Anomaly Detection on FashionMNIST

Deep Learning

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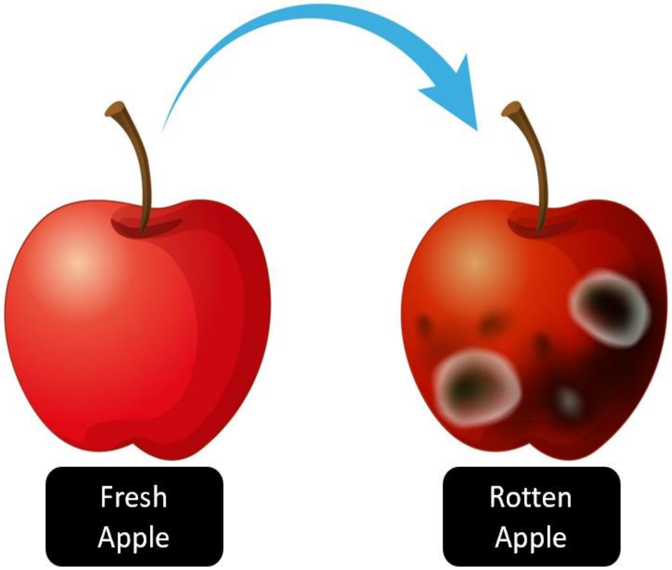
Introduction

Anomaly detection in images involves identifying abnormal or unusual patterns within a given dataset of images.

For Example:

Let's suppose, We have an Apple packaging industry, and our task is to pack only Fresh apples (Normal), But most of the time we get rotten apples, So for that we have to apply anomaly detection in such a way that It's classified 'Fresh apples' as (Normal) and 'Rotten Apples' as (Anomaly). By applying anomaly detection, the system can analyze the visual characteristics of the apples, such as color, texture, shape, and any signs of decay or spoilage. The majority of the normal or fresh apples should be classified as "normal," indicating they meet the quality criteria for packaging. On the other hand, any apples exhibiting anomalies associated with rot, such as discoloration, mold, or a soft texture, should be classified as "anomalies" and rejected from the packaging process.



Task Description

Our task is to find out anomaly detection in FashionMNIST dataset. Anomaly detection on FashionMNIST refers to the process of identifying unusual or anomalous patterns in the FashionMNIST dataset. FashionMNIST is a popular benchmark dataset in the field of computer vision, consisting of 60,000 labeled images of 10 different fashion categories, such as T-shirts, dresses, shoes, and bags. Each image is a 28x28 grayscale picture. Anomaly detection aims to find instances that deviate significantly from the normal patterns present in the dataset. In the context of FashionMNIST, anomalies can be images that do not belong to any of the predefined fashion categories or images that exhibit unusual or unexpected characteristics compared to the majority of the dataset.

Dataset

Here to find out anomaly detection on FashionMNIST dataset, I am considering one FashionMNIST class (label) as normal and rest of nine classes as anomaly.

- **Normal**

T-shirt/Top

- **Anomaly**

Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag ,and Ankle boot

Approach

Here, I am taken two approaches.

