Anomaly Detection Based on Selection and Weighting in Latent Space

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Abstract—With the high requirements of automation in the era of Industry 4.0, anomaly detection plays an increasingly important role in higher safety and reliability in the production and manufacturing industry. Recently, autoencoders have been widely used as a backend algorithm for anomaly detection. Different techniques have been developed to improve the anomaly detection performance of autoencoders. Nonetheless, little attention has been paid to the latent representations learned by autoencoders. In this paper, we propose a novel selection-andweighting-based anomaly detection framework called SWAD. In particular, the learned latent representations are individually selected and weighted. Experiments on both benchmark and real-world datasets have shown the effectiveness and superiority of SWAD. On the benchmark datasets, the SWAD framework has reached comparable or even better performance than the state-of-the-art approaches.

I. INTRODUCTION

The development of automation engineering has been significantly changing the entire industry from different perspectives. On one hand, automation technology has been nowadays widely used in diverse fields, such as autonomous driving systems [1], [2], robotics [3], manufacturing [4]–[6], validation and testing [7]. The successful application of automation technology notably promotes the advancements of industrial society. On the other hand, enjoying the convenience brought by the fast advancements of automation technology, it is inevitably to raise the concerns about the reliability and safety within the technology itself. Accordingly, in order to realize a more reliable automation system, to detect and handle unexpected failures becomes an important issue in both academic and industrial communities.

However, manual identification of failures is not feasible in the era of big data and cannot meet the efficiency requirements. Thereby, to design automatic failure analysis and detection systems is nowadays critical, especially for Industry 4.0. Fortunately, anomaly detection has been intensively studied in literature [8]–[10]. Early anomaly detection methods often relied on explicit defined models for specific systems [11]. These methods requires special expert knowledge and have limited generalization ability. Afterwards, statistical and machine learning methods drew people's attention due to their flexibility. Representative approaches include [12]–[14]. Although these methods achieved notable advancements in anomaly detection, they typically require complex feature engineering and are not robust to different data domains.

Recently, deep learning has achieved dramatic success in many different fields, including image classification [15],

natural language processing [16], as well as anomaly detection [8]. In some cases, when both normal and abnormal data are available during training, it is natural to design a neural network for binary classification and to train it in a supervised way [17]. However, anomalies are generally rare in practice and it is thus difficult to acquire enough abnormal samples to train neural networks. Consequently, it is more appealing to train deep-learning-based methods on normal data only [18], [19], which are easier to collect in practice. In this context, the training itself can be considered as semisupervised, since the model is fully trained on the normal data only [8]. In contrast to supervised anomaly detection, a limited number of abnormal samples are often used to validate the model and fine-tune the hyperparameters in the semi-supervised setup.

Over the last few years, there have been already many previous studies in semi-supervised anomaly detection such as [20]–[22]. Although these methods have different architectures or learning objectives, one interesting observation is that they frequently consist of an autoencoder structure. This design is natural and intuitive because autoencoders are capable of learning the intrinsic structure of data, and this property can be used to detect abnormal samples during inference. However, many of these methods use autoencoders either to learn good latent representations fulfilling certain conditions or to minimize some reconstruction errors by using all features (e.g., all pixels of image data). This might lead to suboptimal anomaly detection performance, because not all information of the input data is necessary and useful. For example, as shown in Fig. 1, the background pixels of a transistor do not have to be well encoded or reconstructed in order to reject abnormal samples, because both abnormal and normal transistor images have similar or even the same background. Therefore, a technique that can automatically focus on the most discriminative parts of input data while assigning less or no attention to the less important parts is expected to be capable of enhancing the anomaly detection performance of all autoencoder-based approaches.



Fig. 1: The first image from left is the defect-free transistor (normal class), while the rest three images present transistors with different defect types. Both normal and abnormal images have similar backgrounds.

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In this paper, a novel selection-and-weighting-based anomaly detection (SWAD) framework is proposed. In contrast to many previous studies, we carry out selection and weighting in a latent space learned by an autoencoder. In this way, the reconstructed normal data from the selected and weighted latent representations are expected to have significantly smaller reconstruction errors than those of unseen abnormal data. Correspondingly, the anomalies are expected to be more effectively rejected during inference. In summary, the major contributions of this work are:

- A novel selection-and-weighting-based anomaly detection framework is proposed by introducing feature selection and weighting mechanism in latent space.
- SWAD is a generic framework that can be used as a wrapper for many existing autoencoder-based anomaly detection approaches.
- Systematic study on the key hyperparameters of SWAD was carried out on different datasets to show the superior performance of SWAD.

