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Anomaly detection using improved deep SVDD model with data structure preservation

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ABSTRACT

Support vector data description (SVDD) is a classical anomaly detection algorithm. How to develop a deep version of SVDD is one valuable problem in the anomaly detection field. Aiming at this problem, an improved SVDD model called deep structure preservation SVDD (DSPSVDD) is proposed by integrating the deep feature extraction with the data structure preservation. Firstly, the typical SVDD methods are revisited in view of model depth profiles and the limitations of the present deep SVDD model are analyzed. Then in order to extract the deep data features more effectively, an enhanced comprehensive optimization objective is designed for the deep SVDD model by considering both the hypersphere volume minimization and the network reconstruction error minimization simultaneously. The experimental results on the MNIST, Fashion-MNIST, and MVTec AD image benchmark datasets show that the proposed DSPSVDD method achieves the better anomaly detection performance compared with the traditional deep SVDD method.

1. Introduction

Anomaly detection is one important branch in the data mining and machine learning field and has been widely applied to many different scenarios including fraud detection [1], hyperspectral image analysis [2], and industrial process monitoring [3]. The goal of anomaly detection is to discern the unusual or abnormal samples based on the trained model [4]. As is known to all, it is usually hard to obtain enough labeled abnormal samples to train a sufficiently reliable classification model via the supervised way. In fact, the samples available in the real world are mostly positive classes. Therefore, anomaly detection is usually known as one-class classification [5].

Some typical anomaly detection methods include Kernel Density Estimation (KDE), Isolation Forest (IForest), Support Vector Data Description (SVDD), etc. Lv et al. [6] designed a KDE based anomaly detection method by firstly applying the variational autoencoder to reduce the data dimension and then detecting the anomaly objects in the low-dimensional space. Hu et al. [7] combined the local KDE with context-based regression for anomaly detection. Considering the data nonlinearity, Li et al. [8] presented a kernel IForest method for hyperspectral anomaly detection. SVDD is a well-known anomaly detection method, which optimizes a hypersphere to enclose the training data and judges the out-of-boundary data as the anomaly targets. In order to detect the anomalies in the multimodal case, Turkoz et al. [9] developed a generalized SVDD method to construct the hyperspheres for each mode. Anomalies in wireless sensor network may degrade the decision making. To reduce the energy consumption, Chen et al. [10] put forward a lightweight anomaly detection algorithm using SVDD, which applies the core-sets to decrease the computation complexity. Sindagi et al. [11] applied an adaptive SVDD to automatic OLED panel defect detection. Among the present methods, SVDD attracts great attention from researchers and has obtained many successfully applications. However, it often performs not well in high-volume and high-dimensional data such as image data. This is because SVDD is a shallow learning method in nature and cannot capture the intrinsic deep data features sufficiently.

Benefiting from the proliferation of computation, the recent years have witnessed the rapid development of deep learning [12]. Deep learning based neural networks achieved great success in various application domains especially in computer vision because of its ability to learn relevant features automatically [13]. Some representative deep learning models consist of stacked autoencoder, convolutional neural network (CNN), and deep belief network (DBN). For identifying the images from the poorly-lit environment, Lore et al. [14] designed a deep autoencoder network to adaptively brighten the low-light images. Bernal et al. [15] reviewed the applications of CNN in the brain image processing. Zeng et al. [16] carried out the quantitative analysis of gold im-

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munochromatographic strip images by DBN. Especially, deep autoencoder have been applied to anomaly detection by learning the representation of data through reconstruct the data with the introduce of bottleneck. Some researchers have studied the application of the autoencoder in anomaly detection [17].

