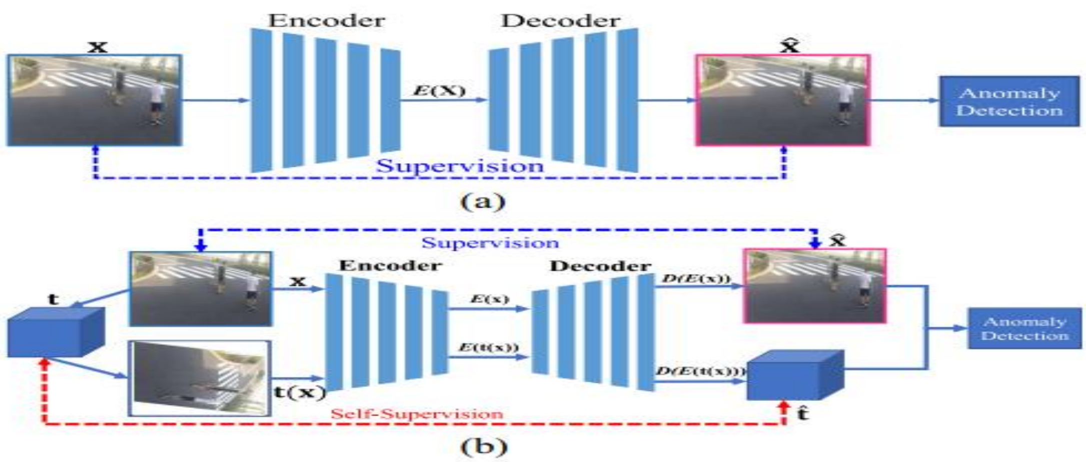
ANOMALY DETECTION WITHOUT MUCH SUPERVISION

MAY 2023



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Problem Statement and Introduction

Supervised Anomaly Detection:
Models use labelled data to classify each data point as normal or anomalous..Training relies on labelled examples of both normal and anomalous data.

Challenges with Long-Tailed Data:

Real-world data often follows a long-tailed distribution. Some categories lack sufficient training examples for deep networks. This project aims to address anomaly detection despite limited supervised data

Motivation Behind Research

Improve Reconstruction Accuracy:

Traditional autoencoders (AE) often struggle with accurately reconstructing the original image. By introducing self-supervision, the authors aim to enhance the model's ability to capture essential features and improve reconstruction accuracy.

Maximise Mutual Information:

The authors propose an autoencoding transformation (AT) that maximises the lower bound of mutual information. This approach aims to better capture the dependencies between the input and output, leading to improved model performance.

Joint Optimization:

The combined approach (AI + AT) jointly optimizes the model by incorporating both image and transformation reconstruction. This method aims to leverage the strengths of both techniques to achieve superior performance.

Address Real-world Challenges:

The research is motivated by the need to address real-world challenges in image processing and computer vision tasks. The proposed model could potentially be applied to various domains, including anomaly detection, image synthesis, and more

Summary

Autoencoders can be used to identify anomalies by analysing how well they can reconstruct the image and the changes made to it. Here's the process:

Specifically, given an input image,

1))it will be first transformed.

2)Then, the original and trans-formed images will be taken as the inputs

3) The proposed SSR-AE needs to reconstruct both the original image and the applied transformation (not the transformed image)

SSR-AE, aims to reconstruct both the original image and the applied transformation itself (not the transformed image). This way, it can identify anomalies. The key idea is that for normal data, the autoencoder will learn the typical transformations and be able to reconstruct them accurately. However, for abnormal data, the large difference between the original image and the transformation creates an "information gap" for SSR-AE. This gap makes it difficult for the autoencoder to reconstruct the applied transformation, effectively signalling the presence of an anomaly.

In contrast, other autoencoder approaches like VAEs (Variational Autoencoders) focus on reconstructing the original image from a compressed representation. AT (Adversarial Transformation) methods, on the other hand, reconstruct the applied transformations from another compressed representation. SSR-AE stands out because it tackles both the image reconstruction and transformation reconstruction simultaneously.

