Assignment 1: Discriminative vs. Generative Models — Report

Dataset: Fashion-MNIST https://github.com/charan-976/Generative-AI

1. Introduction

Both models were trained using the Fashion-MNIST dataset, which contains 70,000 grayscale 28×28 clothing images across 10 classes.

Dataset

Fashion-MNIST: 60,000 training, 10,000 testing images ;Each flattened into a 784-dimensional vector

2.**Discriminative Model — Logistic Regression**

Training Procedure Model: LogisticRegression(max_iter=1000, solver="lbfgs")

Generative Model — GAN

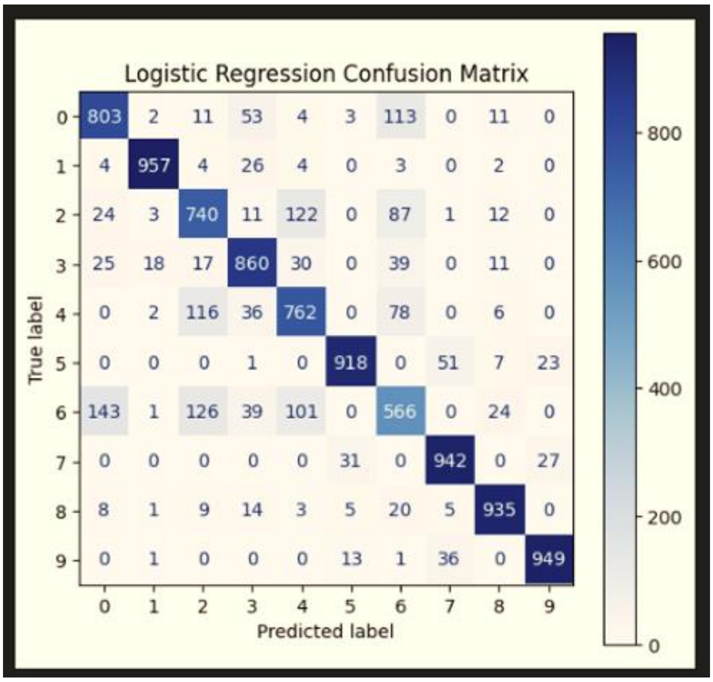
Generator: Input: 100-dimensional noise vector; Architecture: 3 fully connected layers with LeakyReLU activations; Output: 784 units passed through tanh

Discriminator: Input: 784-dim image; Architecture: 3 fully connected layers with LeakyReLU

3. Results

Logistic Regression — Performance

Overall Accuracy: 0.8432

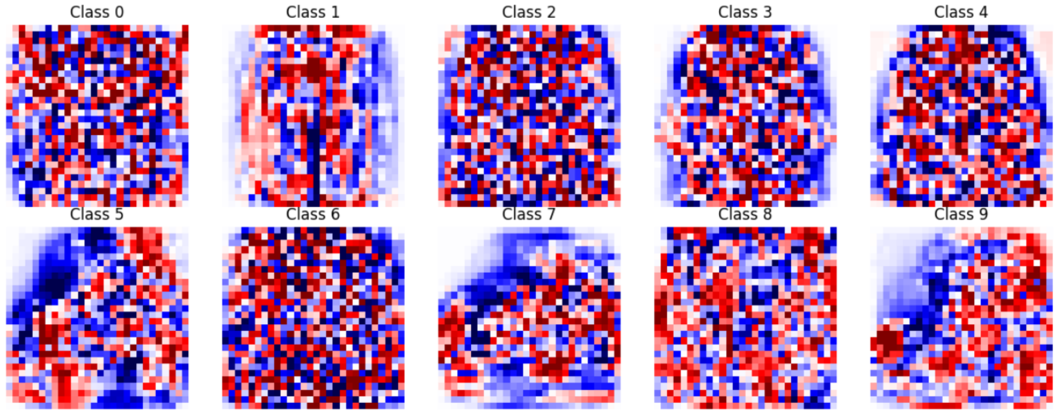


Best predicted classes: Sneaker (class 7) and Ankle boot (class 9)

Hardest classes: Pullover (class 2) and Coat (class 4) (visually similar)