Inspired by the dramatic success of deep learning methods, a natural idea is to apply deep learning theory to improve the basic SVDD model for more effective anomaly detection. Ruff et al. [18] made the initial studies on the combination of deep learning and SVDD and proposed a deep SVDD model (DSVDD) under a neural network framework. DSVDD is an inspiring work but is not an end. One prominent limitation of Ruff et al.'s work is the omission of the data structure information. The present DSVDD version only aims at minimizing the hypersphere volume of deep features, but does not consider if the obtained deep features preserve the effective data structure information. To avoid the trivial solution, DSVDD has to enforce some strict constraints on the network bias and activation function. These constraints may degrade the anomaly detection performance and lead to unstable model. Therefore, how to make a stronger deep SVDD model is a challenging task deserving further studies.

Motivated by the above analysis, this paper proposes an improved deep support vector data description model for anomaly detection. Different from the basic deep SVDD model, the proposed method fuses the autoencoder network with the deep SVDD network. Furthermore, a new optimization objective is designed by minimizing both the hypersphere volume and the reconstruction error simultaneously. As the introduction of data structure preservation, the new method is called deep structure preservation SVDD (DSPSVDD). Compared with the basic deep SVDD model, this method utilizes the data structure information sufficiently in the data clustering so that the dependence on the constraints is leveraged and the training result is more stable.

2. Related work

2.1. Traditional SVDD models

As a variant of support vector machine, SVDD is a typical one-class classification algorithm [19,20]. SVDD identifies anomalies mainly by determining a minimum-volume hypersphere which surrounds the positive samples in feature space. The traditional SVDD models include two categories: linear SVDD and kernel-based nonlinear SVDD. They are described as follows.

Given the normal training sample as $\{\boldsymbol{x}_1, \ \boldsymbol{x}_2, \ \ldots, \ \boldsymbol{x}_n\}$ where $\boldsymbol{x}_i \in \mathcal{R}^m, i = 1, 2, \ldots, n$, the linear SVDD optimization objective is to seek for a tight data description, described as follows.

$$\begin{cases} & \min R^2 + \frac{\gamma}{n}\sum_{i=1}^{n}\sigma_i, \\ s.t. & ||\boldsymbol{x}_i - \boldsymbol{o}||^2 \le R^2 + \sigma_i, \\ & \sigma_i \ge 0, \end{cases} \tag{1}$$

where $||\cdot||$ represents the Euclidean norm, $\boldsymbol{o}$ is the center of the sphere, σ_i is the relaxation variable, R is the hypersphere radius, and γ is the trade-off parameter coordinating the hypersphere volume and the modeling error. $\sum_{i=1}^{l}\sigma_i$ is the penalty term that allows for outliers.

The above optimization applies to the linear case. When nonlinear data relationship exists, the original training data are not spherically distributed so that anomalies can not be isolated by a hypersphere effectively. Therefore, the kernel SVDD is applied. Firstly, a nonlinear mapping function $\phi(.)$ is assumed to map these samples onto a new feature space: $\boldsymbol{x}_i \to \phi(\boldsymbol{x}_i)$, where all the samples are with linear relationship. Then, the basic SVDD optimization is applied as follows.

$$\begin{cases} & \min R^2 + \frac{\gamma}{n}\sum_{i=1}^{n}\sigma_i, \\ s.t. & ||\phi(\boldsymbol{x}_i) - \boldsymbol{o}||^2 \le R^2 + \sigma_i, \\ & \sigma_i \ge 0. \end{cases} \tag{2}$$

To solve the above optimization leads to the following dual expression as [19]

$$\begin{cases} & \max \sum_{i=1}^{n}\alpha_i\langle\phi(\boldsymbol{x}_i), \phi(\boldsymbol{x}_i)\rangle - \sum_{i,j=1}^{n}\alpha_i\alpha_j\langle\phi(\boldsymbol{x}_i), \phi(\boldsymbol{x}_j)\rangle, \\ s.t. & 0 \le \alpha_i \le \gamma, \\ & \sum_{i=1}^{n}\alpha_i = 1, \end{cases} \tag{3}$$

