

# WEEK - 12

## Aim :-

To implement a deep convolutional Generative Adversarial Network (DGAN) of generating complex RGB color image that resemble real-world images.

## Objective :-

- 1.) To understand the working of Generative Adversarial Network (GAN's).
- 2.) To use convolutional layers for image generation and discrimination.
- 3.) To train the generator to produce realistic image and the discriminator to distinguish real from fake.
- 4.) To evaluate the quality of generated images visually after training.

## Pseudo code :-

Begin

    load dataset of real color images

    → Resize and normalize images to  $(-1, 1)$

    define Generator network ( $G$ ):

        Input: random noise vector ( $z$ )

        layers: series of conv transpose 2D + Batch Norm + ReLU

        output: RGB image

    define Discriminator network ( $D$ ):

        Input: RGB image

        layers: series of conv 2D + Batch Norm + Leaky ReLU

        output: single probability.

    Set loss function = binary cross entropy

    Set optimizer = Adam ( $\alpha = 0.0002$ ,  $B_1 = 0.5$ )

    For each epoch:

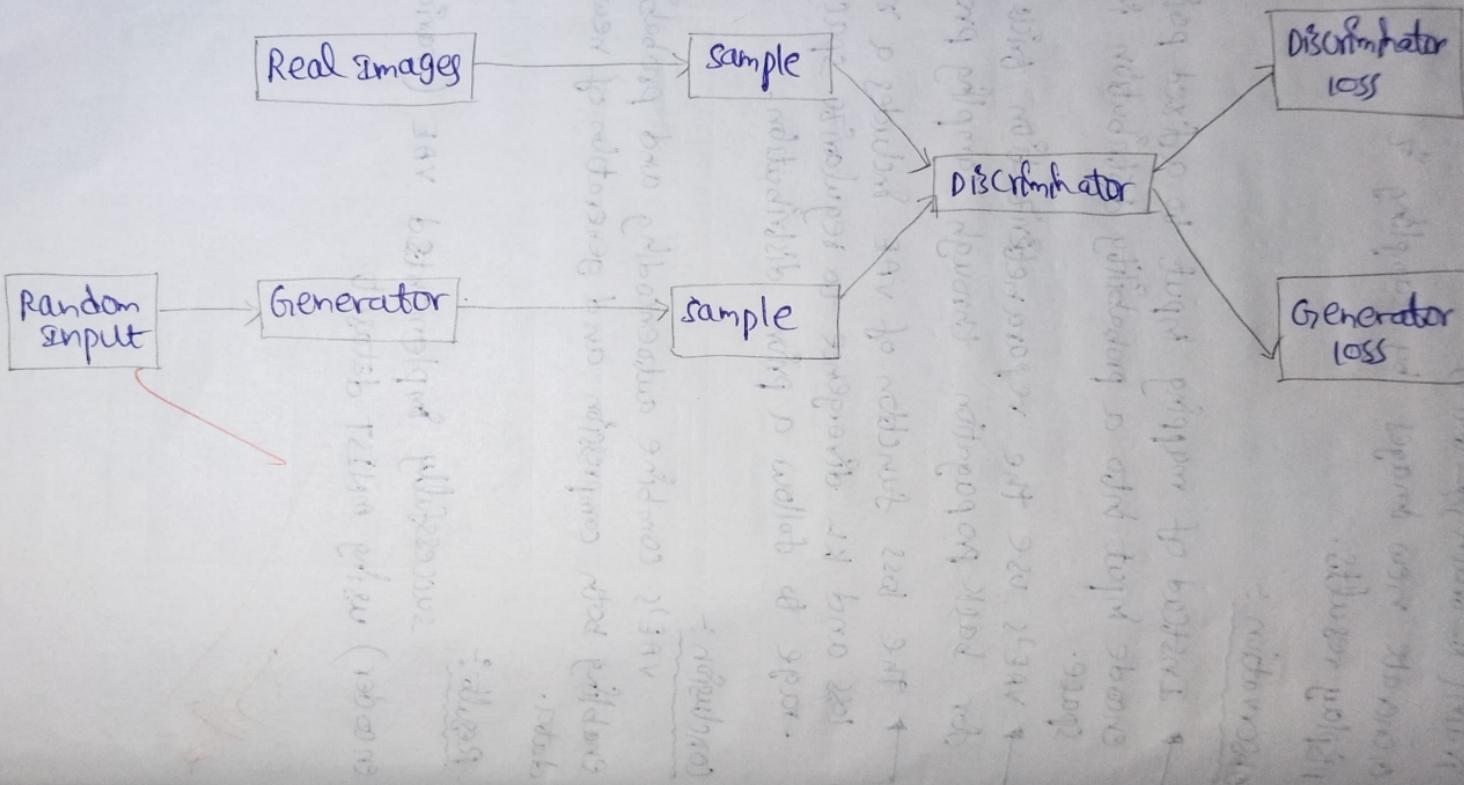
        Train discriminator

        Train generator

    Repeat until generator produces realistic color images

END

## Architecture of GAN



### Algorithm :-

- 1.) Load a color image dataset
- 2.) Normalize pixel values to  $[-1, 1]$ .
- 3.) Define generator using conv 2D transpose layers.
- 4.) Define Discriminator using conv 2D layers.
- 5.) Combine both to form DCGAN.
- 6.) Train using adversarial loss - generator tries to fool discriminator.
- 7.) periodically generate and display fake images.

