RA2311047010038
Deep learning Techniques

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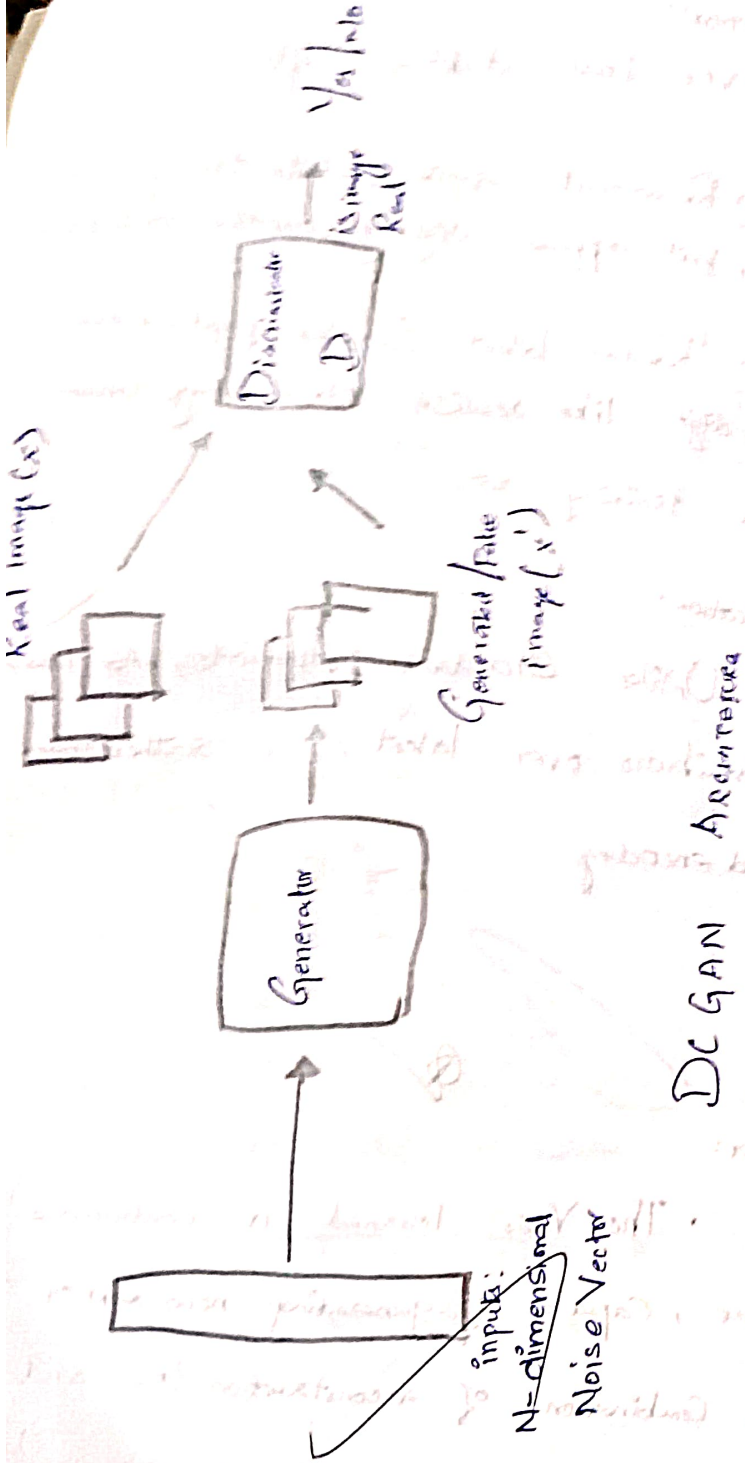


DC GAN Architecture

Exp. no 12
17 Marks

Implementation a Deep learning Convolution Gan to generate Complex Color Images

Aim:

To implement a deep Convolution ~~Gan~~ Generative Adversarial Network (DCGAN) using Pytorch to generate Complex Color images from the Noise.

OBJECTIVES:

→ To implement GAN and adversial loss.

→ To design a DCGAN architecture of generating RGB images.

→ To evaluate the learning Progress through generator and discriminator losses.

Pseudocode:

1. Import required libraries
2. load a Color Image.
3. Defino
   - Generator.
   - Discriminator.
4. Initialize both networks with Xavier Initialization.
5. Train with Adversial loss:

1	1.372	0.873
2	1.102	0.2
3	0.984	1.4
4	0.84	1.6
5	0.75	1.9
6	0.70	21
7	0.66	2.3
8	0.64	2.4
9	0.61	2.5
10	0.59	2.7

- Generator: learn to fool the discriminator.