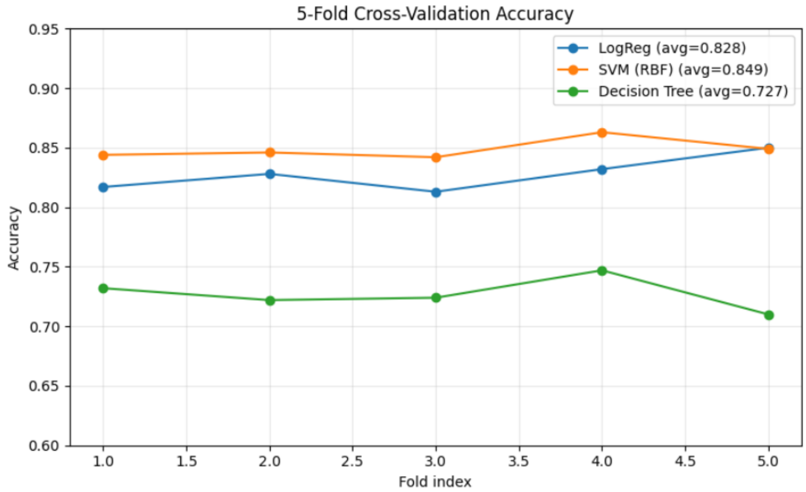
Overall balanced performance

L2-regularized weight maps per class produced interpretable patterns:



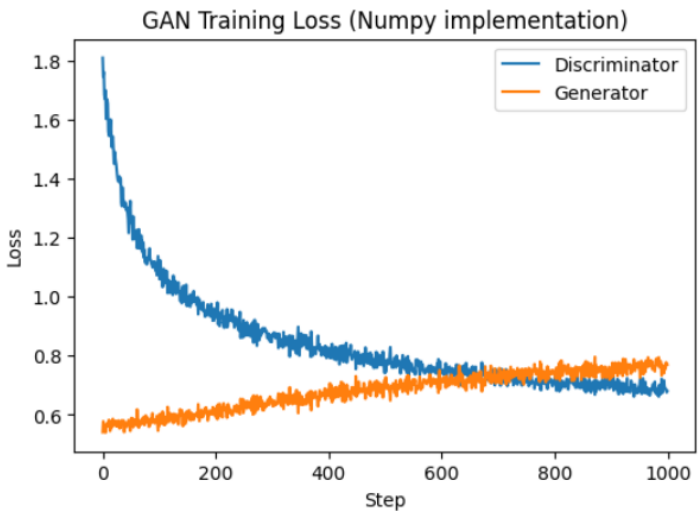
Red = positive influence ; Blue = negative influence

Cross-Validation Results 5-Fold CV plot:



SVM performs best due to nonlinear boundaries. Logistic Regression is strong but linear. Decision Tree shows high variance.

4 GAN Training Behavior Discriminator loss decreases steadily; Generator loss increases slightly

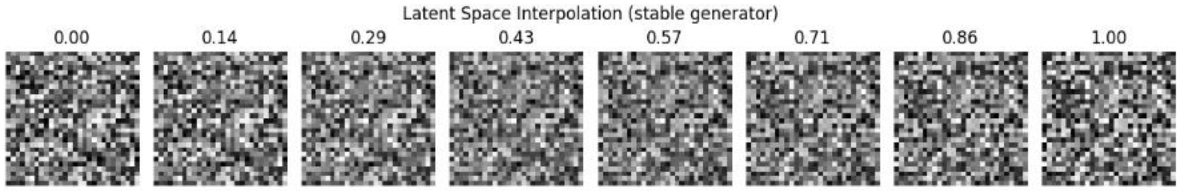


Discriminator loss decreases steadily; Generator loss increases slightly

Generated Samples (Every 500 Steps); All generated samples look like random noise:

Even after 5000 steps, the GAN does not produce Fashion-MNIST-like images.

Latent Space Interpolation



Interpolated images also remain noise → suggests no learned manifold.

Analysis: Fully connected GANs struggle with images. Fashion-MNIST is too complex

GANs require convolutional layers (DCGAN architecture) for spatial understanding.

D becomes too strong too quickly → G receives almost no useful signal

Fashion-MNIST is too complex.Clothing textures and shapes cannot be captured by a small MLP-GAN.

5. Comparison: Discriminative vs Generative Model

Aspect	Logistic Regression (Discriminative)	GAN (Generative)
Goal	Classify images	Generate new images
Training stability	Very stable	Highly unstable
Output quality	>84% accuracy	Pure noise
Convergence	Fast and reliable	Requires careful tuning
Best use cases	Real-world classification tasks	Creative generation, augmentation
Performance on task	Strong	Failed to learn

6. Reflection:Discriminative models are far easier to train.

Even a simple Logistic Regression model achieved >84% accuracy and generalizes well.

A simple MLP-GAN is not powerful enough for images.GAN training is sensitive to hyperparameters.

D loss ↓ and G loss ↑ = D overpowering G; Stable numeric losses ≠ good generation

7. Conclusion

Logistic Regression is simple, stable, and effective for classification.

GANs, while powerful in theory, require complex architectures and careful training to generate realistic samples.

The results clearly show why discriminative models dominate real-world predictive tasks, while generative models require deeper architectures (DCGAN, StyleGAN, etc.) to reach meaningful performance.