where α_i is the Lagrangian multiplier, $\langle\phi(\boldsymbol{x}_i), \phi(\boldsymbol{x}_j)\rangle$ represents the inner product in the mapping space. As the mapping function is usually unknown, the kernel function is applied to compute the inner product as

$$< \phi(\boldsymbol{x}_i), \phi(\boldsymbol{x}_j) >= Ker(x_i, x_j), \tag{4}$$

where Ker is some kernel function satisfying the Mercer theorem. The commonly used kernel function is the Gaussian kernel. With the use of kernel function, the optimization in Eq. (2) can be solved and the sphere center is obtained as $\boldsymbol{o} = \sum_{i=1}^{n}\alpha_i\phi(x_i)$.

To determine if one test vector $\boldsymbol{x}$ represents one anomaly point, a decision index, also called the score index, is developed as

$$D(\boldsymbol{x}) = \|\Phi(\boldsymbol{x}) - \boldsymbol{o}\|^2. \tag{5}$$

The testing sample $\boldsymbol{x}$ with $D(\boldsymbol{x}) > R$ indicates the anomaly. Otherwise, the testing sample belongs to the normal case.

2.2. Deep SVDD

In order to mine the data features more sufficiently, a deep SVDD (DSVDD) with deep neural network structure is proposed by Ruff et al. [18]. Similar to the kernel SVDD, DSVDD aims to find a hypersphere in the feature space. However, the difference lies in the use of deeper data transformation procedure based on the deep neural network. Let $\Phi(\boldsymbol{x}; \boldsymbol{W})$ represents the mapped data given by the network Φ with parameters $\boldsymbol{W}$. To minimize the volume of the hypersphere surrounding the normal data, Ruff et al. [18] defined the DSVDD objective as:

$$\min_{\boldsymbol{W}} R^2 + \frac{\gamma}{n}\sum_{i=1}^{n}\max\{0, ||\Phi(\boldsymbol{x}_i; \boldsymbol{W}) - \boldsymbol{c}||^2 - R^2\} + \frac{\lambda}{2}\sum\|\boldsymbol{W}\|_F^2, \tag{6}$$

where $\boldsymbol{W}$ is the weight matrix of the network, γ and λ are the balancing parameters.

In the case that most of training samples are normal, the above optimization can be rewritten as a simplified version, which is given as [18]

$$\min_{\boldsymbol{W}} \frac{1}{n}\sum_{i=1}^{n}\|\Phi(\boldsymbol{x}; \boldsymbol{W}) - \boldsymbol{c}\|^2 + \frac{\lambda}{2}\sum\|\boldsymbol{W}\|_F^2, \tag{7}$$

The above expression is to contract the sphere by minimizing the average distance of all training samples to the center with the network weights as the regularization term.

3. The proposed method

3.1. Model depth profile investigation and motivation analysis

To sum up the present three SVDD models of linear SVDD, kernel SVDD, and DSVDD, they have the similar methodology of seeking the compact data description. However, they are different in view of the optimization space. To demonstrate this, we depict the

