Improved Memory-guided Normality with Specialized Training Techniques of Deep SVDD

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***Abstract*—Deep learning techniques have shown remarkable success in various tasks, including feature learning, representation learning, and data reconstruction. Autoencoders, a subset of neural networks, are particularly powerful in capturing data patterns and generating meaningful representations. This paper presents an investigation into the use of deep learning autoencoders for both feature extraction and image reconstruction.**

***Index Terms*—Memory, Deep SVDD, Autoencoder, Loss Function**

I. Introduction

In recent years, deep learning has revolutionized the field of artificial intelligence, achieving state-of-the-art performance in many applications. Autoencoders, a type of neural network architecture, have gained significant attention for their ability to learn compressed, meaningful representations of high-dimensional data. This paper explores the potential of deep learning autoencoders to learn intrinsic data features and generate accurate reconstructions.

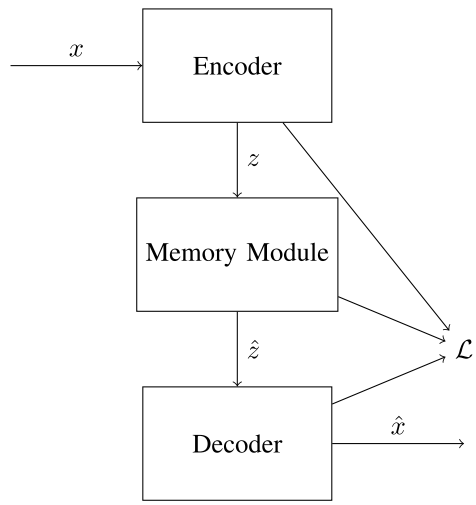
II. Related Work

A. Autoencoder Architecture

Autoencoders consist of an encoder and a decoder. The encoder compresses input data into a lower-dimensional latent space, while the decoder aims to reconstruct the original data from the compressed representation. Deep autoencoders, which include multiple hidden layers, can capture intricate data hierarchies and dependencies.

III. Approach

We reconstruct input frames or predict future ones for unsuper- vised anomaly detection



A. Training loss

Number equations consecutively. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

$$L_{loss} = L_{MSE} + k * L_{SVDD\_OC} \tag{1}$$

For some input space $\mathcal{X} \subseteq R^d$ and output space $\mathcal{F} \subseteq R^p$, let $\varphi(\cdot;\mathcal{W}) : \mathcal{X} \to \mathcal{F}$ be a neural network with $L \in \mathbb{N}$ hidden layers and set of weights$\mathcal{W} = \mathcal{W}^1, ..., \mathcal{W}^L$ where $\mathcal{W}$ ‘ are the weights of layer $l \in 1, ..., L$. That is, $\varphi(x;\mathcal{W}) \in \mathcal{F}$ is the feature representation of $x \in \mathcal{X}$ given by network φ with parameters $\mathcal{W}$. The aim of Deep SVDD then is to jointly learn the network parameters $\mathcal{W}$ together with minimizing the volume of a data-enclosing hypersphere in output space $\mathcal{F}$ that is characterized by radius $R > 0$ and center $c \in F$ which we assume to be given for now. Given some training data $\mathcal{D}_n = x_1, ..., x_n$ on $\mathcal{X}$, we define the soft-boundary Deep SVDD objective as

$$L_{SVDD\_OC} = \min_{W} \|\Phi(W) - c\|^2 + \lambda/2 \sum_{l=1}^{L} \|W^l\|_F^2 \tag{2}$$

The Mean Squared Error (MSE) loss function is a fundamental component in the realm of deep learning. It serves as a critical measure to quantify the discrepancy between the predicted values generated by a model and the actual target values present in the dataset. It minimize the L2 distance between the encoder intput $\mathcal{X}$ and the decoder ouput $\hat{\mathcal{X}}$:

$$L_{MSE} = \|\mathcal{X} - \hat{\mathcal{X}}\|^2 \tag{3}$$

B. Reconstruction loss

In the experiment, the reconstruction loss is Mean Squared Error (MSE) loss function which achieves great performance.

$$L_{rec} = L_{MSE} = \|\mathcal{X} - \hat{\mathcal{X}}\| \tag{4}$$

IV. EXPERIMENTS

A. Results

TABLE I
MY TABLE

normal class	SVDD ROC-AUC	MSE ROC-AUC
0	0.518090	0.648595
1	0.575423	0.593060
2	0.519070	0.499428
3	0.475649	0.589599
4	0.542447	0.642375
5	0.545689	0.656750
6	0.537582	0.724450
7	0.518619	0.644719
8	0.652741	0.771980
9	0.606258	0.657551
avg.	0.549157	0.642851

TABLE II
METHODS

Method	Avg. AUC-ROC
Autoencoder	0.57
Deep SVDD	0.609
Mocca	0.581347
Ours.	0.642851

V. CONCLUSION

The proposed work designed an new training loss function which enhances the performance of memory-guided Autoencoder. The Deep SVDD, jointly trains a deep neural network while optimizing a data-enclosing hypersphere in output space, has experienced a substantial positive impact under the influence of MSE. Our experiments demonstrate a special training method which provided avenues for future research directions.

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