II. AUTOENCODER-BASED ANOMALY DETECTION

In this section, we briefly review the basic idea of autoencoder-based anomaly detection methods. Generally, it is assumed that an autoencoder can well capture the hidden structure of the normal data, if the autoencoder is trained on these normal data only. After the training, the autoencoder can therefore well reconstruct the normal data, while it is expected to be incapable of correctly reconstructing abnormal samples. Consequently, by comparing the reconstruction errors between a test sample and its reconstruction, anomalies can be detected; i.e., normal samples typically have smaller reconstruction errors than those of abnormal samples.

Formally, a training dataset is denoted as $X = [x_1, x_2, \ldots, x_N]^\top \in \mathbb{R}^{N \times D}$, where each sample $x_i \in \mathbb{R}^D$ is from the normal class. An autoencoder is typically composed of an encoder $f_{enc}(\cdot; \Theta_{enc})$ and a decoder $f_{dec}(\cdot; \Theta_{dec})$ parameterized by $\Theta = \{\Theta_{enc}, \Theta_{dec}\}$. The encoder first maps the input data x_i into a latent representation $z_i = f_{enc}(x_i)$ with $z_i \in \mathbb{R}^L$, and L is typically significantly smaller than the original dimension D. Subsequently, the decoder learns to map the latent representation back to the original space as $\hat{x}_i = f_{dec}(z_i)$. Accordingly, the overall learning objective of autoencoder is to minimize the reconstruction errors between the original input x_i and its reconstruction \hat{x}_i over the entire training dataset. One frequently used loss function is the mean squared error (MSE) loss defined as

$$\mathcal{L}_{\text{AE}} = \frac{1}{N} \sum_{i=1}^{N} ||\boldsymbol{x}_i - \hat{\boldsymbol{x}}_i||_2^2.$$
(1)

During inference, given a test sample denoted as $\boldsymbol{x}_{\text{test}}$, its reconstruction can be obtained as $\hat{\boldsymbol{x}}_{\text{test}} = f_{\text{dec}}(f_{\text{enc}}(\boldsymbol{x}_{\text{test}}))$. Thereby, the reconstruction error is calculated as $\varepsilon_{\text{test}} =$ $||\boldsymbol{x}_{\text{test}} - \hat{\boldsymbol{x}}_{\text{test}}||_2^2$. According to a predefined threshold ε_0 , the test sample is detected as anomaly if $\varepsilon_{\text{test}} > \varepsilon_0$, whereas the test sample is affiliated with the normal class if $\varepsilon_{\text{test}} \leq$ ε_0 . It should be noted that the threshold is, in practice, either determined by a separate validation set with abnormal samples, or set by special requirements of certain use cases or practitioners.

III. METHOD

The key idea of the proposed method is to introduce feature selection to the learned latent representations, and we can thus identify the important (selected) and the less informative (non-selected) features in the latent space. Accordingly, the selected and non-selected features of the latent representations are separately weighted. Subsequently, the resulting weighted latent representations are fed into the trained decoder to reconstruct the inputs. By comparing the differences between the input data and reconstructions obtained by the weighted latent representations, we can therefore detect anomalies. In the following, we first present the proposed framework and then explain the implementation details of each individual module within the framework.

A. SWAD Framework

The novel Selection-and-Weighting-based Anomaly Detection (SWAD) framework is composed of two major parts as shown in Fig. 2: i) an autoencoder as a backend model for learning the latent representations of normal data; ii) a feature selection model for identifying the most informative features from the less important features in the learned latent space and for the subsequent weighting during inference.

1) Training: The training procedure is designed as a twostage process. At the first stage, an autoencoder is trained on the given normal data, aiming to minimize a reconstruction loss. After training the autoencoder, we use the trained encoder to obtain the latent representations of the training data. At the second stage, the latent representations are used as new inputs to train a feature selection model. Consequently, the feature selection results can identify the more essential dimensions (*selected* features) of the normal data in the latent space, and indicate the redundant or noisy dimensions (*nonselected* features) that may mislead the anomaly detection. Therefore, by retaining the values of the selected features while down-weighting the non-selected features in latent space, it is expected to highlight the most discriminative characteristics of the normal data.