- Traditional GAN model
- State-of-the-art (SOTA) model

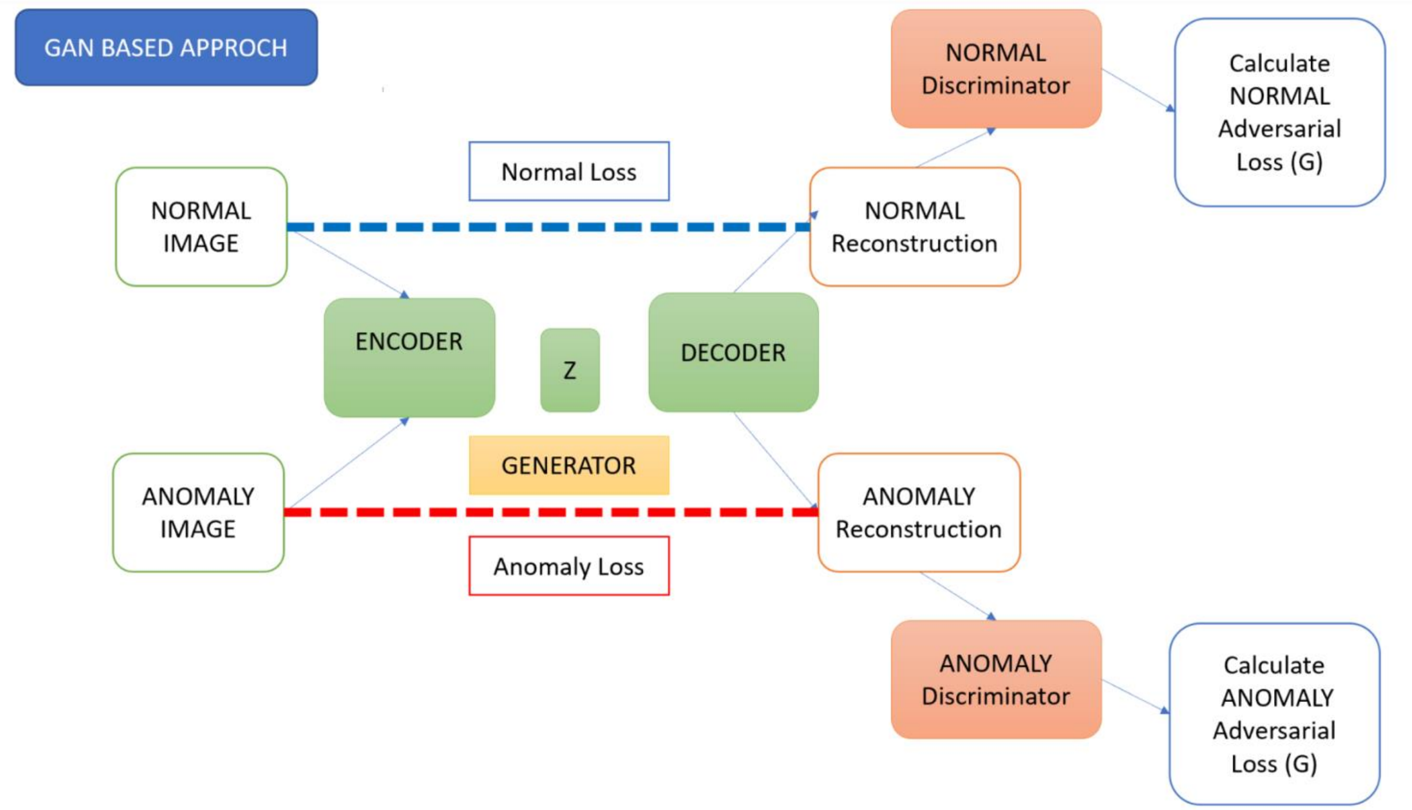
Metrics

Here the metrics is **“AUROC”** for anomaly detection, Because anomaly detection datasets often have a significant class imbalance, with normal instances outnumbering anomalies. AUROC is robust to imbalanced datasets and provides a comprehensive evaluation of the model's performance in distinguishing between the two classes.