### Observation :-

- The generator gradually learned to produce realistic color images.
- The discriminator ~~process~~ improved in distinguishing real and fake images.
- Generated images were visually similar to the training dataset after sufficient epochs.
- Training demonstrated the adversarial learning process of GAN effectively.

### Result :-

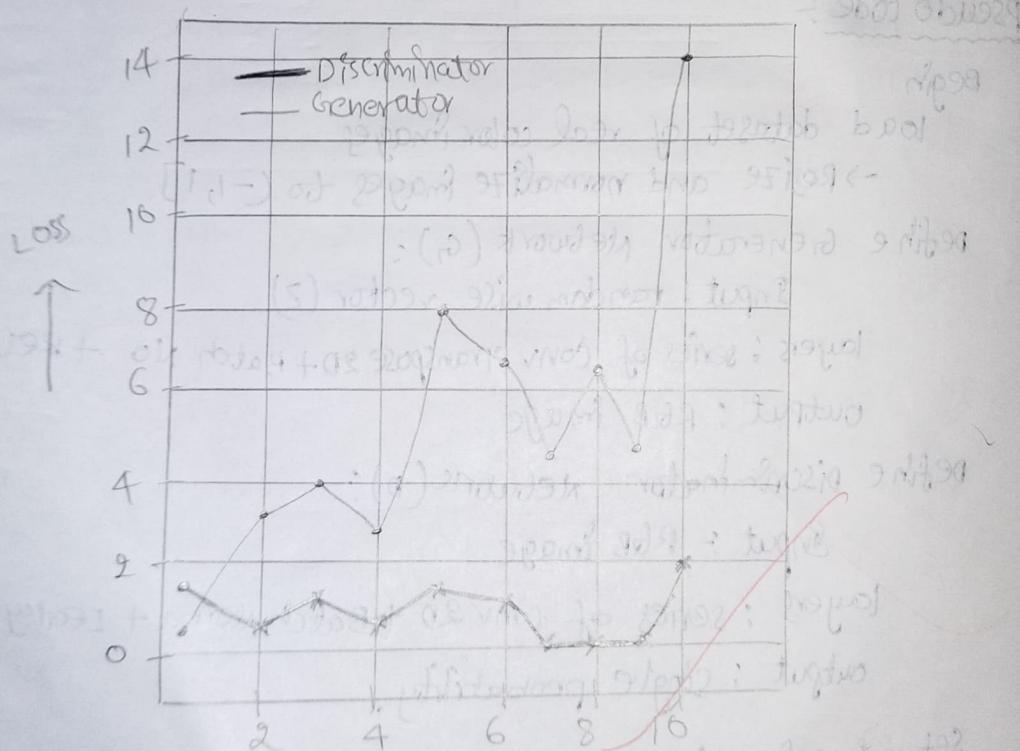
The DCGAN successfully generated realistic-looking color images, proving the effectiveness of adversarial learning.

~~Q11~~

Output:

Epoch [1/10] D LOSS : 1.0992, G LOSS : 0.5538  
Epoch [2/10] D LOSS : 0.5060, G LOSS : 2.7113  
Epoch [3/10] D LOSS : 1.2431, G LOSS : 3.9827  
Epoch [4/10] D LOSS : 0.4229, G LOSS : 2.2684  
Epoch [5/10] D LOSS : 1.486, G LOSS : 8.1007  
Epoch [6/10] D LOSS : 1.0081, G LOSS : 6.7625  
Epoch [7/10] D LOSS : 0.6252, G LOSS : 4.5718  
Epoch [8/10] D LOSS : 0.0043, G LOSS : 6.3371  
Epoch [9/10] D LOSS : 0.1880, G LOSS : 4.7353  
Epoch [10/10] D LOSS : 2.3294, G LOSS : 14.0363

Epoch vs LOSS (GAN)



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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
(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)

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(3, (5,5), strides=(2,2), padding="same", use_bias=False, activation="tanh"),
    ])
    return model

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()

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)
        real_output = discriminator(images, training=True)
        fake_output = discriminator(generated_images, training=True)
        gen_loss = cross_entropy(tf.ones_like(fake_output), fake_output)
        disc_loss = (
            cross_entropy(tf.ones_like(real_output), real_output)
            + cross_entropy(tf.zeros_like(fake_output), fake_output)
        )
```