6. After training, generating new fake images using random noise.

7. Visualize generated color images.

OBSERVATIONS:

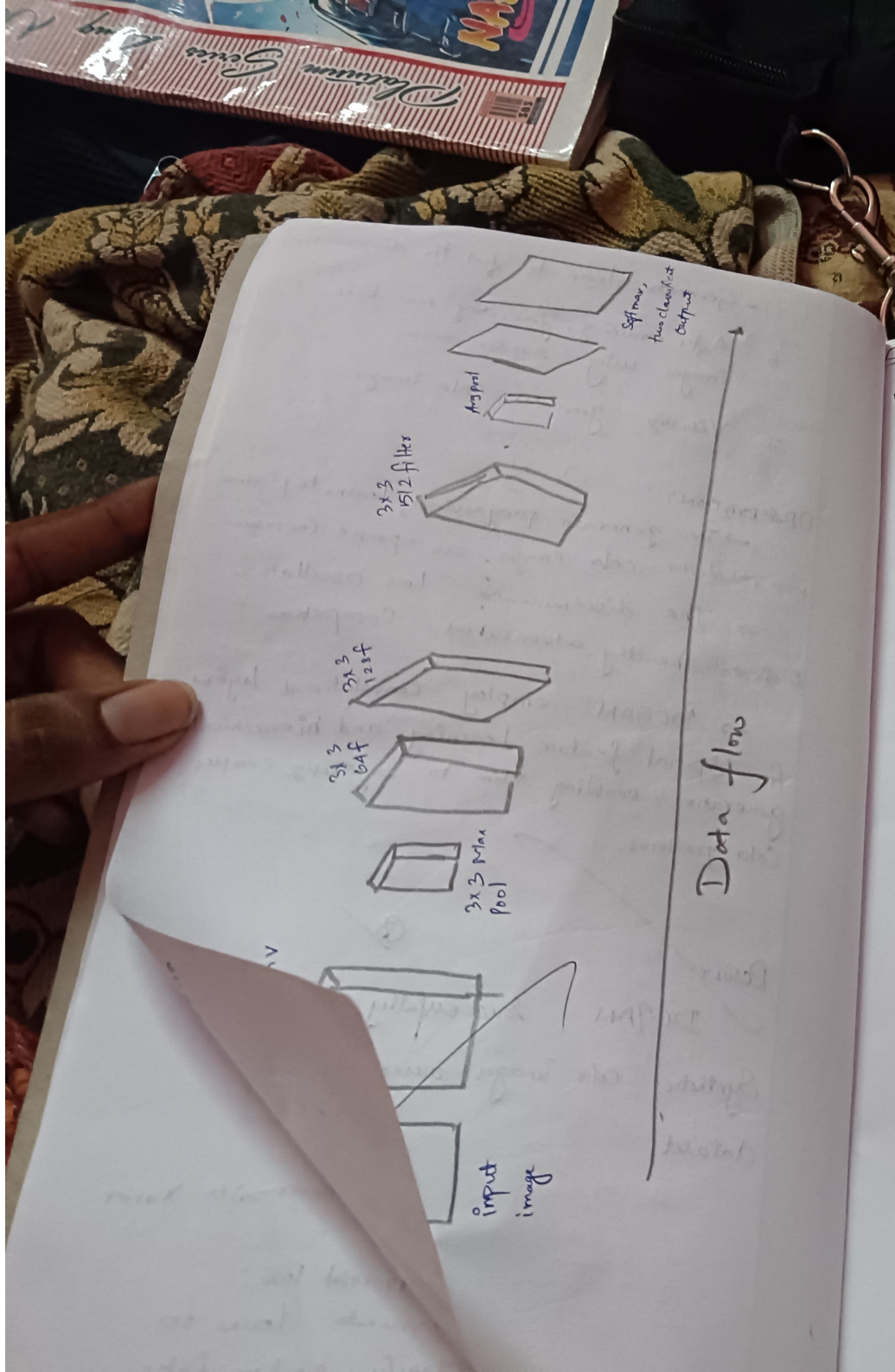
→ The generator progressively learns to produce more relalistic color images as epochs increase.

→ The discriminator loss oscillates indicates healthy adversarial Competion.

→ DCGAN employ convolutional layers for spatial feature learning and hierachical generation, enabling them to synthesize complex color patterns.

RESULT:

DCGAN succesfully Generated Synthetic color images resembling the CIFAR-1 dataset.



Exp No: 13
17/10/25

Understand the Architecture of Pre-Trained Models.