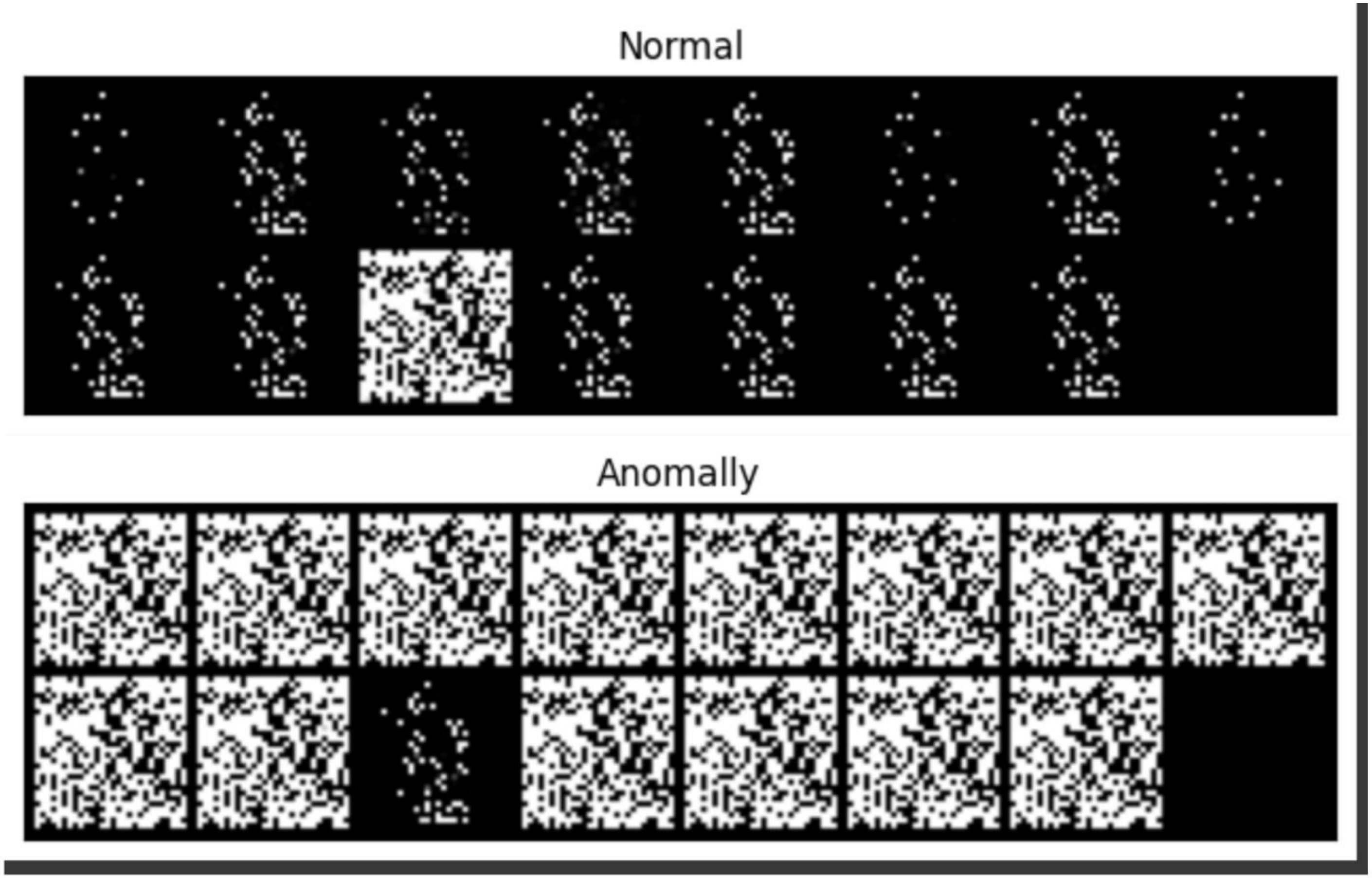
Traditional GAN model

- This model is based on traditional GAN, and Generator is based on autoencoder.
- "I am taken the same methodology given in the SOTA model research paper". But here the approach is traditional GAN instead of DCGAN.
- Here I am using a single loss function, Mean Squared Error (MSE) Loss. No multiple losses mention in the SOTA model paper.
- The traditional GAN approach and the use of MSE loss provide a straightforward and easy-to-implement solution. This approach may be suitable for initial exploratory research or as a baseline to compare against more complex models.

