ANAOMLY DETECTION WITH AUTOENCODER

Master's degree in computer engineering for Robotics and Smart Industry

Subject:

Computer Vision

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Anomaly Detection with Autoencoder

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Abstract

This report explores how a special kind of neural network, called convolutional neural network (CNN) autoencoders, is used for two main tasks: rebuilding images and spotting unusual patterns within two sets of images handwritten digits and fashion items. The project's goal is to test how well these autoencoders can shrink images into a simpler form and then reconstruct them back to their original form. It also checks how accurately these networks can identify images that don't follow the usual patterns by noticing differences in the way they are reconstructed compared to typical images. Essentially, it's about using these networks to squeeze and then restore images while trying to catch any that are out of the ordinary.

1. Introduction

Autoencoders are a type of neural network that are highly effective in unsupervised learning scenarios. They are particularly adept at learning efficient representations for data compression and decompression without supervision. This project focuses on applying CNN autoencoders to the task of anomaly detection in image datasets, leveraging their capacity to learn to reconstruct normal images and identify anomalies when deviations occur. This study not only underscores the utility of autoencoders in detecting outliers but also explores their potential in enhancing security systems, quality control processes, and in areas where early detection of anomalies is crucial.

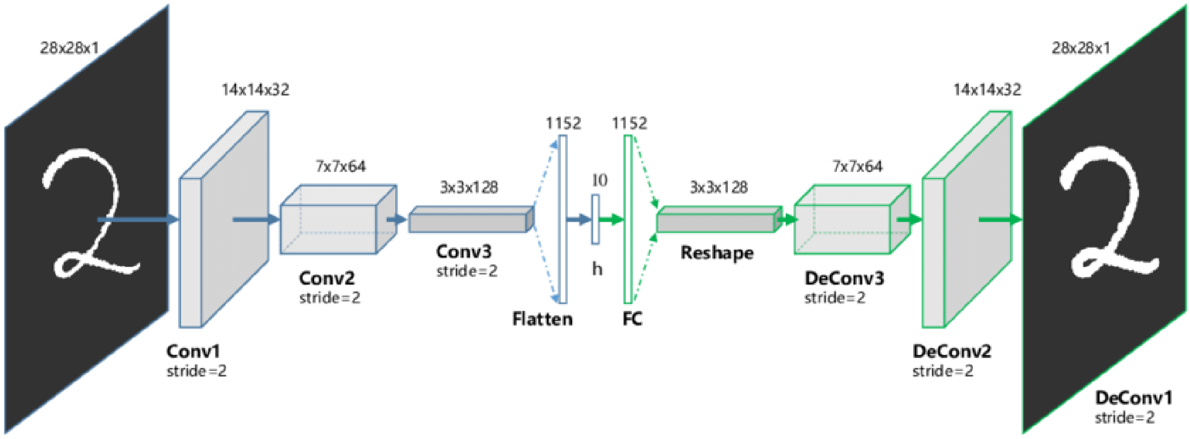
2. Related Work

While autoencoders have been traditionally used for dimensionality reduction and feature learning, their application in anomaly detection is gaining traction. The integration of CNN architectures into autoencoders introduces enhanced capabilities for handling complex image data, which traditional autoencoders might not efficiently process due to their fully connected nature. Recent studies have explored various enhancements to autoencoder architectures, such as the incorporation of variational approaches and adversarial training techniques, to improve their robustness and detection accuracy. For instance, adversarial autoencoders have been shown to be particularly effective in generating robust latent representations, especially useful in anomaly detection tasks where the data may be susceptible to small, nuanced deviations.