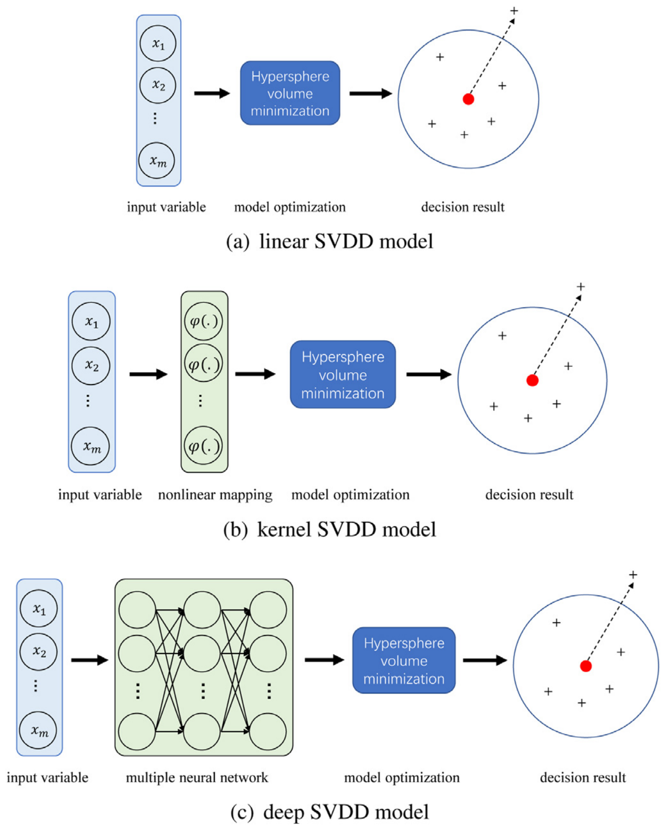

Fig. 1. The model depth profile for different SVDD methods.

feature extraction and optimization procedure of these three methods, as shown in Fig. 1. By Fig. 1(a), it is seen that linear SVDD optimization is performed in the original input space. This is the simplest version and is only suitable to the linear data analysis. The kernel SVDD schematic, shown in Fig. 1(b), involves one nonlinear feature extraction procedure (or called data mapping step), which is in fact implemented by the kernel function. Due to the use of one nonlinear feature extraction procedure, kernel SVDD is able to deal with the nonlinear data relationship. For better data feature representation with one-class classification, DSVDD is designed with the structure in Fig. 1(c). From the model depth profile, DSVDD can be equipped with as many feature layers as required. Therefore, it is certain that DSVDD has the potential to provide better anomaly detection performance.

However, it should be noted that, the premise of a good DSVDD model is that the deep network is well trained. In fact, the DSVDD model has some strict constraints [18]. By Eq. (7), it is found that the center vector $\boldsymbol{c}$ can not be set to zero. Otherwise, this will lead to the trivial solution $\Phi(\boldsymbol{x};\boldsymbol{W}) = 0$ and $\boldsymbol{W} = 0$. This is not the real solution and does not describe any data information. Similar constraints include that the deep SVDD network cannot apply the bias term and the used activation functions can not be bounded. If the bias term is applied in the deep SVDD network, there exists the unexpected solution $\boldsymbol{W} = 0$ with $\Phi(\boldsymbol{x};\boldsymbol{W}) = constant$. This is so-called hypersphere collapse [18]. Therefore, the bias term should be avoided in this network. The bounded activation function is not suggested due to the same reason. To investigate the reason for these limitations, the root cause lies in that the optimization objective in Eq. (7) only goes after the data-enclosing sphere with the smallest volume, but does not consider how to preserve the main data structure information. In other words, if all the samples are mapped to the zero, the sphere is the minimal but does not preserve any effective data structure information. This problem motivates our method, which is clarified in the next section.

3.2. Improved deep SVDD with data structure preservation

Aiming at the shortcomings of the basic deep SVDD model, this paper proposes an improved deep SVDD model with data structure preservation, called DSPSVDD. The main idea is to build a deep SVDD network with two goals. One goal is to obtain the compact data description by nonlinear network mapping, which means the data points are mapped to the data center as closely as possible. This has been done in the previous deep SVDD model. Another goal is that the network output should preserve the original data structure information as much as possible. That means the network output should describe the principal data changes and discard the noise influence. The schematic of the proposed method is shown in Fig. 2.

To retain the data structure information, this paper introduces the autoencoder to enhance the deep network optimization. Usually, an autoencoder compresses data by means of an information bottleneck formed by a funnel-shaped network structure. In fact, what makes autoencoder effective is the introduction of information bottlenecks that allow networks to learn the latent features of input data rather than simply copying it. Considering the image processing task, a convolutional multi-layer autoencoder is shown in Fig. 3.