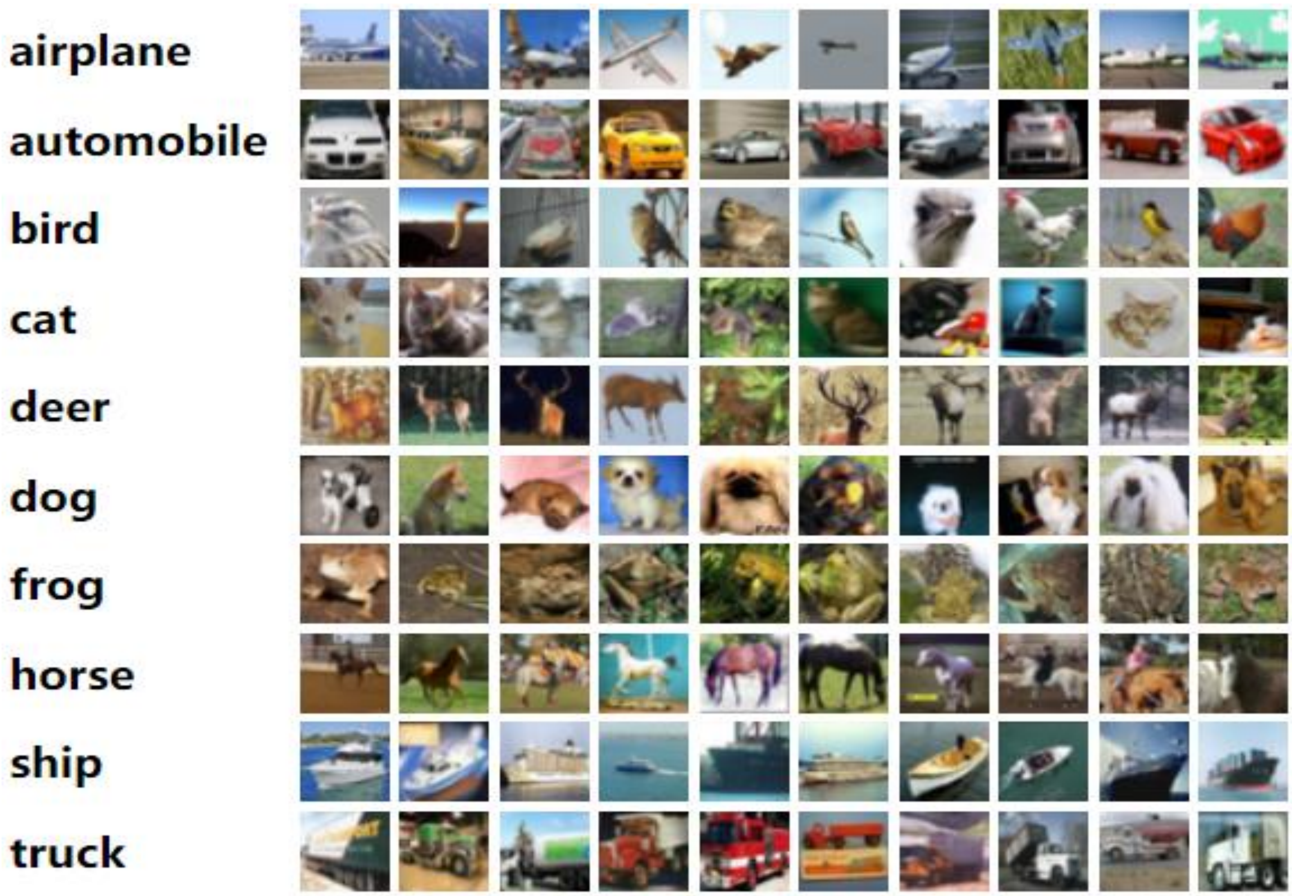
Dataset Analysis

Dataset Used: CIFAR-10

Size and Format: It contains 60,000 small (32x32 pixels) colour images in RGB format. This compact size pushes algorithms to efficiently extract relevant features.

Class Distribution:Dataset contains 10 classes. Each class contains 6,000 images per class (e.g., aeroplanes, cars, dogs). This prevents models from becoming biassed towards frequently occurring categories.

Splits: It's pre-partitioned into 50,000 training images and 10,000 testing images. This clear separation allows us to train models and rigorously evaluate their generalisation capabilities on unseen data.