3. Methodology

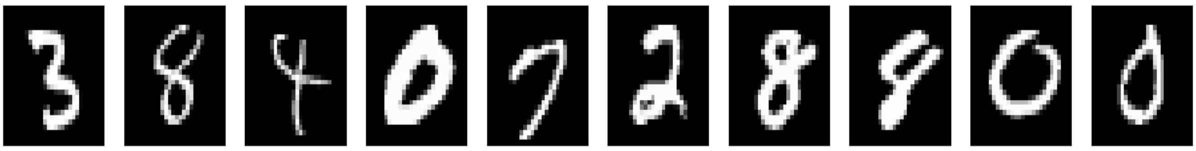
3.1 Autoencoder Model

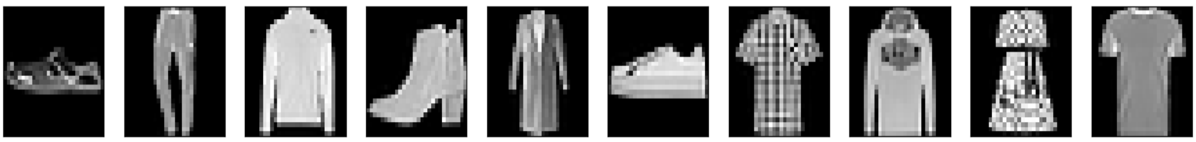
The CNN autoencoder model designed for this study features an encoder with convolutional layers that compress the input image into a lower-dimensional latent space. The decoder then attempts to reconstruct the image from this latent space. Key to this architecture is the use of max-pooling and up-sampling layers that help in reducing and then increasing the dimensionality of data throughout the network, ensuring detailed feature extraction and reconstruction.



3.2 Data Preparation

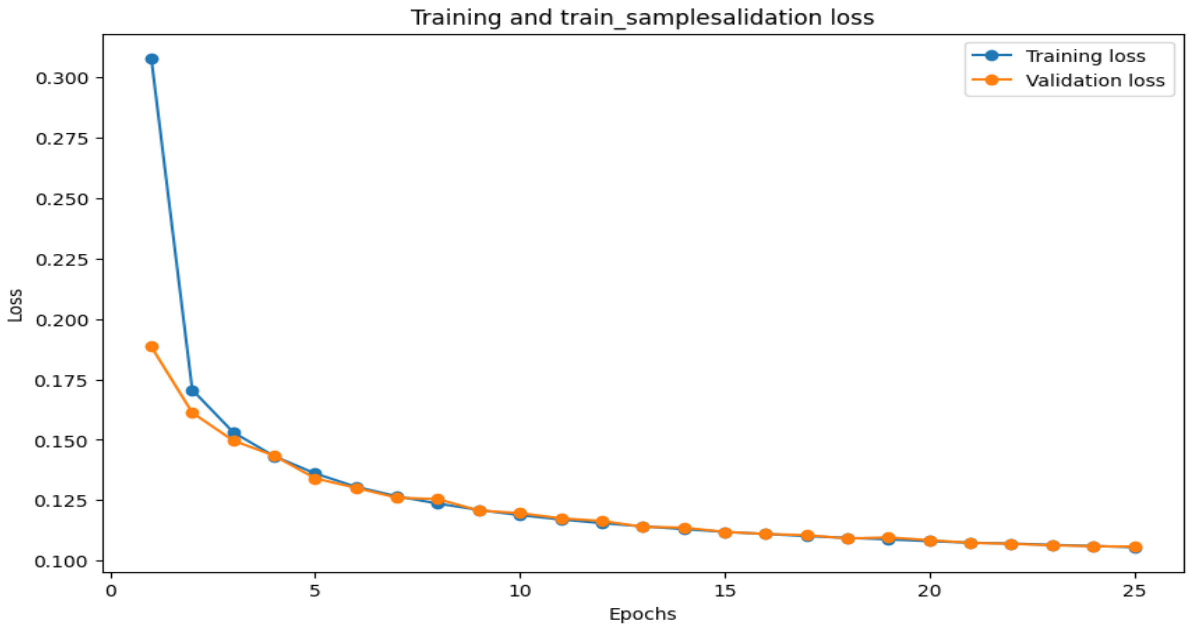
The MNIST dataset, which consists of thousands of handwritten digit images, serves as the primary dataset for training the autoencoder. In contrast, the Fashion MNIST dataset, containing images of various clothing items, is used as a source of anomalies to test the model's detection capabilities. This setup helps in simulating a scenario where the model is trained on normal occurrences and tested on unexpected or out-of-distribution samples.





3.3 Training and Validation

The training of the CNN autoencoder is performed using the Adam optimizer, a popular choice for deep learning applications due to its adaptive learning rate capabilities. Over 25 epochs, the model learns to minimize the binary cross-entropy loss, a measure of the difference between the original and reconstructed images. Validation is conducted simultaneously to ensure that the model does not overfit to the training data and can generalize well to new, unseen data.