Given some training samples $\{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n\}$, the objective function of convolutional autoencoder is defined as follows.

$$\min_{\boldsymbol{W}} \sum_{i=1}^{n} \|\hat{\boldsymbol{x}}_i - \boldsymbol{x}_i\|^2 + \frac{\lambda}{2}\sum \|\boldsymbol{W}\|_F^2, \tag{8}$$

where $\hat{\boldsymbol{x}}_i$ denotes the output of the decoder part. The feature extraction of autoencoder is to retain the data structure information so that the reconstructed $\hat{\boldsymbol{x}}_i$ is close to the original sample $\boldsymbol{x}_i$. By combining the Eqs. (7) and (8), the modified DSVDD optimization objective is designed as

$$\min_{\boldsymbol{W}} \frac{1}{n}\sum_{i=1}^{n} \|\Phi(\boldsymbol{x};\boldsymbol{W}) - \boldsymbol{c}\|^2 + \frac{\gamma}{n}\sum_{i=1}^{n} \|\hat{\boldsymbol{x}}_i - \boldsymbol{x}_i\|^2 + \frac{\lambda}{2}\sum \|\boldsymbol{W}\|_F^2. \tag{9}$$

The network should be pre-trained using an autoencoder. The center $\boldsymbol{c}$ is defined as the average vector of the encoder outputs corresponding to all the training samples.

By the above expression, the improved deep SVDD is to not only minimize the volume of the hypersphere in feature space, but also retain the original information as much as possible. To optimize the parameters of this model, Adam algorithm, a variant of stochastic gradient descent (SGD) algorithm [21], is applied in our work. Adam performs well on the large scale datasets because of its parallel processing ability which has get widely used in various models. Its pseudocode can be seen in Kingma and Ba [22].

For the giving test sample, we define the anomaly score $D(\boldsymbol{x})$ as its distance to the hypersphere center in feature space as follows:

$$D(\boldsymbol{x}) = \|\Phi(\boldsymbol{x};\boldsymbol{W}^*) - \boldsymbol{c}\|^2, \tag{10}$$

where $\boldsymbol{W}^*$ is the weights of the trained network. For a input data, if the anomaly score is over the detection threshold, it is considered as abnormal; otherwise, it is normal.

4. Experiments

This section conducts the experiments on the three datasets to validate the proposed anomaly detection method. The involving datasets include the MNIST, Fashion-MNIST, and MVTec AD datasets. The experiment settings and results are given as follows.

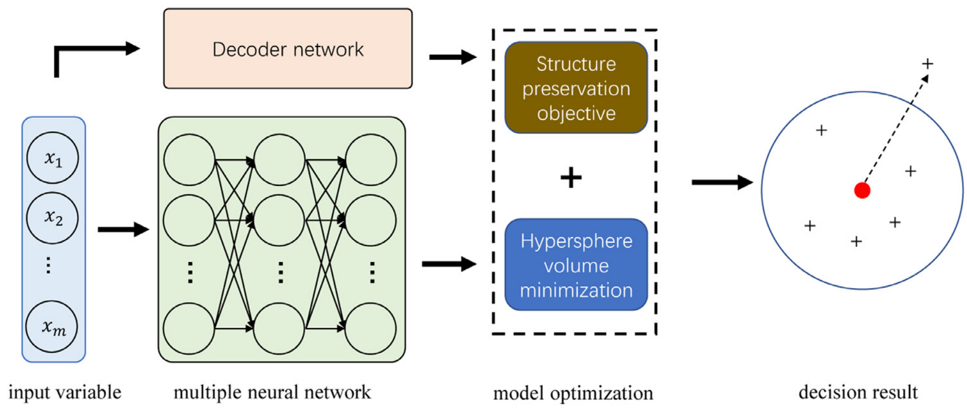

Fig. 2. The modified deep SVDD model with data structure preservation.