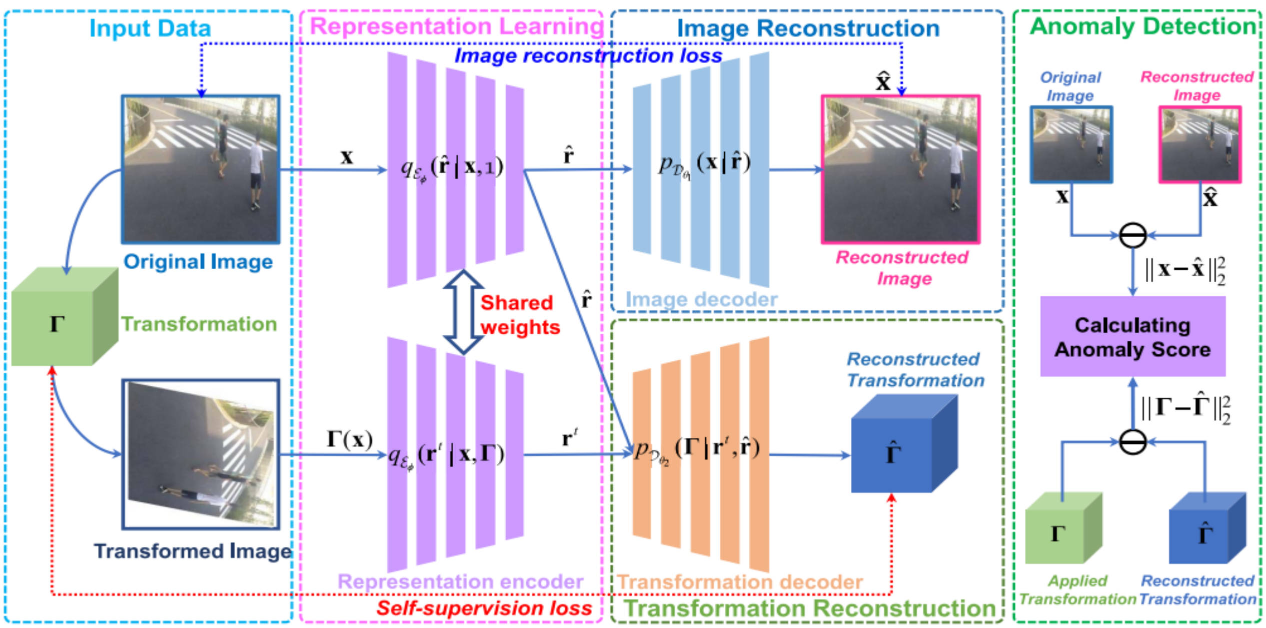
Experiments

Auto Encoder(AE):

Autoencoders are a special type of artificial neural network designed to learn efficient representations of data. Unlike supervised learning models that require labelled data, autoencoders function in an unsupervised manner. They work by compressing the input data into a lower-dimensional hidden representation, often called the latent space. This compressed version captures the essential characteristics of the data. Then, the autoencoder attempts to reconstruct the original data from this latent space using a decoder component. By minimising the difference between the original input and the reconstructed output, the autoencoder learns to identify the key features that best represent the data. This makes them valuable for tasks like dimensionality reduction, anomaly detection etc.

Average AUC: 58.1%

Autoencoding Image(AI):