AIM:

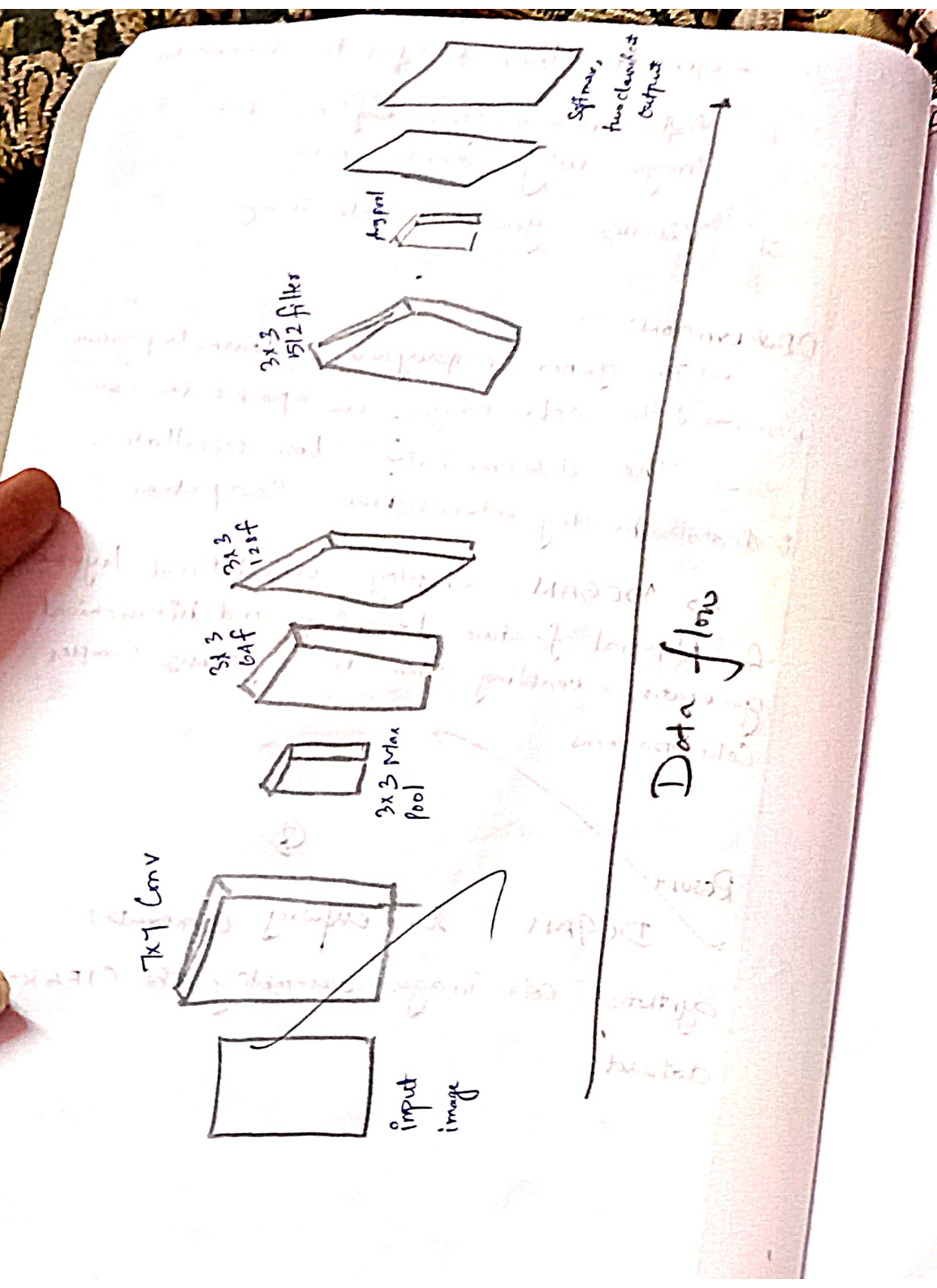
To analyse and understand the architecture and feature extraction of a Pre-trained deep learning model in PyTorch.

OBJECTIVES:

- To load and explore a pre-trained CNN model from Pytorch's model zoo
- To understand the structure of Convolution, Pooling, fully Connected layers
- To visualized intermediate feature maps and comprehend learned representation

PSEUDOCODE:

1. Import library
2. Print model architecture layer-wise
3. Pass a sample image through a model.
4. Visualize the feature map
5. Observe how filters detect low to high level features.



Exp No: 13 Understand the Architecture of
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To analyse and understand the architecture and feature extraction of a Pre-trained deep learning model in PyTorch.

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PSEUDOCODE:

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Epoch

Discriminator

Layer	Feature type	Description
Conv1	Edges, Colors	Basic Visual fea
layer1	Textures	Detect Stripes
layer 2	Shapes	Recognize Pattern
layer3	object	Detect Object
layer 4	Semantic	High level Context

OBSERVATION:

→ The initial Convolution layers detect edges and color gradient

→ Deeper layers capture Complex features like shapes and textures.

→ The hierarchical structure helps the network learn from low-level to semantic representation.

→ Pre trained models like ResNet, VGG are rich hierarchical feature extraction

RESULT:

A Pre trained ResNet 18 model was succesfully analyzed and used to Visualize interral features map.