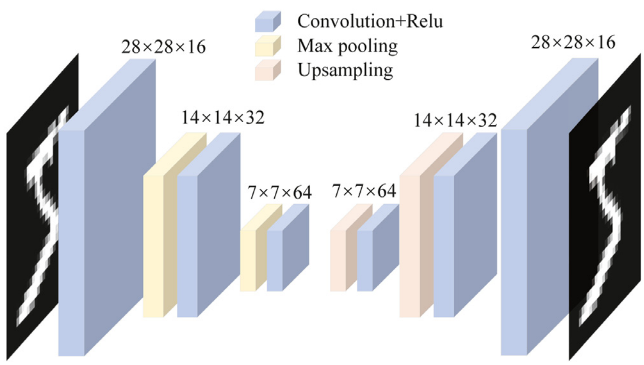

Fig. 3. Autoencoder based data structure analysis.

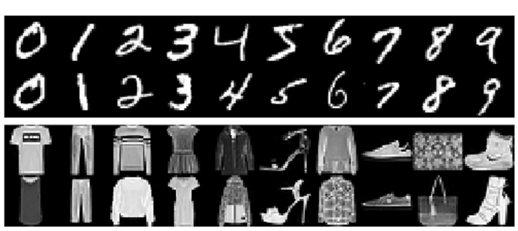

Fig. 4. Examples of MNIST and Fashion-MNIST datasets.

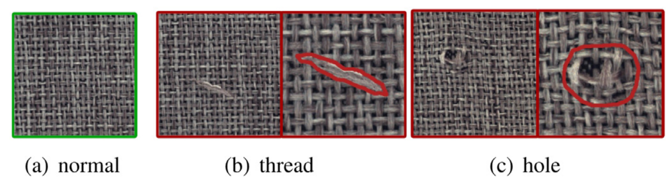

Fig. 5. Examples of the carpet subset. (a) is a normal sample. (b) and (c) are two different defect images respectively, and the right is the enlarged image of the defect region.

Table 1
Average AUCs (%) with StdDevs (%)(10 seeds) per method on MNIST.

Class	IForest	DCAE	SSIM	DSVDD	DSPSVDD
0	98.0 ± 0.3	97.6 ± 0.7	98.0 ± 0.0	98.0 ± 0.7	**99.8** $\pm$ 0.0
1	97.3 ± 0.4	98.3 ± 0.6	98.0 ± 0.4	99.7 ± 0.1	**99.9** $\pm$ 0.0
2	88.6 ± 0.5	85.4 ± 2.4	82.2 ± 1.7	91.7 ± 0.8	**96.2** $\pm$ 0.4
3	89.9 ± 0.5	86.7 ± 0.9	88.8 ± 1.1	91.9 ± 1.5	**96.6** $\pm$ 0.3
4	92.7 ± 0.6	86.5 ± 2.0	92.5 ± 0.7	94.9 ± 0.8	**97.4** $\pm$ 0.3
5	85.5 ± 0.8	78.2 ± 2.7	89.7 ± 1.3	88.5 ± 0.9	**97.3** $\pm$ 0.2
6	95.6 ± 0.3	94.6 ± 0.5	94.8 ± 1.9	98.3 ± 0.5	**99.7** $\pm$ 0.0
7	92.0 ± 0.4	92.3 ± 1.0	95.7 ± 0.3	94.6 ± 0.9	**98.0** $\pm$ 0.2
8	89.9 ± 0.4	86.5 ± 1.6	79.6 ± 1.3	**93.9** $\pm$ 1.6	92.4 ± 0.5
9	93.5 ± 0.3	90.4 ± 1.8	79.6 ± 1.3	96.5 ± 0.3	**98.1** $\pm$ 0.1
mean	92.3 ± 0.5	89.7 ± 1.4	89.9 ± 1.0	94.8 ± 0.8	**97.5** $\pm$ 0.2

4.1. Datasets

MNIST and Fashion-MNIST are widely-used datasets for image anomaly detection [18], which are shown in Fig. 4. The former is about the handwritten digits, while the latter is about the fashion products. Both datasets have the same setups and each dataset contains 60,000 training samples and 10,000 testing samples evenly distributed. The MNIST dataset has ten classes for different numbers 0, 1, …, 9, and the Fashion-MNIST involves ten different kinds of fashion products. The recognition of each class can be thought as a one-class classification task. The specific class is taken as the normal class and the rest nine classes represent the abnormal classes.