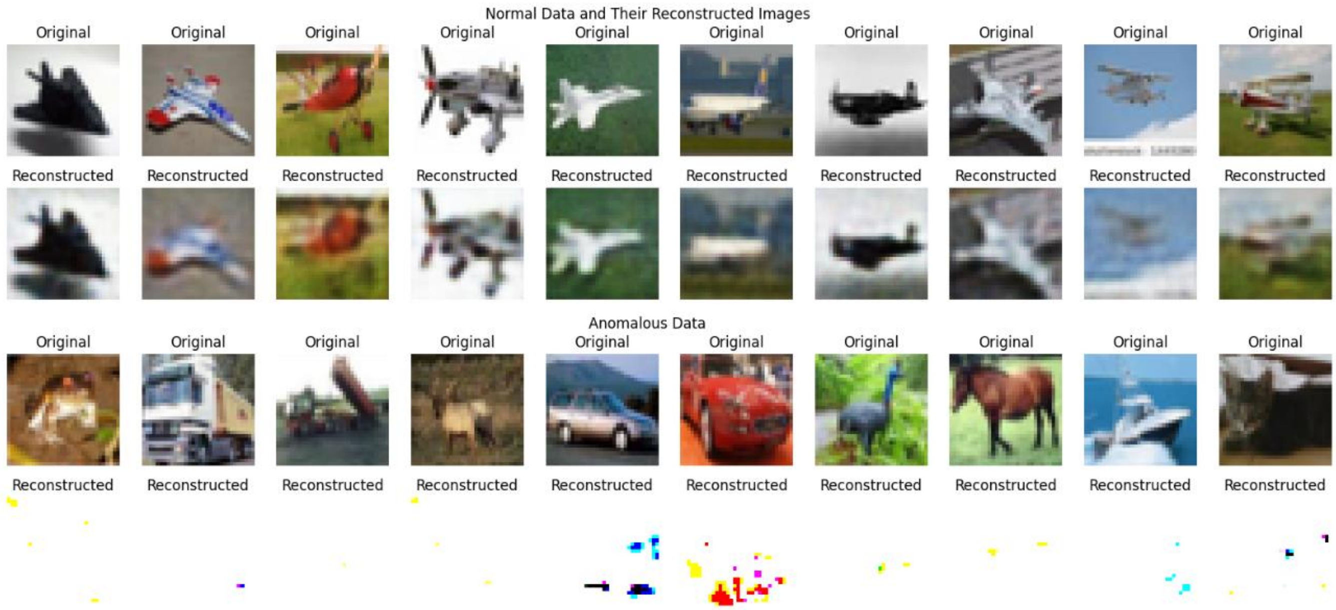
In image autoencoders, the primary objective is to reconstruct the input image with the highest possible fidelity. This reconstruction is achieved through a neural network architecture consisting of an encoder and a decoder. The encoder compresses the input image into a lower-dimensional latent space representation, capturing its essential features. The decoder then leverages this compressed representation to reconstruct the original image. The quality of this reconstruction is evaluated using the Peak Signal-to-Noise Ratio (PSNR) metric. Higher PSNR signifies a more accurate reconstruction, indicating the autoencoder's ability to effectively extract and represent the core visual information within the image. This approach finds applications in tasks like image denoising, where the autoencoder, by optimising for PSNR, learns to differentiate between the actual image content and noise.