Fig. 2: The structure of the proposed SWAD framework.

2) Inference: Two hyperparameters k and τ are additionally introduced to carry out inference after training the SWAD framework. k is the number of the most important features (i.e., the selected features) in the latent space, and $\tau \in (0,1)$ is the weighting factor for the non-selected features. To weight the latent representations, a fixed τ is multiplied to the non-selected features, while the k selected features retain their values. In this case, it can be understood that the selected features are multiplied with $\tau = 1$ to retain their values, while the non-selected features are downweighted by $\tau < 1$. This is different from the ordinary feature selection, where non-selected features are typically removed or set to zeros. The proposed selection and weighting procedure can be therefore interpreted as a soft selection. The soft selection is expected to be more practical for anomaly detection because we frequently have only limited knowledge about the anomalies. Then, the weighted latent representations are fed into the trained decoder $f_{dec}(\cdot)$ from the first stage to obtain reconstructions. Consequently, the reconstruction errors between the original inputs and the reconstructions are calculated as an indicator of the affiliation of the data. In a semi-supervised anomaly detection setup [8], we use a separate validation set (consisting of a few abnormal samples) to determine the threshold. Accordingly, a test sample with a reconstruction error greater than the threshold is detected as an abnormal sample.

B. Autoencoder

The autoencoder is the core backend model for the first training stage. Generally, the proposed SWAD framework has no special requirements on the architectures of autoencoders. Thereby, the formal structure of the autoencoder is the same as the one introduced in Section II, and the MSE loss defined in Eq. 1 can be used as the learning objective for SWAD.

Nonetheless, we implemented a shallow autoencoder to demonstrate the effectiveness of the SWAD framework. In particular, the autoencoder consisted of three fully connected layers with 256, 128 and 256 neurons, respectively. A LeakyReLU layer with the rate of 0.2 was used as the activation layer after first and the last fully connected layer, while the activation function for the second hidden layer was $sigmoid(\cdot)$ to guarantee a bounded latent representation, which is more meaningful for training feature selection model at the second stage as suggested in [23].

C. Selection

In order to identify the important features of the latent representations more effectively, we use the recently proposed feature mask (FM) method [23] as the feature selection model for the second training stage. The original FM method consists of two major parts: an FM-module $f_{\rm FM}(\cdot; \Theta_{\rm FM})$ to generate the feature mask and a learning network targeting classification or regression. In this work, we followed the architecture of FM-module in [23], while replaced the learning network by a decoder sharing the same architecture as the one in the autoencoder for the first training stage denoted as $g(\cdot; \Theta_{\rm g})$, where the parameters $\Theta_{\rm FM}$ and

 $\Theta_{\rm g}$ are learned during the second training stage. It should be noted that the learning network $g(\cdot)$ has the same architecture with the decoder $f_{\rm dec}(\cdot)$ from the first training stage only for a simpler implementation. In general, these two networks are independent of each other.

Specifically, the inputs of the FM-module are the learned latent representations z_i of the training data x_i from the first training stage. Subsequently, the feature mask m generated by FM-module is element-wisely multiplied with the latent representations and fed into the learning network $g(\cdot)$ to reconstruct the original training data. Correspondingly, during each training iteration, we aim to minimize

$$\mathcal{L}_{SE} = \frac{1}{N_B} \sum_{i=1}^{N_B} ||\boldsymbol{x}_i - g(\boldsymbol{z}_i \odot f_{FM}(\boldsymbol{Z}_{batch}; \boldsymbol{\Theta}_{FM}); \boldsymbol{\Theta}_g)||_2^2,$$
(2)

where $Z_{\text{batch}} = [\boldsymbol{z}_1, \boldsymbol{z}_2, \dots, \boldsymbol{z}_{N_B}]^\top$ is a minibatch of learned latent representations of the training data during each iteration, and N_B is the minibatch size. After the second training stage, the final feature mask \boldsymbol{m} can be calculated by applying the learned $f_{\text{FM}}(\cdot)$ on the latent representations of the entire training data, where \boldsymbol{m} is automatically bounded in the range of [0, 1]. Thereby, the *i*-th element of \boldsymbol{m} indicates the importance of the corresponding latent feature. Accordingly, we can select the top k features with the highest importance scores, whereas the left L - k features are considered as non-selected (less important) features. It should be noted that, analogous to training autoencoder at the first stage, we use the MSE loss in Eq. 2 to demonstrate one possible implementation and other learning objectives for reconstructions can be used as well.

