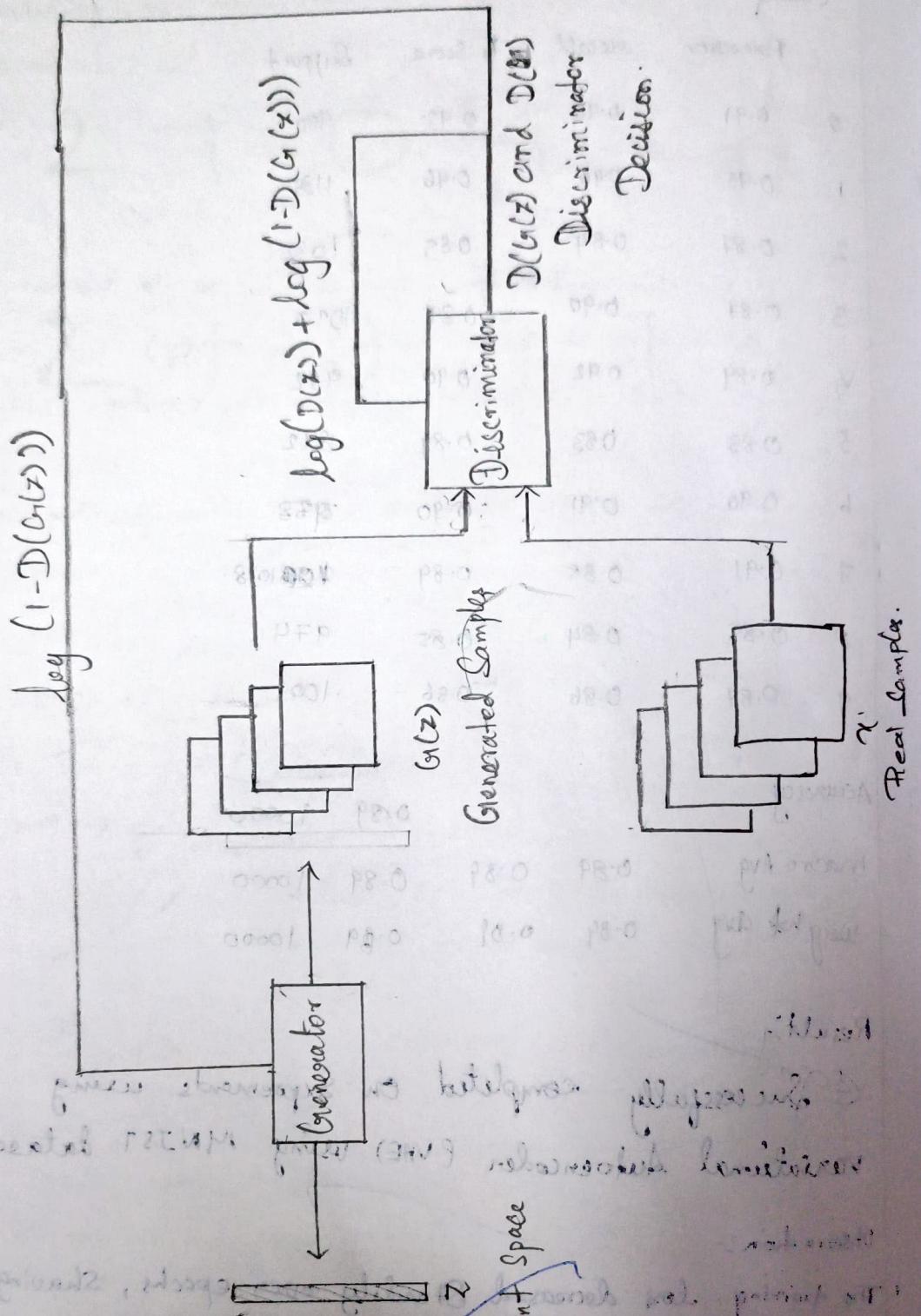


Architecture Diagram GAN...



Yours Exp: 12 : Implement a Deep Convolution GAN To generate Complex Color image.

Aim:-

To implement a Deep Convolution GAN that generates Complex-looking Color image and to Evaluate generated images via a Simple classifier producing a classification report for real vs fake images.

Objectives:-

1. Implement a lightweight Deep Convolution GAN (Generator + Discriminator) in pytorch.
2. Create a simple Coloured - Shaped dataset (32×32 RGB) so training is fast and reproducible.
3. Train the GAN and plot training losses for the Generator and Discriminator.
4. Generate images samples and save an image grid of Samples.
5. Train a small CNN classifier to distinguish real and fake images and output a classification report.
6. observe and report findings.

