loss: 0.0707 | G Loss: 5.1831
Epoch 19/50: 100%|██████████| 391/391 [01:01<00:00,  6.32it/s]
Epoch [19/50] | D Loss: 0.0091 | G Loss: 10.3721
Epoch 20/50: 100%|██████████| 391/391 [01:01<00:00,  6.33it/s]
Epoch [20/50] | D Loss: 0.1215 | G Loss: 3.9262
Epoch 21/50: 100%|██████████| 391/391 [01:01<00:00,  6.35it/s]
Epoch [21/50] | D Loss: 0.1854 | G Loss: 3.4378
Epoch 22/50: 100%|██████████| 391/391 [01:00<00:00,  6.45it/s]
Epoch [22/50] | D Loss: 0.0475 | G Loss: 4.6454
Epoch 23/50: 100%|██████████| 391/391 [01:00<00:00,  6.48it/s]
Epoch [23/50] | D Loss: 0.0428 | G Loss: 4.1088
Epoch 24/50: 100%|██████████| 391/391 [01:00<00:00,  6.48it/s]
Epoch [24/50] | D Loss: 0.6810 | G Loss: 3.2551
Epoch 25/50: 100%|██████████| 391/391 [01:00<00:00,  6.48it/s]
```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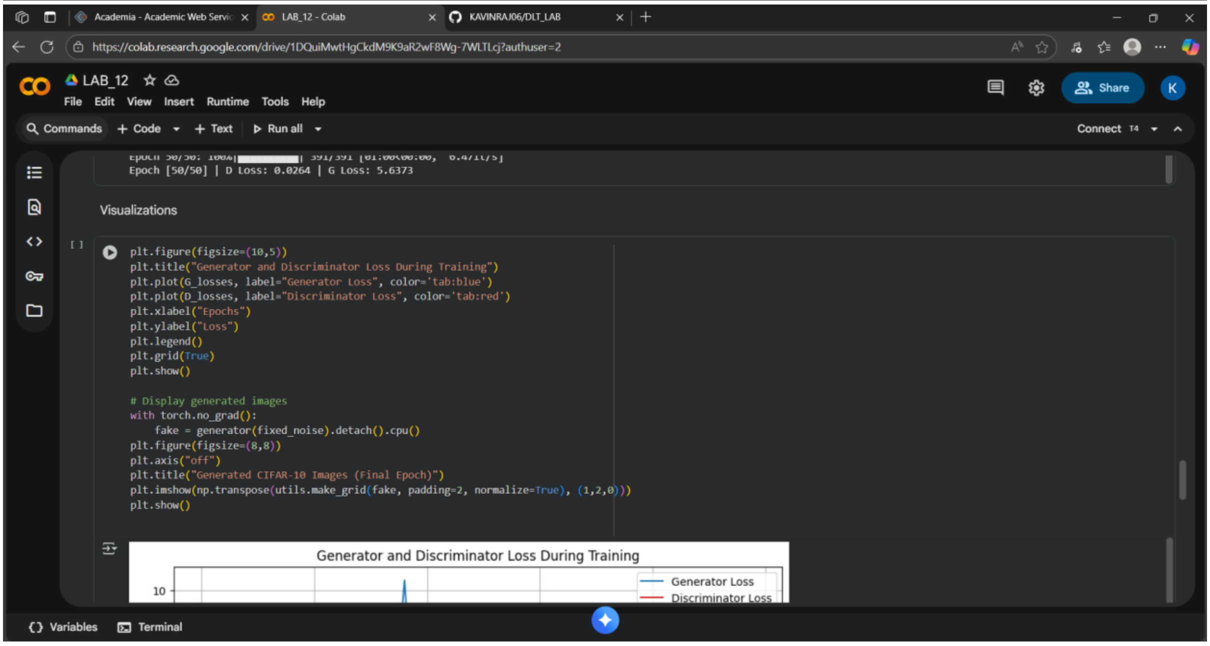
Epoch [41/50] | D Loss: 0.0374 | G Loss: 4.4274
Epoch 42/50: 100%| 391/391 [01:00<00:00, 6.49it/s]
Epoch [42/50] | D Loss: 0.6363 | G Loss: 2.2881
Epoch 43/50: 100%| 391/391 [01:00<00:00, 6.50it/s]
Epoch [43/50] | D Loss: 0.1242 | G Loss: 5.1184
Epoch 44/50: 100%| 391/391 [01:00<00:00, 6.49it/s]
Epoch [44/50] | D Loss: 0.0016 | G Loss: 9.0231
Epoch 45/50: 100%| 391/391 [01:00<00:00, 6.49it/s]