D. Weighting and Detection

Although the feature mask m generated by the FMmodule can already identify the most informative latent features, as mentioned before, it can be hard for detecting anomalies if we trivially remove the non-selected features as in conventional feature selection. This is because the encoding procedure of the autoencoder takes into account the information of entire data, i.e. all original features. Therefore, even the non-selected features of the latent representations can still possess certain information about the normal class. Due to this concern, the latent representations are weighted based on the selection results. In particular, the weighting process is defined as

$$\tilde{z}_{i,j} = \begin{cases} z_{i,j} & \text{, if } z_{i,j} \in \text{selected } k \text{ features} \\ \tau \cdot z_{i,j} & \text{, otherwise} \end{cases}$$
(3)

where $z_{i,j}$ is the *j*-th element of the learned latent representation z_i of the sample x_i . In this way, the resulting weighted latent representation is denoted as $\tilde{z}_i = [\tilde{z}_{i,1}, \tilde{z}_{i,2}, \dots, \tilde{z}_{i,L}]^{\top}$. Consequently, for each test sample x_i , the reconstruction error is calculated as:

$$\varepsilon_i = ||\boldsymbol{x}_i - f_{\text{dec}}(\tilde{\boldsymbol{z}}_i)||_2^2.$$
(4)

Finally, as introduced in Section II, a test sample is rejected as anomaly if $\varepsilon_i > \varepsilon_0$.

IV. EXPERIMENTS

This section evaluates the proposed novel SWAD framework for anomaly detection. Specifically, we aim to empirically show: *i*) the SWAD framework can significantly improve the anomaly detection performance on both benchmark and real-world datasets; *ii*) the SWAD framework has comparable or even better performance than state-of-the-art approaches; *iii*) a systematic study of the newly introduced hyperparameters k and τ of the SWAD framework.

A. Setup

In this work, we followed the semi-supervised anomaly detection setup, meaning that only normal samples were used for training, while used a separate validation set (consisting of both normal and a few abnormal samples) for each experiment to stop the training when the model reached the best performance on the validation set. Specifically, we only report the results on the test set in the following. AUC [24] was used as the metric to measure the anomaly detection performance as in the previous studies [18], [19]. In all experiments, we used the Adam optimizer [25] with a learning rate of 10^{-3} . The batch size was 512 for the benchmark datasets and 256 for the real-world datasets. The key hyperparameters of the SWAD framework and the vanilla autoencoder were individually optimized on the validation set for each experiment. The implementation was based on TensorFlow [26]. It should be noted that each experiment was repeated five times with different random seeds, and only the averaged results with their standard deviations are presented in the following subsections.

1) Datasets: In this study, the experiments were carried out on four datasets, including two image datasets MNIST [27] and CIFAR-10 [28] which are frequently used to benchmark deep learning algorithms, and two challenging real-world datasets. Specifically, the two benchmark datasets have originally 10 classes. Therefore, in order to create an anomaly detection setup, data from one specific class are considered as normal, while the data affiliated with the left 9 classes were considered abnormal. The two real-world datasets are solar cell images [17] and MVTec AD [29]. On both real-world datasets, normal samples are defectfree products, while the abnormal samples are products with different defects.

2) *Reference Methods:* The key reference method is a vanilla autoencoder (AE) with the same architecture as the one used in the SWAD framework. In addition, we also include two representative methods from literature to identify the anomaly detection ability of SWAD on benchmark datasets. One is the deep support vector domain description (DSVDD) [19] and the other is the one-class support vector machine (OCSVM) [12].

B. Experiments on Benchmark Datasets

The experiments conducted on benchmark datasets aim to demonstrate the effectiveness of the proposed framework and provide a preliminary comparison between SWAD and existing state-of-the-art approaches. TABLE I and TABLE II

TABLE I: AUC on the MNIST dataset.