MVTec AD, proposed by Paul Bergmann [23], is a dataset used to benchmark anomaly detection methods with emphasis on industrial detection. It contains 15 different categories of objects and textures. For each category, the training set consists of only normal samples, while the test set contains different types of defect and normal samples. Here we evaluate the methods by selecting the carpet subset with 280 training images and 117 testing images. This dataset involves texture data and the size of each image is 1024×1024. The examples of this dataset are shown in Fig. 5. To maintain the consistency with the above experiments, we makes further processing on this dataset. First, all the images are resized to 512×512 and then cut to to 32×32. What is different from training data is that the testing sets comprise slices with defect area over 30% together with all the normal patc hes.

As to the MVTec AD dataset, considering that it is more complicated than the simple images above, we adopt the pre-training network for preliminary feature extraction. We borrowed Rakhlin's work and adopted the method known as deep convolution feature representation [24]. By global average pooling and concatenation of different convolution layers, the low-dimensional feature descriptor of the input images can be obtained through the pre-trained feature extraction network. In this paper, we take VGG-19 as our feature extraction network [25]. Finally, we can obtain the feature descriptor with 1408 elements and then feed it into our DSPSVDD model.

4.2. Experiment setups

To illustrate the competitiveness of ours, we select the following representative one-class classification models for comparison.

Table 2
Average AUCs (%) with StdDevs (%) (10 seeds) per method on Fashion-MNIST.

Class	IForest	DCAE	SSIM	DSVDD	DSPSVDD
T-shirt	86.8 ± 0.6	87.4 ± 0.4	85.6 ± 0.8	86.9 ± 1.6	**89.8** $\pm$ 0.2
Trouser	97.7 ± 0.1	98.4 ± 0.1	95.4 ± 0.6	96.7 ± 0.8	**99.1** $\pm$ 0.1
Pullover	87.1 ± 0.3	83.9 ± 3.7	85.0 ± 0.4	86.4 ± 1.6	**89.7** $\pm$ 0.4
Dress	90.1 ± 0.7	90.1 ± 0.3	85.6 ± 1.5	87.7 ± 1.7	**91.4** $\pm$ 0.2
Coat	89.8 ± 0.4	84.9 ± 0.8	85.9 ± 0.3	89.0 ± 1.5	**89.9** $\pm$ 0.1
Sandal	88.7 ± 0.2	84.8 ± 0.4	78.6 ± 1.3	78.4 ± 2.7	**90.4** $\pm$ 0.6
Shirt	79.7 ± 0.9	78.8 ± 2.0	**82.6** $\pm$ 0.1	80.3 ± 1.5	81.6 ± 0.6
Sneaker	98.0 ± 0.1	98.1 ± 0.1	96.7 ± 0.3	96.4 ± 0.3	**98.9** $\pm$ 0.1
Bag	88.3 ± 0.6	75.6 ± 1.0	81.3 ± 0.7	84.3 ± 3.4	**93.1** $\pm$ 0.4
Ankle boot	97.9 ± 0.1	95.3 ± 0.4	95.3 ± 0.7	98.4 ± 0.2	**98.9** $\pm$ 0.1
mean	90.4 ± 0.4	87.7 ± 0.9	87.2 ± 0.7	88.5 ± 1.5	**92.3** $\pm$ 0.3

Table 3
Average AUCs (%) with StdDevs (%) on MVTec AD dataset.