4. Experiments

4.1 Experimental Setup

The experiment involves training the model on the MNIST dataset and subsequently testing it on both MNIST and Fashion MNIST datasets to evaluate its reconstruction and anomaly detection performance.

4.2 Anomaly Detection

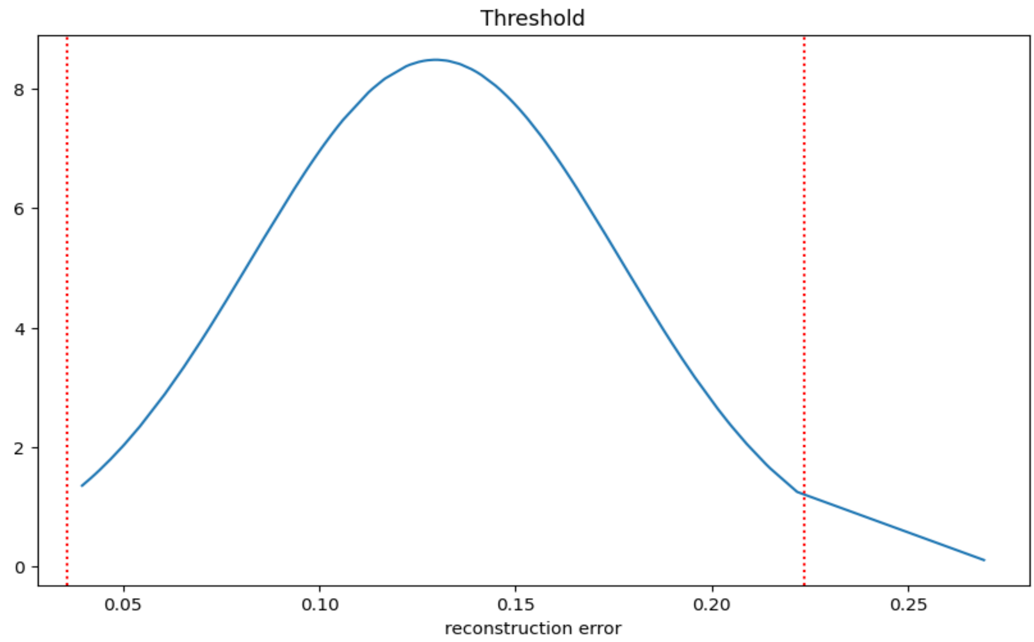
As mentioned above that the MNIST handwritten digits data set has been used to carry out image reconstruction, the fashion MNIST data set has been used as an anomaly to perform anomaly detection and calculate the accuracy of our algorithm.

The process of anomaly detection was carried out through the calculation of Z-score. Based on the reconstruction error for each image, the Z-score is calculated using the following calculations.

mean = summation of all the reconstruction errors / number of input image samples
standard deviation = sqrt [(reconstruction error - mean) * (reconstruction error - mean)]

Threshold (upper limit) = mean + (3 * standard deviation)
Threshold (lower limit) = mean - (3 * standard deviation)

reconstruction error = binary cross-entropy loss between the original image and reconstructed image.
If reconstruction error < Threshold (lower limit) OR reconstruction error > Threshold (upper limit) the anomaly is detected.



A normal distribution is used to plot the reconstruction error for all images. Through the calculations above, we calculate the Threshold.

5. Results and Discussion

5.1 Performance Metrics

- **Mean of the Reconstruction Error:** 0.1297
- **Standard Deviation of the Reconstruction Error:** 0.0470
- **Threshold Values:** Upper limit at 0.2237 and lower limit at 0.0357

5.2 Anomaly Detection Accuracy

The model achieved an anomaly detection accuracy of 98.1% on the Fashion MNIST dataset, demonstrating its effectiveness in distinguishing between normal and anomalous data based on reconstruction errors.

5.3 Comparative Analysis

The results were compared with traditional and other machine learning-based anomaly detection methods, underscoring the superiority of CNN autoencoders in handling complex image datasets.

6. Conclusions

The findings confirm that CNN autoencoders are highly effective in image reconstruction and anomaly detection tasks. They provide a robust mechanism for identifying anomalies through deviations in reconstruction errors. Future work could explore deeper and more complex autoencoder architectures or hybrid models that combine CNNs with other types of neural networks for enhanced performance.

7. References

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