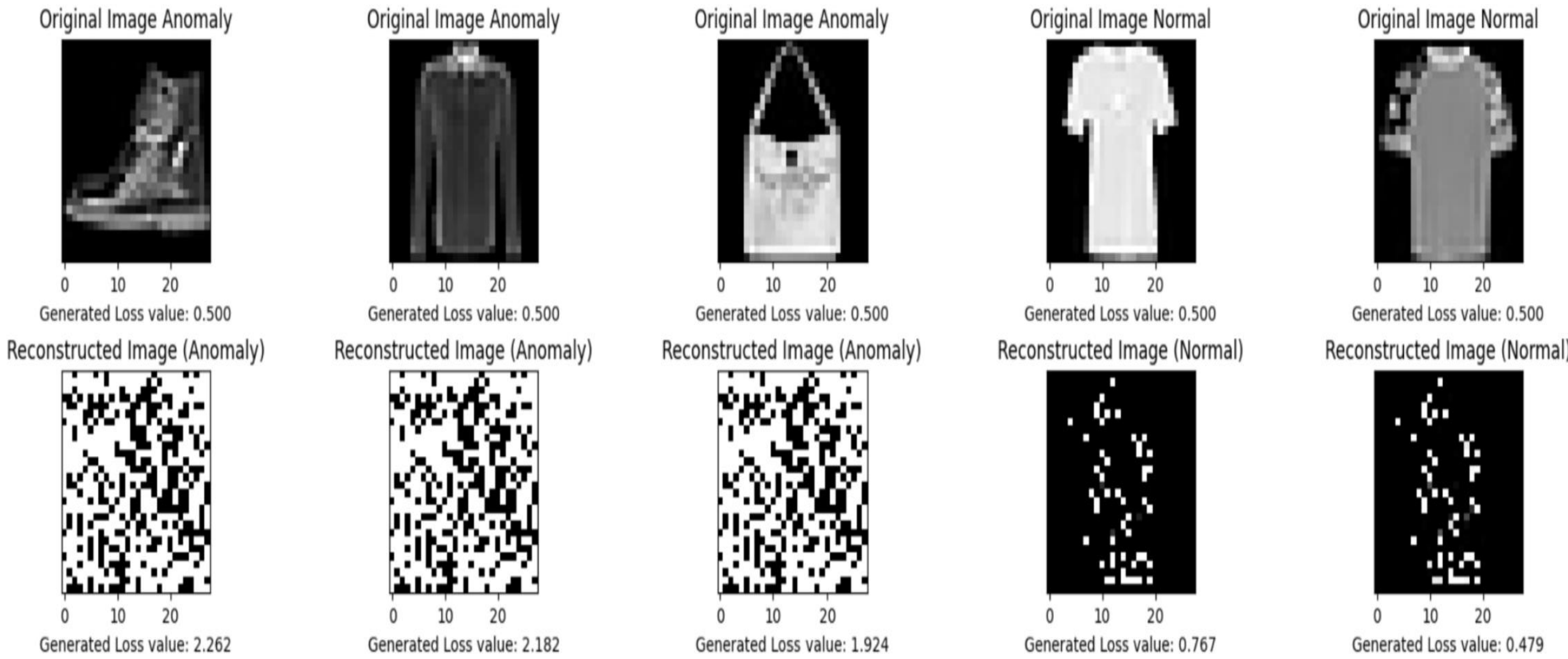
Flow Diagram



Model Results (Training Data)



Model Results (Testing Data)



"The model have some noise, It's not generating the accurate image of Normal."

Model AUROC Result

Test metric	DataLoader 0
AUROC Test	0.8698956370353699

AUROC result = Approx 87%

Limitation of Traditional GAN model

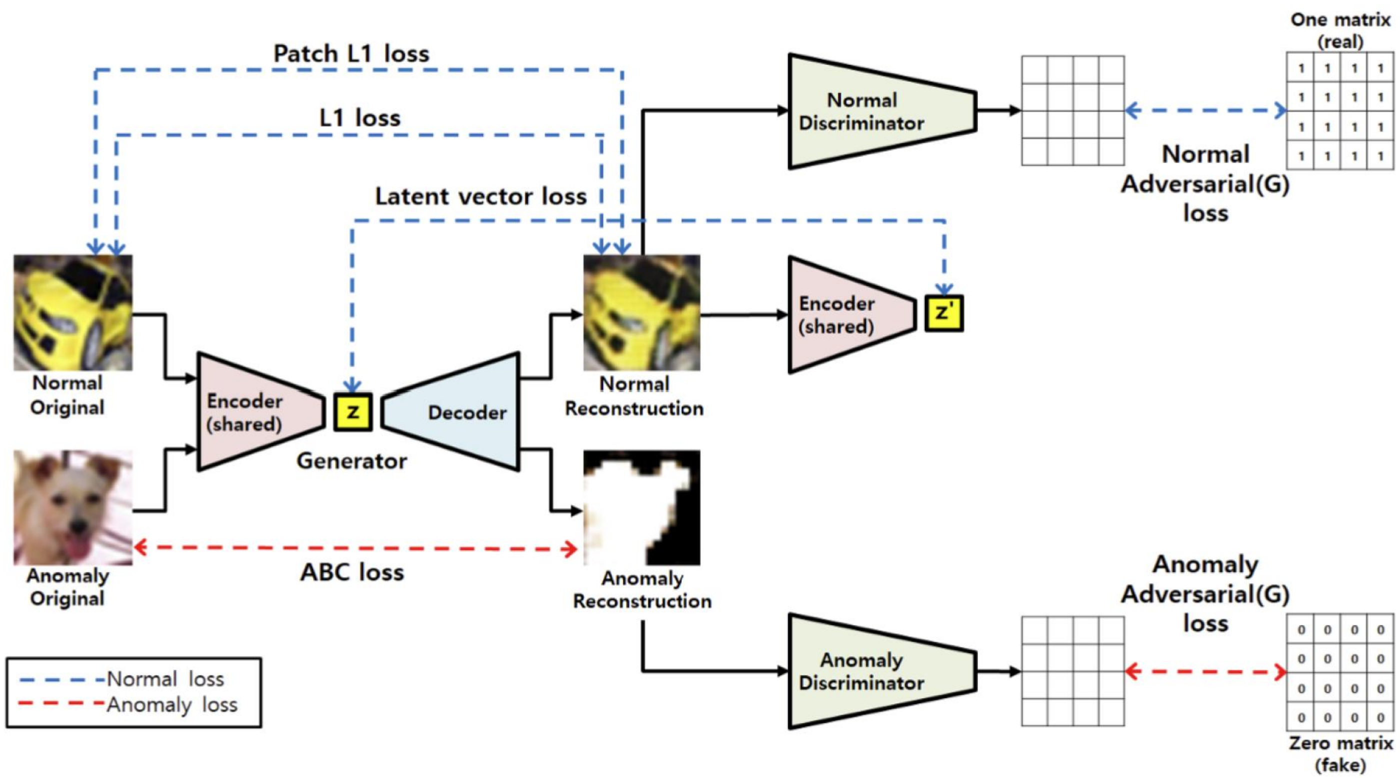
Why "Traditional GAN model" is not work? Because of two factors.