Epoch [45/50] | D Loss: 0.0025 | G Loss: 7.8578
Epoch 46/50: 100%| 391/391 [01:00<00:00, 6.49it/s]
Epoch [46/50] | D Loss: 0.3838 | G Loss: 4.2818
Epoch 47/50: 100%| 391/391 [01:01<00:00, 6.34it/s]
Epoch [47/50] | D Loss: 0.1003 | G Loss: 3.6491
Epoch 48/50: 100%| 391/391 [01:01<00:00, 6.37it/s]
Epoch [48/50] | D Loss: 0.0333 | G Loss: 5.6246
Epoch 49/50: 100%| 391/391 [01:00<00:00, 6.44it/s]
Epoch [49/50] | D Loss: 0.0240 | G Loss: 5.2035
Epoch 50/50: 100%| 391/391 [01:00<00:00, 6.47it/s]
Epoch [50/50] | D Loss: 0.0264 | G Loss: 5.6373
Visualizations
plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(G_losses, label="Generator Loss", color='tab:blue')
plt.plot(D_losses, label="Discriminator Loss", color='tab:red')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
Variables
Terminal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KAVINRAJ06/DLT_LAB
https://colab.research.google.com/drive/1DQuiMwtHgCkdM9K9aR2wF8Wg-7WLTLcj?authuser=2
LAB_12
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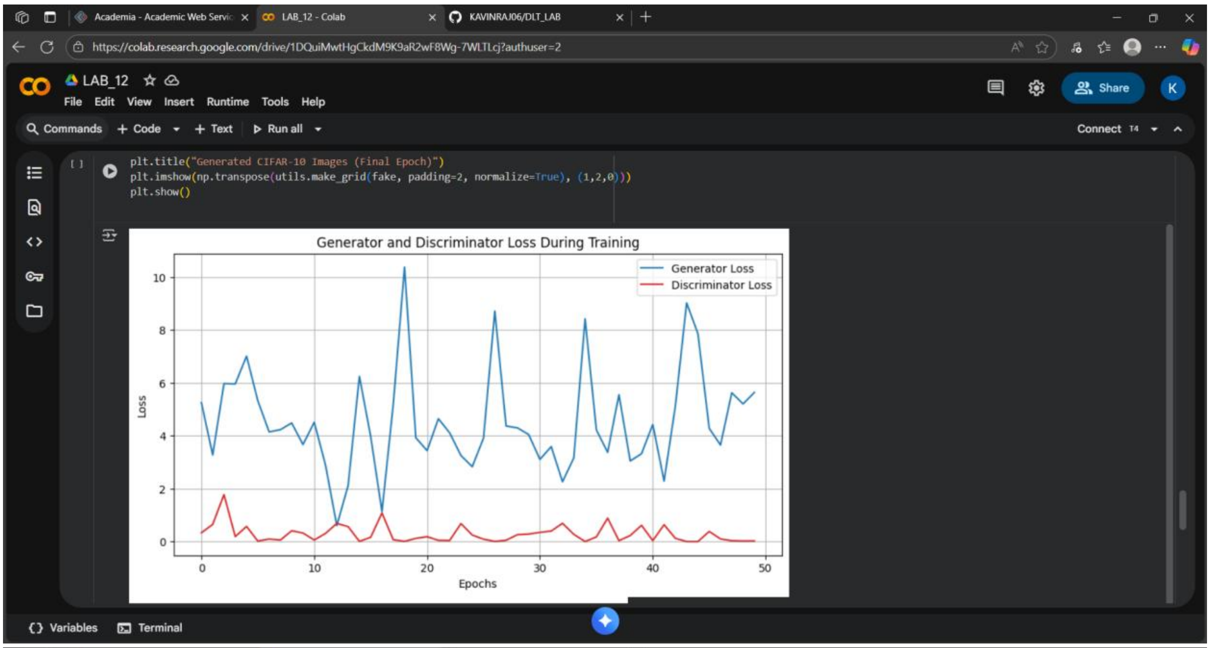
Connect
Epoch [50/50] | D Loss: 0.0264 | G Loss: 5.6373
Visualizations
plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(G_losses, label="Generator Loss", color='tab:blue')
