

### AIM

To implement a deep convolutional gan to generate complex color images.

### objective

To understand GAN architecture

To train model on color image dataset

To observe training dynamics and quality of generating images.

### pseudocode

import libraries and set device

Load CIFAR-10 dataset, normalize to  $[-1, 1]$ , create dataloader

define DCGAN generator : series of convtranspose 2D, BatchNormed, ReLU

Initialize weights (Normal with mean = 0, std = 0.02)

define loss & optimizers

for each epochs

a) Train discriminator real images

b) Train generator to fool discriminator

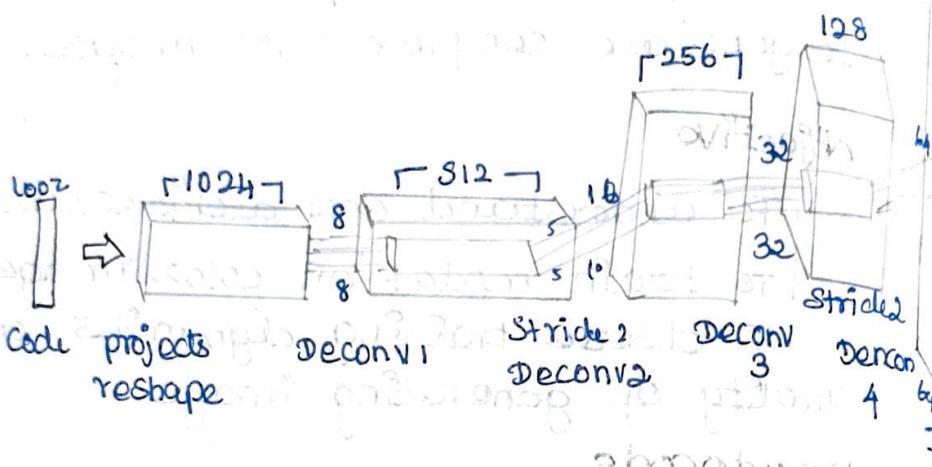
c) Save generator batch of generator image for visualization.

monitor losses

### observation

The discriminator and generator losses usually fluctuate. This is expected in GAN training as one improves, other responds.

## DCGAN architecture



Output

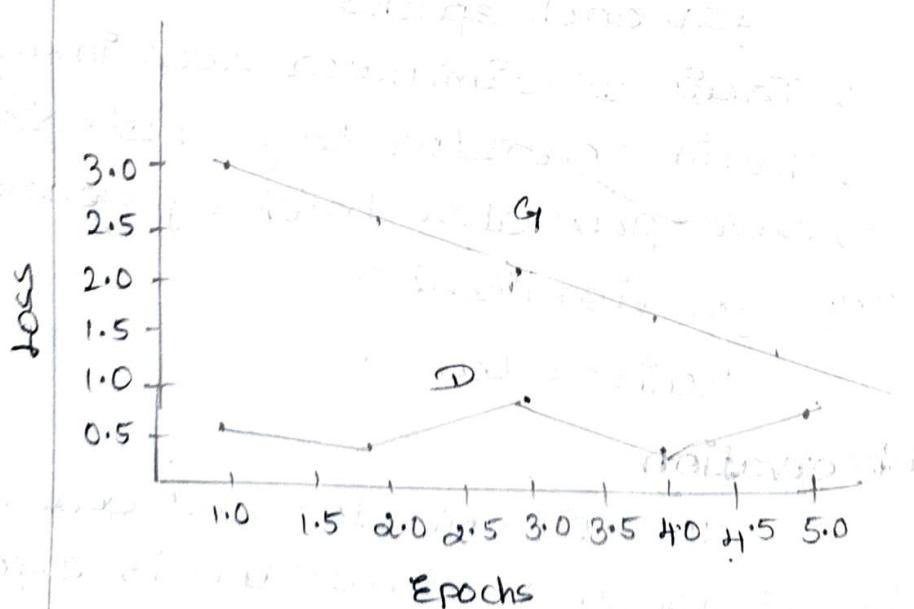
Epoch [1/5] LOSS D : 0.4934 LOSS G : 2.9012

Epoch [2/5] LOSS D : 0.5894 LOSS G : 2.66182

Epoch [3/5] LOSS D : 0.7406 LOSS G : 2.3580

Epoch [4/5] LOSS D : 0.5590 LOSS G : 2.0222

Epoch [5/5] LOSS D : 1.3862 LOSS G : 1.5855



initially generator images are noisy  
random patterns

over epochs starts showing structure  
(colors, shape)

Saving images each epoch helps  
visualize progression from noise → structure  
+ clearer images.



Result

Successfully implemented DCGAN.  
(8g.)

# UNDERSTANDING THE ARCHITECTURE OF PRE-TRAINED MODEL

## Aim

To understand the architecture of pre-trained model.

## Objective

To learn the concept of transfer learning and how it reduces training time.

To explore the layer wise architecture of pretrained models such as VGG16, Alexnet

To identify the role

To visualize how these models extract features.

## Pseudocode

import libraries

Load a pre-trained model

Model Display if

Observe : input and output shapes  
Layers names, types and no.of parameter

Visualize the architecture using

Load a sample input image and  
preprocess it for model

pass image through the model and  
get prediction

optionally visualize activation.

Output

(MPA)

Linear (in-features = 2048, out-features = 10,  
bias = True)

NNA (3 layers with initial or

final (features) or sequential (

(0) Conv2d (3, 64, kernel\_size = (3, 3), stride = 1, padding = (1, 1), dilation = (1, 1))

(1) : ReLU (inplane = True)

(2) : conv2d (64, 64, kernel\_size = (3, 3), stride = 1, padding = (1, 1))

(3) : ReLU (inplane = True)

(4) maxpool2d (kernel\_size = 2, stride = 2, padding = 0, dilation = 1, cell = node = false)

:

(20) : maxpool2d (kernel\_size = 2,

stride = 2, padding = 0, dilation = 1, cell = node = false)

(avg pool) = Adaptive Avg pool (output\_size = 1)

(0) : Linear (inplane = True, output\_size = 1)

(1) : ReLU (inplane = True)

(2) : Dropout (p = 0.5, inplane = False)

Total Trainable parameters : 13835751

## Observation

The pre-trained model contains millions of parameter spread across convolutional of dense layers.

Early layer extract edges and texture while deeper layers capture high level feature such as object parts.

The use of pre-trained weights drastically reduces training time and improves model accuracy for new tasks.

## Result

~~Ques~~ successfully implemented pre-trained model.