- **Architecture:** The Traditional GAN model may have a less sophisticated architecture compared to the SOTA model based on DCGAN (Deep Convolutional Generative Adversarial Network). The DCGAN architecture is specifically designed for image generation tasks and captures spatial features and patterns more effectively. In contrast, the baseline model may lack the necessary complexity or depth to accurately identify anomalies in the dataset.
- **Loss Functions:** The SOTA model utilizes specific loss functions designed for anomaly detection. These specialized loss functions are tailored to enhance the model's ability to distinguish between normal and anomalous instances. In contrast, the Traditional GAN model may use generic loss functions that are not specifically optimized for anomaly detection. This difference in loss functions can significantly impact the model's performance in accurately identifying anomalies.

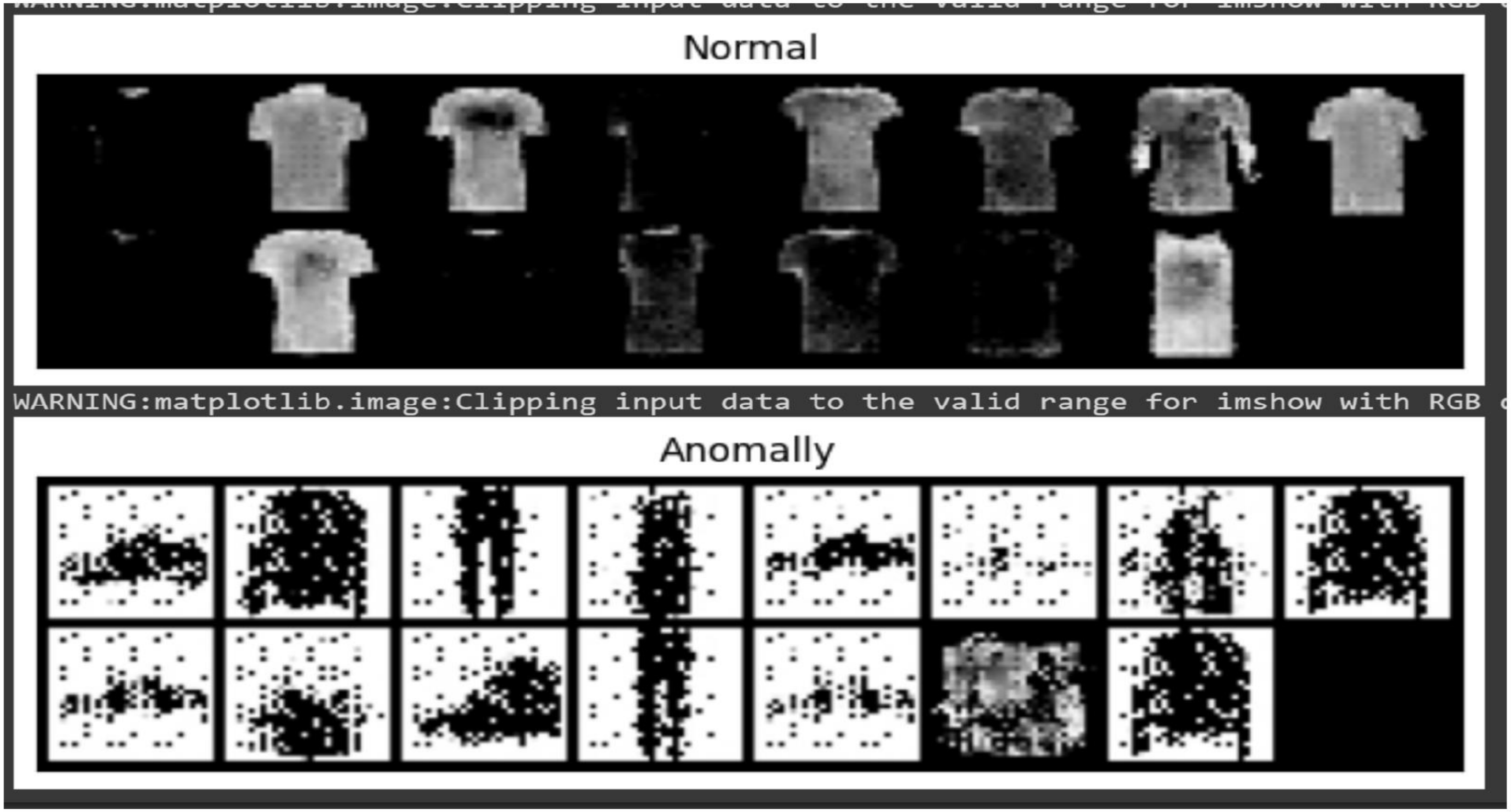
State-of-the-art (SOTA) Model

- I try to make the model according to the SOTA model paper. https://paperswithcode.com/paper/gan-based-anomaly-detection-in-imbalance.
- Here, I am using DCGAN instead of traditional GAN.
- The losses will be calculated according to the SOTA model paper.

Flow Diagram



Model Results (Training Data)



Model Results (Testing Data)

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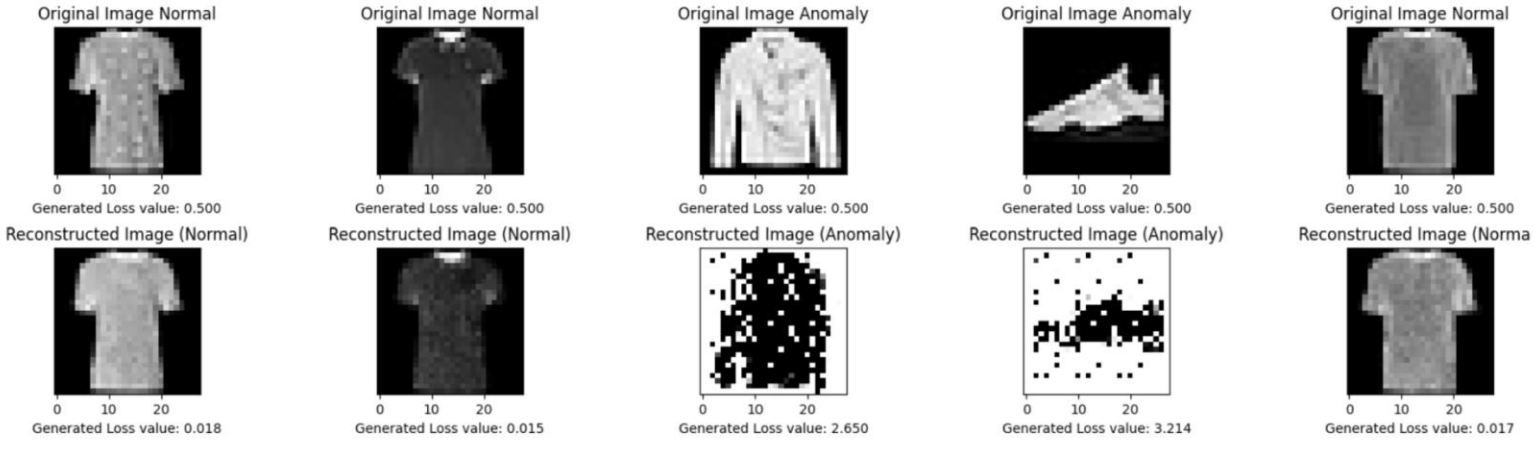

“The model has not generated noise now, It is generating approx the same result as a normal image and changing the image for an anomaly image.”

Model AUROC Result

Test metric	DataLoader 0
AUROC Test	0.8992706537246704

AUROC result = Approx 90%

THANK YOU FOR YOUR KIND ATTENTION