

12 Implement a Deep convolutional GAN to generate complex color image

### Aim:

Train a Deep convolutional Generative Adversarial network to generate high quality, realistic color images by learning the distribution of a dataset of color images

### Algorithm:

- \* prepare dataset, load and preprocess images.
- \* Define models:
  - Generator: transposed convolutional network that upsamples a latent vector
  - Discriminator: convolutional network that down samples the image to scalar logit.
- \* Initialize weights.
- \* Training loop,

Update D: Maximize  $\log(D(x)) + \log(1 - D(G(z)))$

Using BCE loss

Train on a batch of real images

Train on a batch of fake images produced by  $G(z)$

Update G: minimize BCE with logits loss ( $D(G(z))$ ), 1

- \* Logging & checkpoints: save samples periodically and checkpoint models weights per epoch.

## Pseudo code:

SET hyperparameters (nz, ngs, ndf, nc, image-size, (r, beta1, batch-size, epochs)

Prepare dataset with transforms:

Resize (image-size), CenterCrop, ToTensor(),  
Normalize ( $0.5^3$ ,  $(0.5)^3$ )

Create Data loader (dataset, batch-size, shuffle=True)

Define Generator G:

Input:  $z(nz \times 1 \times 1)$

sequence of convTranspose2d layers to upsample  
to image-size

BatchNorm2d + ReLU between layers

Final layer: convTranspose2d  $\rightarrow$  Tanh  $\rightarrow$  output  
image ( $nc \times H \times w$ )

Define Discriminator D:

Input: image ( $nc \times H \times w$ )

Sequence of conv2d layers to downsample to  
 $4 \times 4$

BatchNorm2d + leaky ReLU between layers

Final layer: conv2d  $\rightarrow$  output logit

Flatten logit to shape (batch,)

Initialize weights (normal, mean=0, std=0.02)

Set optimizers: Adam (G.Parameters(), (r, betas=  
(beta1, 0.999))

fixed\_noise = random tensor (sample-size, nz, 1, 1)

```

for epoch in range(1..epochs):
    For each batch real-images in dataloader:
        # 1. update D
        D.zero_grad()
        labels_real = ones(batch-size)
        output_real = D(realimages)
        loss_real = BCE with logits loss (output_real, labels_real)
        loss_real.backward()
        noise = random normal (batch_size, nz, 1, 1)
        fake_images = G(noise)
        labels_fake = zeros(batch-size)
        output_fake = D(fake_images.detach())
        loss_fake.backward()
        optimizerD.step()

```

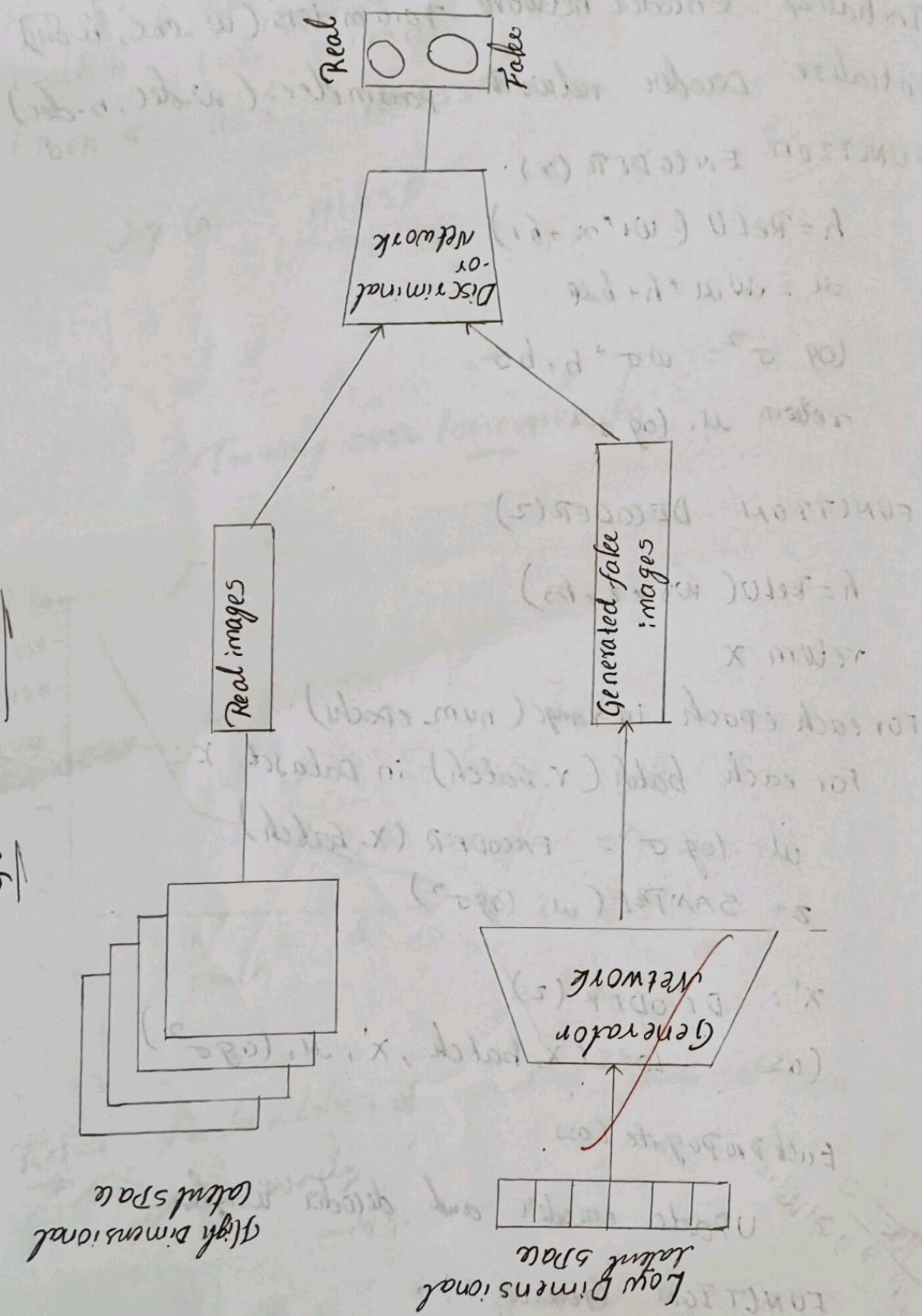
### Observation:

- \* The generator gradually learned to produce realistic color images
- \* The discriminator improved in distinguishing real and fake images
- \* Generator images were visually similar to the training dataset after sufficient epochs

### Result:

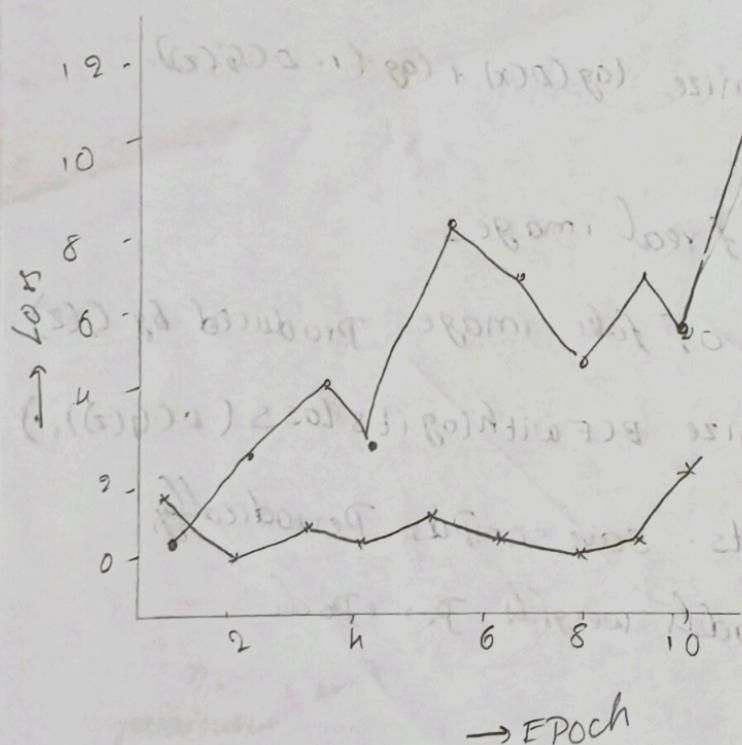
The DCGAN successfully generated realistic looking color images, proving the effectiveness of Adversarial learning.

## GAN Architecture



outPut:  
 EPOCH [1/10] DLoss : 1.0992 , GLoss : 0.5678  
 EPOCH [2/10] DLoss : 0.506 , GLoss : 2.7113  
 EPOCH [3/10] DLoss : 1.2431 , GLoss : 3.9827  
 EPOCH [4/10] DLoss : 0.4224 , GLoss : 2.2604

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 EPOCH [8/10] DLoss : 0.0043 GLoss : 6.3371  
 EPOCH [9/10] DLoss : 0.1380 , GLoss : 4.73  
 EPOCH [10/10] DLoss : 2.3294 GLoss : 1.403



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▶ # ✓ Lab 12 (Fast Version): DCGAN to Generate Color Images (CIFAR-10)
import tensorflow as tf
from tensorflow.keras import layers
import matplotlib.pyplot as plt
import numpy as np
import time

# 1 Load & Preprocess CIFAR-10 (subset for speed)
(x_train, _), (_, _) = tf.keras.datasets.cifar10.load_data()
x_train = (x_train.astype("float32") - 127.5) / 127.5 # normalize to [-1,1]
x_train = x_train[:5000] # only 5k images for faster training