Method	AUC
IForest	77.2 ± 4.5
DCAE	81.1 ± 4.4
DSVDD	83.2 ± 1.0
DSPSVDD	**87.7** $\pm$ 0.48

(1) IForest: This model applies isolation forest method with the tree number set as 200 to build the one-class classifier.
(2) DCAE: This model applies the deep convolutional autoencoder (DCAE) method to build the one-class classifier. The model is trained by the MSE loss between the original data and their reconstructions.
(3) SSIM: This model has the same structure to DCAE above. However, the model is trained by a different objective, which is the the error based on the image structure similarity. The related method details are given in Ref. [26].
(4) DSVDD: This model is the deep SVDD model, which has the same settings as Ref. [18].
(5) DSPSVDD: The model is developed by the proposed method in this paper, which combines the basic deep SVDD model with the data structure preservation in the optimization.

For the first two datasets, all the used deep model structures are set to the AlexNet-type [27] convolutional neural network with two fully connected layers of 128 units. As to the third dataset MVTec AD, the VGG-19 network is applied to perform the convolutional feature extraction while the five-layer fully connected network is used to train the deep models. In the method training, we adopt a batch size of 200 with 100 epochs. The parameter γ in DSPSVDD is set as 0.1. To facilitate the comparison, we perform the same preprocessing steps with global contrast normalization for all data sets and rescale all the inputs to [0,1].

4.3. Results and discussions

For the MNIST and Fashion-MNIST datasets, five methods are applied including IForest, SSIM, DCAE, DSVDD, and DSPSVDD. The commonly used AUC (area under curve) index is applied to evaluate the methods. Tables 1 and 2 show the quantitative results of the above competition approaches. Each model is run ten times and the results with mean and standard deviation are given. It should be noted that the results of IForest, DCAE and DSVDD are from the Ref. [18]. It's obvious that the proposed method shows great superiority over other methods and achieves better results on 18 subsets. For the MNIST dataset, DSVDD does better than the DSPSVDD only in the case of number 8. For this dataset, DSPSVDD achieves the mean AUC of 97.5% with the standard deviation of 0.2. By contrast, DSVDD performance index is $94.8\% \pm 0.8\%$. Evidently, DSPSVDD has better anomaly detection performance. In fact, our approach increases the results for all subsets to 96% except number 8. Similarly, we also obtain competitive results on the Fashion-MNIST dataset. Except for the case of skirt, the proposed DSPSVDD model does better in view of the AUC in the other nine fashion cases.

Regarding to the MVTec AD dataset, we utilize the four methods of IForest, DCAE, DSVDD, and DSPSVDD for performance analysis. The final result of the experiments on Mvtec AD dataset is shown in Table 3. Considering SSIM is based on the image structure similarity but not the vector similarity, its result is not listed. As we can see in this table, our approach has achieved competitive result than the other three methods. Especially, for the three deep learning based techniques DCAE, DSVDD and DSPSVDD, our method DSPSVDD has the average AUC of 87.7%, which is 6.6%, 4.5% higher than the other two methods, respectively. Furthermore, DSPSVDD has the smallest standard deviation of AUC. To sum up, among the all tested methods, our approach performs best for all the three datasets.

5. Conclusion

In this work, we proposed an improved deep SVDD model with data structure preservation, referred to as DSPSVDD. The key job of the proposed model is to integrate the data structure analysis with the basic deep SVDD optimization. By introducing the structure preservation based on autoencoder, the improved method can avoid the enforced constraints in the original deep SVDD model and provide better anomaly detection performance. The experiments on three benchmark datasets demonstrate that the proposed method has higher mean AUC values with the smaller standard deviations. That shows the proposed DSPSVDD method can detect the anomalies more precisely and more stably than the basic deep SVDD and other compared methods. Although DSPSVDD has demonstrated the obvious advantages in prompting the anomaly detection performance on the tested datasets, the structure preservation based on the autoencoder may be not enough in more complicated anomaly detection tasks. In fact, the autoencoder is only one of the structure analysis method. In future, some more efficient structure preservation methods deserve the further studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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