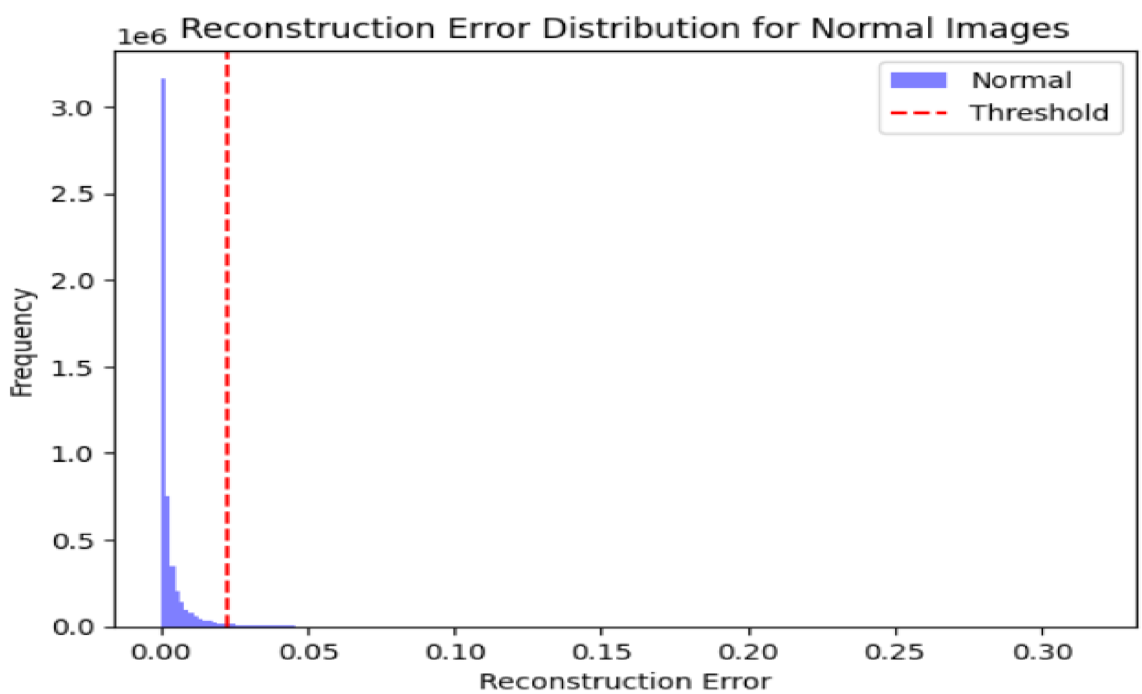
Average AUC: 76.4%

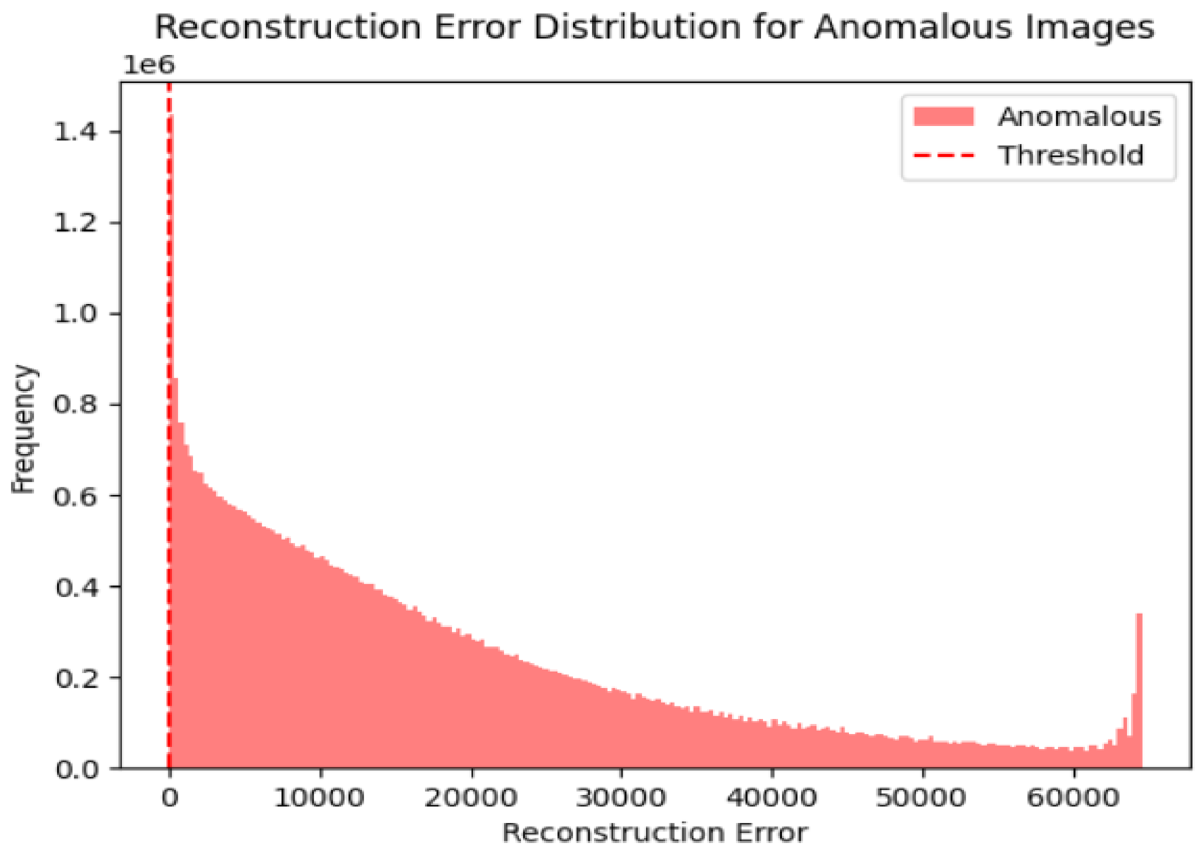
Results

MODEL-1:

Original Data in the below case in PLANE dataset whereas images of other classes are considered anomalies. We can clearly observe that images of plane reconstructed better when compared images of other classes


Normal Data and Their Reconstructed Images
Original
Reconstructed
Anomalous Data
Original
Reconstructed


Reconstruction Error Distribution for Normal Images
1e6
Normal
Threshold
Frequency
Reconstruction Error
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0.00
0.05
0.10
0.15
0.20
0.25
0.30

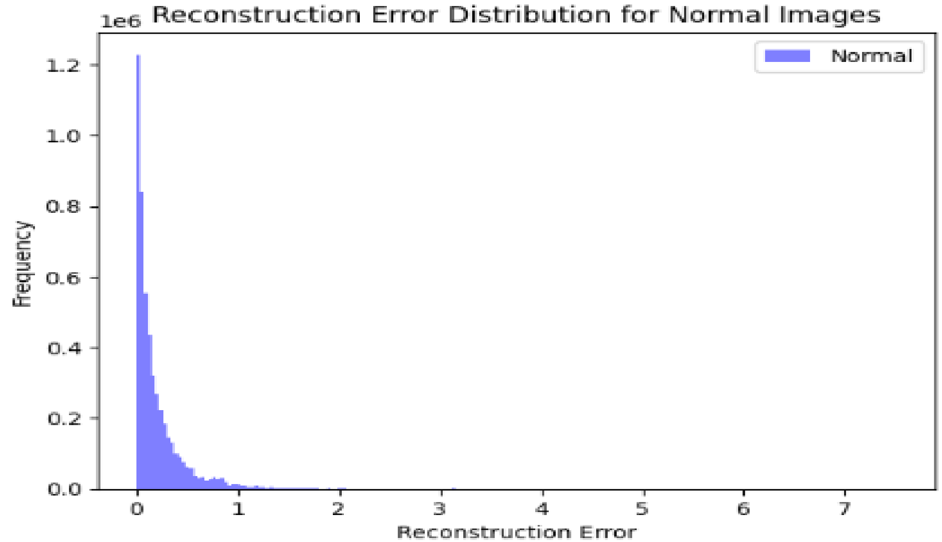


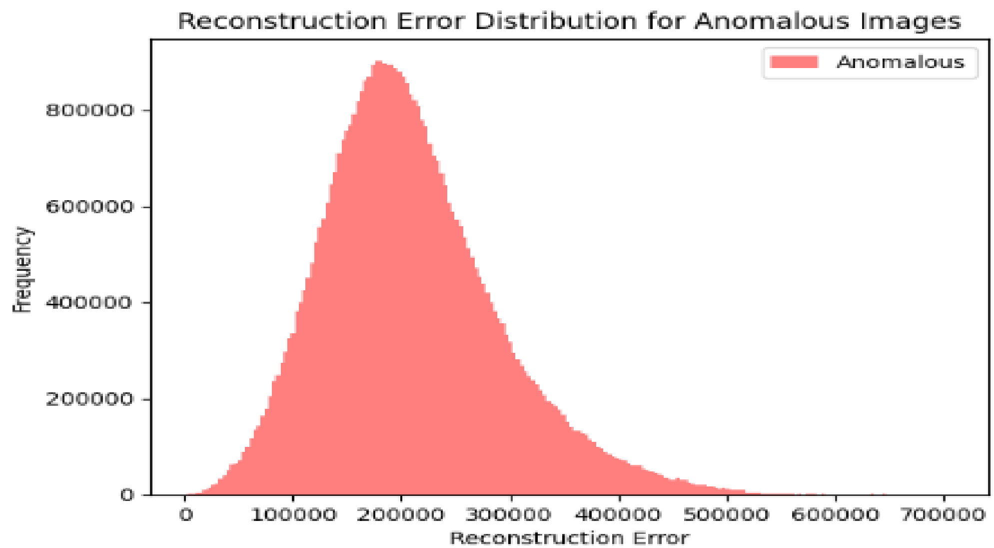
From the above graphs you can observe that for the normal images the reconstruction error is below a threshold value whereas for the anomaly images the reconstruction error above the threshold value.