plt.plot(D_losses, label="Discriminator Loss", color='tab:red')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
# Display generated images
with torch.no_grad():
fake = generator(fixed_noise).detach().cpu()
plt.figure(figsize=(8,8))
plt.axis("off")
plt.title("Generated CIFAR-10 Images (Final Epoch)")
plt.imshow(np.transpose(utils.make_grid(fake, padding=2, normalize=True), (1,2,0)))
plt.show()
Generator and Discriminator Loss During Training
10
Generator Loss
Discriminator Loss
Variables
Terminal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https://colab.research.google.com/drive/1DQuiMwtHgCkdM9K9aR2wF8Wg-7WLTLcj?authuser=2
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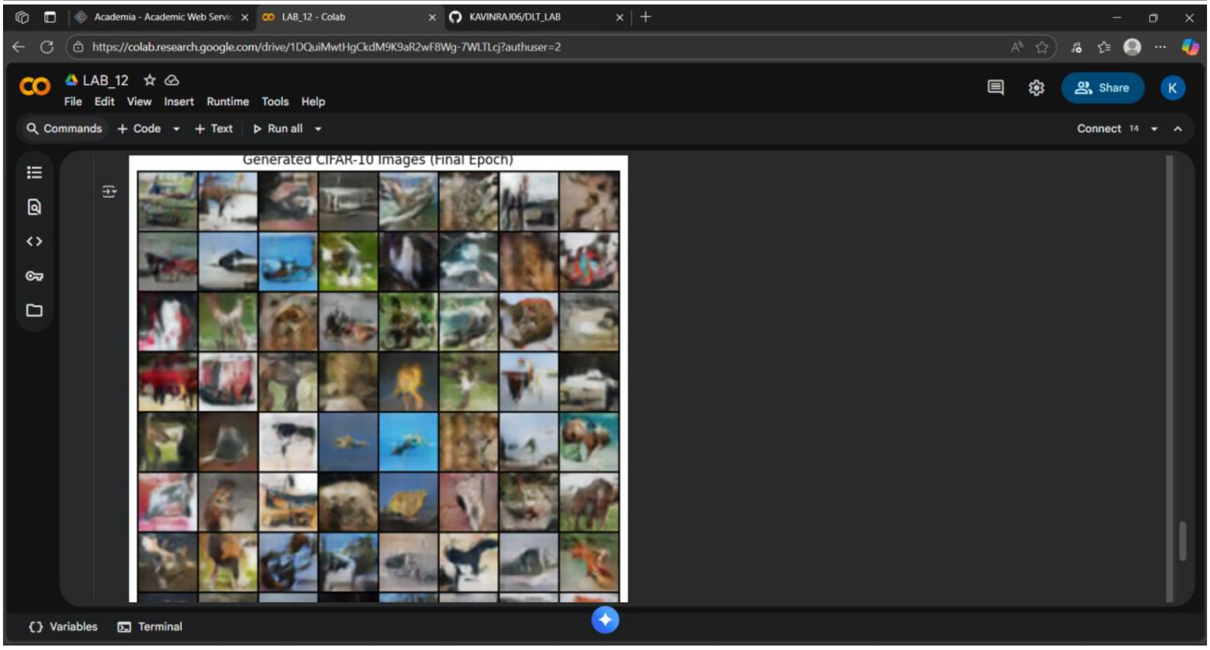
Connect
plt.title("Generated CIFAR-10 Images (Final Epoch)")
plt.imshow(np.transpose(utils.make_grid(fake, padding=2, normalize=True), (1,2,0)))
plt.show()
Generator and Discriminator Loss During Training
Generator Loss
Discriminator Loss
Loss
Epochs
Variables
Terminal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https://colab.research.google.com/drive/1DQuiMwtHgCkdM9K9aR2wF8Wg-7WLTLcj?authuser=2
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Generated CIFAR-10 Images (Final Epoch)
Variables
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