```
with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
    generated_images = generator(noise, training=True)
    real_output = discriminator(images, training=True)
    fake_output = discriminator(generated_images, training=True)
    gen_loss = cross_entropy(tf.ones_like(fake_output), fake_output)
    disc_loss = (
        cross_entropy(tf.ones_like(real_output), real_output)
        + cross_entropy(tf.zeros_like(fake_output), fake_output)
    )
grads_gen = gen_tape.gradient(gen_loss, generator.trainable_variables)
grads_disc = disc_tape.gradient(disc_loss, discriminator.trainable_variables)
gen_optimizer.apply_gradients(zip(grads_gen, generator.trainable_variables))
disc_optimizer.apply_gradients(zip(grads_disc, discriminator.trainable_variables))
return gen_loss, disc_loss

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())

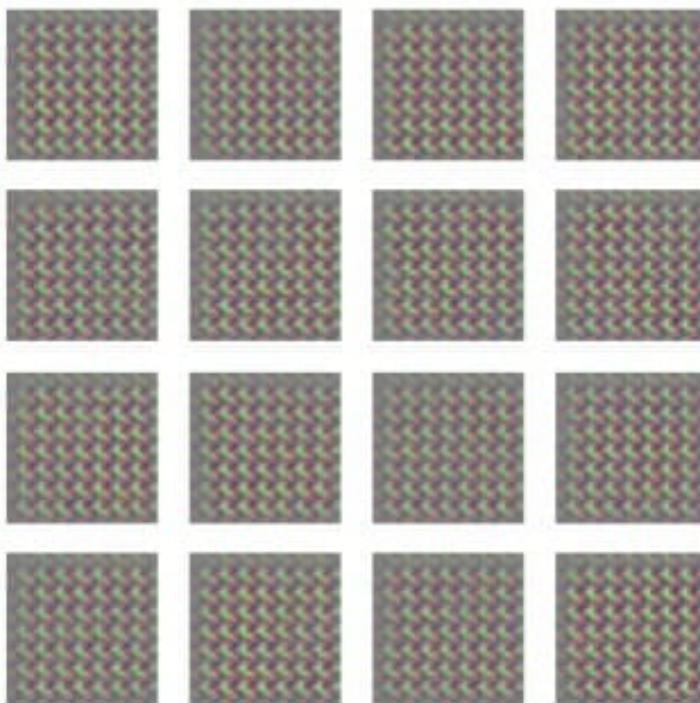
    print(f"Epoch {epoch+1}/{EPOCHS} | Gen Loss: {g_loss:.4f} | Disc Loss: {d_loss:.4f} | Time: {time.time()-start:.2f}s")

    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(f"Generated Images - Epoch {epoch+1}")
    plt.show()

plt.figure(figsize=(7,5))
plt.plot(gen_losses, label="Generator Loss")
plt.plot(disc_losses, label="Discriminator Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.title("DCGAN Training Loss")
plt.show()
```

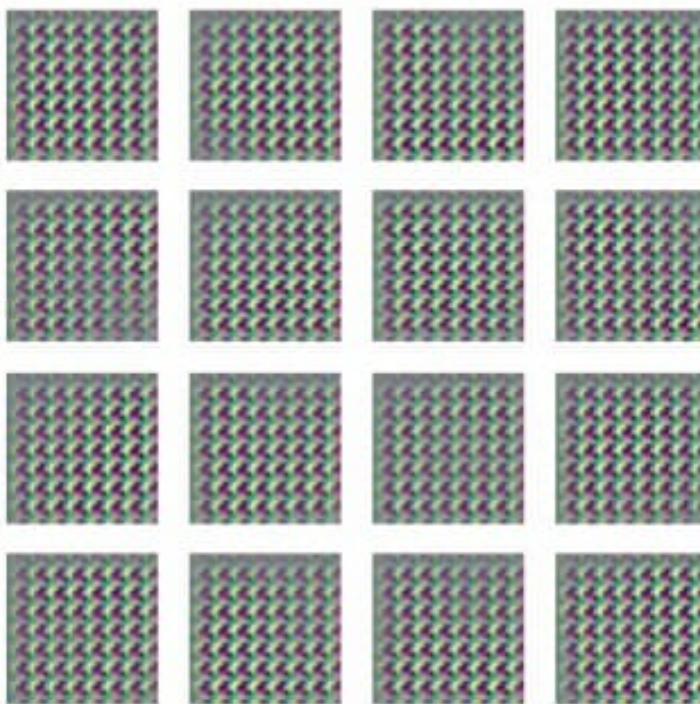
Epoch 1/2 | Gen Loss: 2.6986 | Disc Loss: 0.2989 | Time: 36.21s

### Generated Images - Epoch 1



Epoch 2/2 | Gen Loss: 4.3347 | Disc Loss: 0.0647 | Time: 29.22s

### Generated Images - Epoch 2



## DCGAN Training Loss

