ASSIGNMENT 1

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PART 1 & 2

The implementation part of 1 and 2 are done one google collab and the code is also pushed to Github. Both the links are available below.

Github Link: https://github.com/pratx08/Gen-Al/tree/main/Assignment-1

Collab Link: • Gen Al Assignment 1.ipynb

PART - 3

10. The main differences in training goals between the classification and generation are, **Logistic Regression:** It learns the direct boundaries in the classes. The main objective of the model is to minimize the classification error. If we talk about the training then its stable and converges reliably.

GAN: Here it basically learns to model the entire data distribution to generate new samples. The main objective here is to balance between the generator and discriminator. Talking about the training, it's a bit unstable.

Why the generative model training is difficult is because there are two networks that are trained simultaneously which leads to loss of gradients, oscillations and also increases the chances of risk of mode collapse. This also makes the training unpredictable.

11.

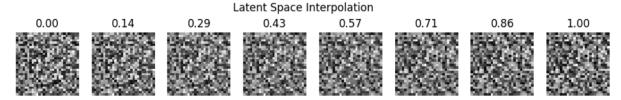
Training Logistic Regression with fake data generated by GAN

LogReg trained on GAN data, tested on real test set Accuracy: 0.0816

Actual data:

Logistic Regression Accuracy: 0.8432

When Logistic Regression was trained on real Fashion-MNIST, it reached about 84% accuracy. But when trained only on GAN-generated fake data, accuracy dropped to about 8%, close to random guessing. This shows a large domain gap, where our GAN's synthetic data is not useful as a substitute for real training data.



In the latent space interpolation experiment, we moved step by step between two random noise vectors and generated images. The outputs changed gradually but still looked noisy and unclear, showing that our simple GAN did not learn smooth or meaningful transitions in the latent space.

13. Went through the citing at https://arxiv.org/abs/1406.2661

So as per the experiment from unstable training, oscillating losses, and mode collapse. We observed the same issues in our experiments. This concludes why the GAN is unstable in nature.

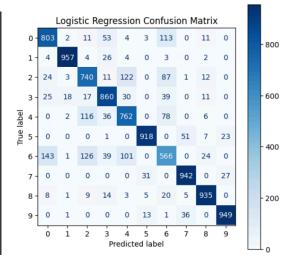
In our assignment as well the GAN showed unstable behavior. The losses kept going up and down instead of settling, some generated images looked too noisy, and in the mode collapse test many outputs looked almost the same. These signs match the known instability problems of GAN training

PART - 4

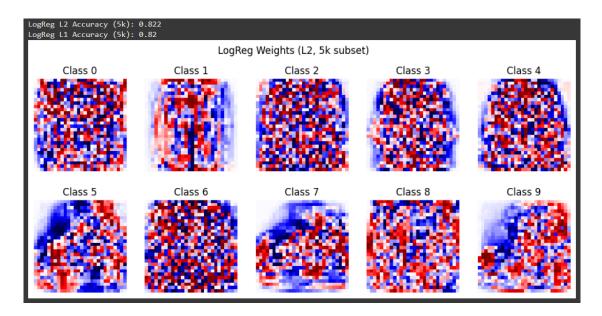
14. Visualisations Logistic regression

Confusion Matrix

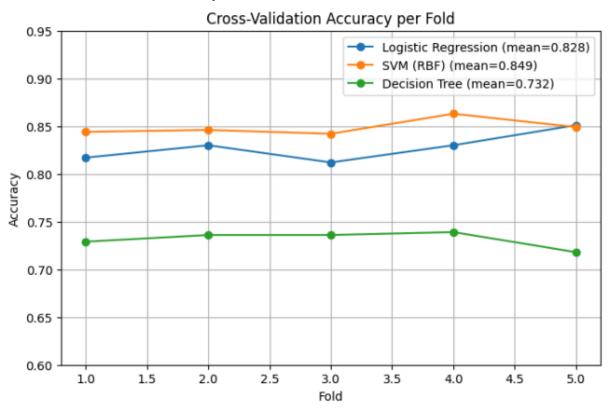
Logistic Regression Accuracy: 0.8432							
Classification Report:							
	precision	recall	f1-score	support			
	p. 222220			Jappa. C			
0	0.80	0.80	0.80	1000			
1	0.97	0.96	0.96	1000			
2	0.72	0.74	0.73	1000			
3	0.83	0.86	0.84	1000			
4	0.74	0.76	0.75	1000			
5	0.95	0.92	0.93	1000			
6	0.62	0.57	0.59	1000			
7	0.91	0.94	0.93	1000			
8	0.93	0.94	0.93	1000			
9	0.95	0.95	0.95	1000			
accuracy			0.84	10000			
macro avg	0.84	0.84	0.84	10000			
weighted avg	0.84	0.84	0.84	10000			