Pseudocode:-

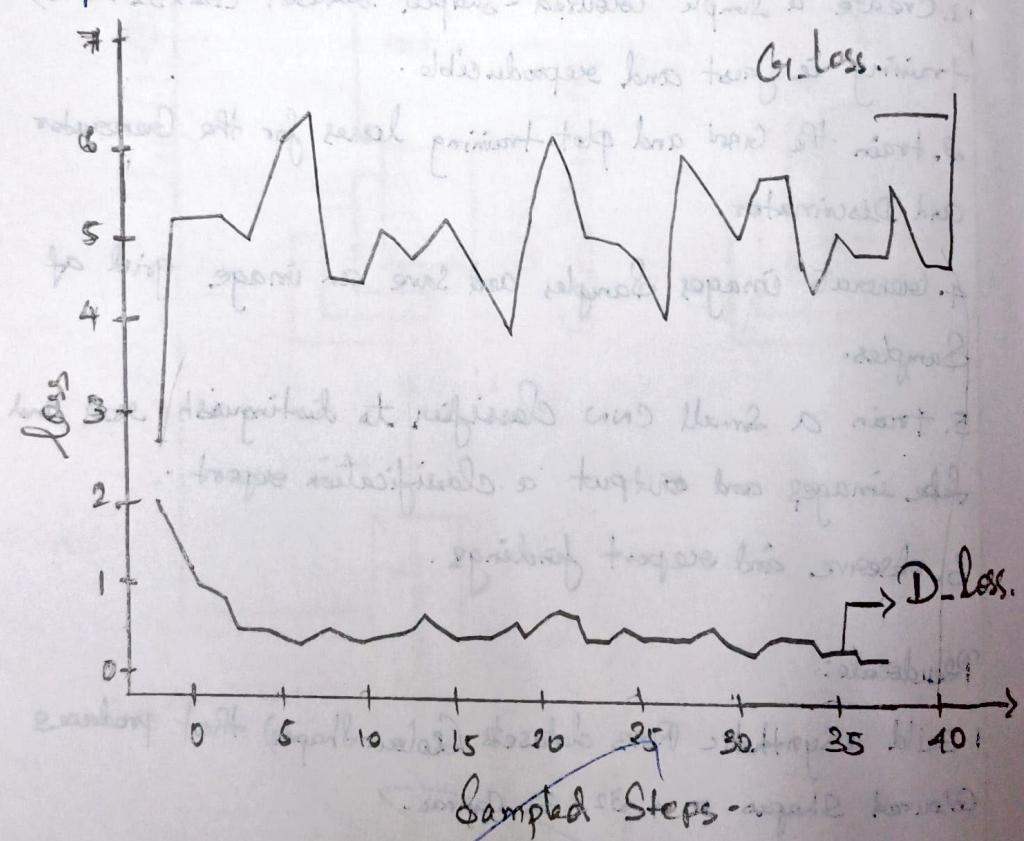
1. Build a Synthetic RGB datasets (ColourShapes) that produces Coloured Shapes on a 32×32 canvas.
2. Deep convolution GAN to :-
 - Generator : ConvTranspose layer \rightarrow Batch Norm \rightarrow ReLU \rightarrow Tanh, Output $32 \times 32 \times 3$
 - Discriminator :- ConvNet \rightarrow Batch Norm \rightarrow Leaky ReLU \rightarrow Sigmoid, output a probability real / fake.

Classification Report:-

	Precision	Recall	F1-Score	Support
Fake	0.993	0.993	0.993	143.000
real	0.994	0.994	0.994	177.000
accuracy	0.994	0.994	0.994	0.994
macro avg	0.994	0.994	0.994	320.000
Weighted avg	0.994	0.994	0.994	320.000

GIAN Losses. loss is decreasing

Graph:-



Sampled Steps - apne karte

3. Train loop:-
 - For each batch:-
 - Update Discriminator on real batch (label=1) and fake batch (label=0).
 - Update Generator to fool Discriminator (label=1 for generated outputs).
 - Collect losses.
4. After training:-
 - Generate a grid of samples from fixed noise vector.
 - Build evaluation set: N real images + N generated images.
 - Train a small CNN classifier on real vs ~~fake~~ fake
 - Compute classification-report on
5. Save grid image and report to disk; Plot losses.

Observations:-

- Observation 1 (Training): Generator and discriminator losses oscillate; stable growth w.r.t sample quality. Comes from balanced updates.
- Observation 2 (Samples): After training, generated images appear colored shaped similar to the dataset. But may show artifacts if the model capacity or epochs are limited.

Result:-

The implemented DCGAN successfully generated color images that visually match training distribution; the classification report gives quantitative support for Generator's quality.

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