BUFFER_SIZE = 5000
BATCH_SIZE = 32
train_dataset = tf.data.Dataset.from_tensor_slices(x_train).shuffle(BUFFER_SIZE).batch(BATCH_SIZE)

# 2 Generator
def build_generator():
    model = tf.keras.Sequential([
        layers.Input(shape=(100,)),
        layers.Dense(8*8*128, use_bias=False),
        layers.BatchNormalization(),
        layers.LeakyReLU(),
        layers.Reshape((8, 8, 128)),
        layers.Conv2DTranspose(64, (5,5), strides=(2,2), padding="same", use_bias=False),
        layers.BatchNormalization(),
        layers.LeakyReLU(),
        layers.Conv2DTranspose(32, (5,5), strides=(2,2), padding="same", use_bias=False),
        layers.BatchNormalization(),
        layers.LeakyReLU(),
        layers.Conv2DTranspose(3, (5,5), strides=(2,2), padding="same", use_bias=False),
        layers.LeakyReLU(),
        layers.Flatten(),
        layers.Dense(3)
    ])
    return model

# 3 Discriminator
def build_discriminator():
    model = tf.keras.Sequential([
        layers.Input(shape=(32, 32, 3)),
        layers.Conv2D(64, (5,5), strides=(2,2), padding="same"),
        layers.LeakyReLU(),
        layers.Dropout(0.3),
        layers.Conv2D(128, (5,5), strides=(2,2), padding="same"),
        layers.LeakyReLU(),
        layers.Dropout(0.3),
        layers.Flatten(),
        layers.Dense(1)
    ])
    return model

generator = build_generator()
discriminator = build_discriminator()

# 4 Loss + Optimizers
cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)
gen_optimizer = tf.keras.optimizers.Adam(1e-4)
disc_optimizer = tf.keras.optimizers.Adam(1e-4)

@tf.function
def train_step(images):
    noise = tf.random.normal([BATCH_SIZE, 100])
    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        generated_images = generator(noise, training=True)

```

```

▶ # 5 Training (Quick Version)
EPOCHS = 2
seed = tf.random.normal([16, 100])
gen_losses, disc_losses = [], []

for epoch in range(EPOCHS):
    start = time.time()
    for image_batch in train_dataset.take(100): # only 100 batches for speed
        g_loss, d_loss = train_step(image_batch)
    gen_losses.append(g_loss.numpy())
    disc_losses.append(d_loss.numpy())

    print(f"Epoch {epoch+1}/{EPOCHS} | Gen Loss: {g_loss:.4f} | Disc Loss: {d_loss:.4f} | Time: {time.time()-start:.2f}s")

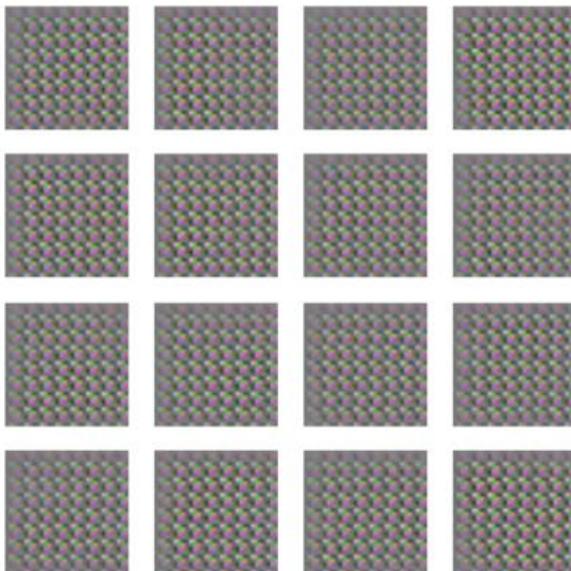
# Show generated samples
predictions = generator(seed, training=False)
fig = plt.figure(figsize=(4, 4))
for i in range(predictions.shape[0]):
    plt.subplot(4, 4, i + 1)
    plt.imshow((predictions[i] * 0.5 + 0.5))
    plt.axis("off")
plt.suptitle("Generated Images - Epoch {epoch+1}")
plt.show()

# 6 Plot Loss Graph
plt.figure(figsize=(7,5))
plt.plot(gen_losses, label="Generator Loss")
plt.plot(disc_losses, label="Discriminator Loss")

```

... Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>  
**170498071/170498071** ————— 5s 0us/step  
 Epoch 1/2 | Gen Loss: 2.1477 | Disc Loss: 0.3164 | Time: 6.95s

Generated Images - Epoch 1



Epoch 2/2 | Gen Loss: 1.8096 | Disc Loss: 0.2626 | Time: 0.75s

Generated Images - Epoch 2

Generated Images - Epoch 2