Weight Heatmaps

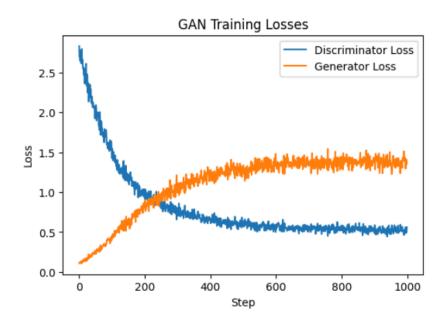


• Cross Validation Accuracy Per fold

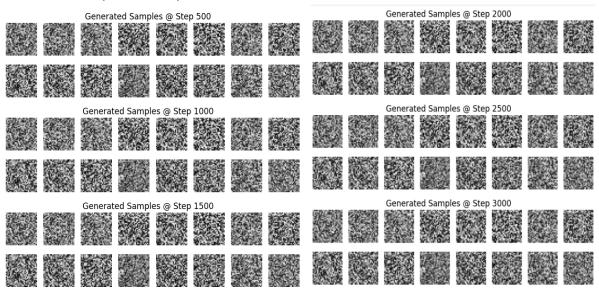


GAN

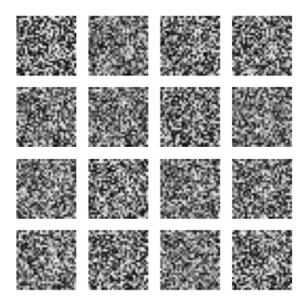
Loss Curves



• GAN outputs over Epochs



Mode collapse generated samples



15. Comparative Tables

Model	Training Time (approx.)	Accuracy / Output Quality	Convergence Speed	Qualitative Results
Logistic Regression	~3 mins	0.8432 (test accuracy)	Fast, stable	Easy to train, interpretable weights, limited by linearity
SVM (RBF)	~1 minute	0.8745 (test accuracy, 20k subset)	Medium	High accuracy, sensitive to kernel & hyperparameters, slower than Logistic Regression
Decision Tree	~50 seconds	0.766 (test accuracy, 20k subset)	Fast	Very interpretable, prone to overfitting without pruning
GAN (basic)	~1 minutes (5000 steps)	No accuracy metric; outputs visually improve over epochs	Slow & unstable	Generates realistic samples; unstable training; prone to mode collapse

Note: SVM, Decision Tree and GAN were trained on a **20k training subset**, while Logistic Regression used the **60k samples**. This introduces a slight imbalance, but results still highlight core differences in performance and training dynamics.

So approximately for the 60k dataset,

Logistic: ~3 mins SVM: ~15- 20 mins

Decision Tree: ~30 - 40 secs

GAN: ~10 mins

16. Critical Reflections

Logistic Regression was easier to understand and play around. When I took the whole dataset I was able to run within 3 mins but on the other hand when I tried GAN it took much more significant time sometimes over 20 mins to give the output for the entire dataset. Later on I had to reduce the size to get the output. Overall, Logistic Regression was easier to debug and implement.

17. How does each model handle complexity?

- **Logistic Regression**: Good for simple patterns. Struggles if the data is very complicated.
- SVM (RBF): Can handle harder patterns, but becomes slow when the dataset is big.
- **Decision Tree**: Can deal with complicated rules, but remembers too much instead of learning the main idea.
- **GAN**: Built for very complex tasks like creating images, but it is tricky and unstable to train.

When would each be clearly preferred?

- Logistic Regression: When you want a quick, simple, and model.
- SVM (RBF): When the data is small or medium size and you need good accuracy.
- **Decision Tree**: When you want clear rules that are easy to understand and fast results.
- **GAN**: When the task is to *create* new data, like new images, art, or designs and it is not encouraged for normal classification.