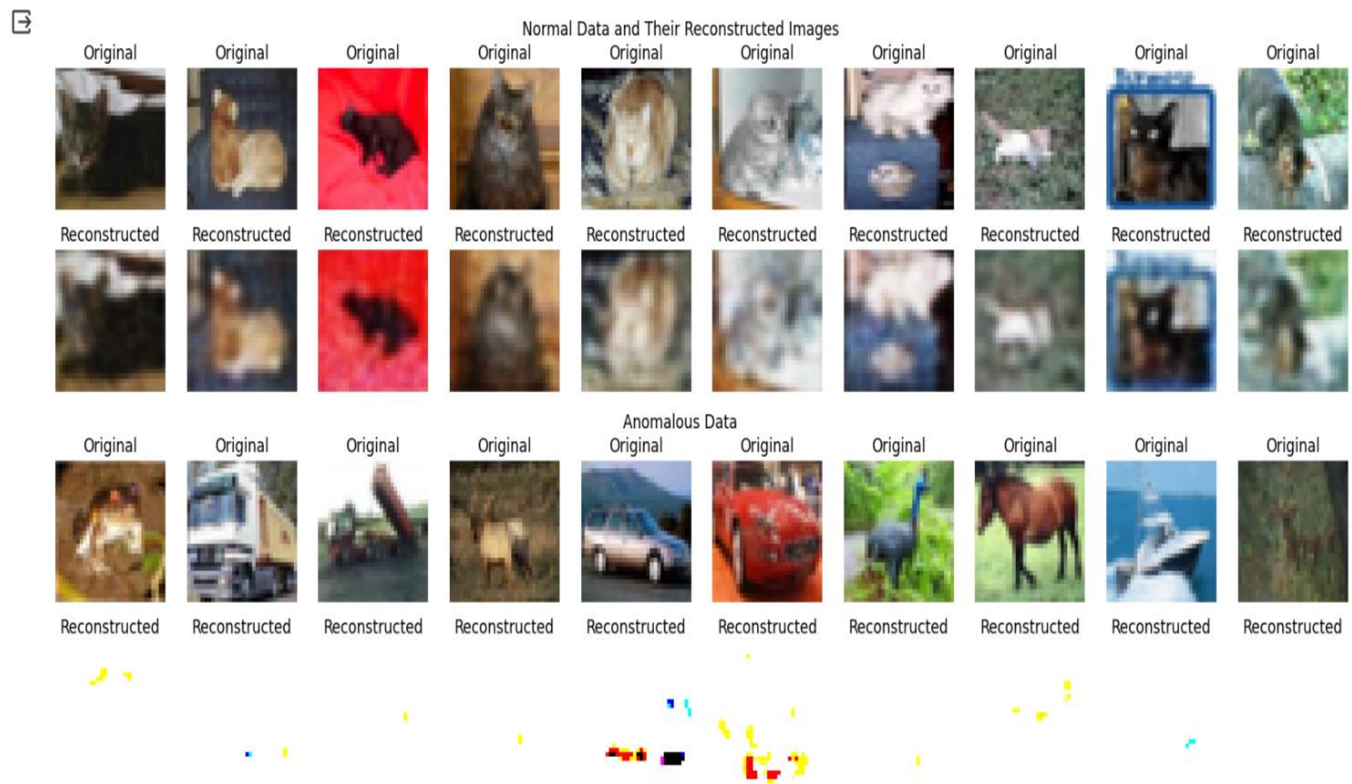
Threshold value is:

```
threshold = np.mean(normal_errors) + 3 * np.std(normal_errors)
```

MODEL 2:


Reconstruction Error Distribution for Normal Images
1e6
Normal
Frequency
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
3
4
5
6
7
Reconstruction Error


Reconstruction Error Distribution for Anomalous Images
Anomalous
Frequency
800000
600000
400000
200000
0
0
100000
200000
300000
400000
500000
600000
700000
Reconstruction Error



In the above image you images of normal dataset are constructed with better accuracy when compared to the anomaly images.We achieve better accuracy in case of AI when compared to AE because we perform data augmentation in AI model.