| | DSVDD [19] | OCSVM [12] | AE | SWAD | Gain |
|---------|---------------------------|-----------------------------|------------------------|---------------------------|-----------------|
| Digit 0 | 0.980 (± 0.007) | 0.982 (± 0.000) | $0.988 \\ (\pm 0.000)$ | 0.996 (± 0.001) | $0.8\%\uparrow$ |
| Digit 1 | 0.997 (± 0.001) | $0.992 \\ (\pm 0.000)$ | 0.999 (± 0.001) | 1.000 (± 0.000) | $0.1\%\uparrow$ |
| Digit 2 | 0.917 (± 0.008) | 0.821 (± 0.000) | 0.931 (± 0.003) | 0.937 (± 0.009) | $0.6\%\uparrow$ |
| Digit 3 | 0.919 (± 0.015) | 0.861 (± 0.000) | 0.960 (± 0.002) | 0.971 (± 0.003) | $1.1\%\uparrow$ |
| Digit 4 | 0.949 (± 0.008) | $0.948 \\ (\pm 0.000)$ | $0.945 (\pm 0.002)$ | 0.969 (± 0.004) | 2.5%↑ |
| Digit 5 | 0.885 (± 0.009) | $0.774 (\pm 0.000)$ | $0.975 (\pm 0.000)$ | 0.993 (± 0.000) | 1.8%↑ |
| Digit 6 | 0.983 (± 0.005) | $0.948 \\ (\pm 0.000)$ | 0.996 (± 0.001) | 0.997 (± 0.001) | $0.1\%\uparrow$ |
| Digit 7 | 0.946 (± 0.009) | 0.934 (± 0.000) | $0.971 \\ (\pm 0.005)$ | 0.987 (± 0.002) | 1.6%↑ |
| Digit 8 | 0.939 (± 0.016) | 0.902 (± 0.000) | 0.912 (± 0.006) | 0.936 (± 0.023) | 2.6%↑ |
| Digit 9 | $0.965 \\ (\pm 0.003)$ | $0.928 \\ (\pm 0.000) \\ -$ | $0.963 \\ (\pm 0.008)$ | 0.976 (± 0.002) | 1.3%↑ |
| Average | 0.948 (± 0.008) | 0.909 (± 0.000) | 0.964 (± 0.003) | 0.976 (± 0.005) | 1.3%↑ |

TABLE II: AUC on the CIFAR-10 dataset.

| | DSVDD [19] | OCSVM [12] | AE | SWAD | Gain |
|------------|---------------------------|--------------------|------------------------|---------------------------|-----------------|
| Airplane | 0.617 (± 0.041) | 0.619 (± 0.000) | 0.681 (± 0.001) | 0.733 (± 0.005) | 7.6%↑ |
| Automobile | 0.659 (± 0.021) | 0.385 (± 0.000) | 0.494 (± 0.010) | 0.551 (± 0.013) | 11.5%↑ |
| Bird | $0.508 \\ (\pm 0.008)$ | 0.606 (± 0.000) | 0.669 (± 0.001) | 0.677 (± 0.005) | $1.2\%\uparrow$ |
| Cat | 0.591 (± 0.014) | 0.494 (± 0.034) | 0.581 (± 0.004) | $0.584 \\ (\pm 0.004)$ | 3.3%↑ |
| Deer | 0.609 (± 0.011) | 0.713 (± 0.000) | 0.707 (± 0.000) | 0.730 (± 0.002) | 1.5%↑ |
| Dog | 0.657 (± 0.025) | 0.520 (± 0.011) | 0.607 (± 0.002) | 0.616 (± 0.010) | 3.3%↑ |
| Frog | 0.677 (± 0.026) | 0.638 (± 0.000) | 0.668 (± 0.005) | 0.679 (± 0.001) | 1.6%↑ |
| Horse | 0.673 (± 0.009) | 0.482 (± 0.000) | 0.493 (± 0.003) | $0.501 \\ (\pm 0.028)$ | 1.6%↑ |
| Ship | 0.759 (± 0.012) | 0.637 (± 0.000) | 0.697 (± 0.001) | 0.723 (± 0.007) | 3.7%↑ |
| Truck | 0.731 (± 0.012) | 0.488 (± 0.000) | $0.425 \\ (\pm 0.008)$ | $0.568 \\ (\pm 0.014)$ | 33.6%↑ |
| Average | 0.648 (± 0.018) | 0.558 (± 0.000) | 0.602 (± 0.004) | 0.636 (± 0.009) | 6.9%↑ |

show the entire experimental results on MNIST and CIFAR-10, respectively. Generally, the SWAD framework notably improves the anomaly detection performance of the autoencoder. For example, on CIFAR-10, SWAD achieved about 6.9% better performance than autoencoder in average with up to 33% improvement in extreme cases (class truck as normal class). On MNIST, the improvement brought by the new framework is slightly less notable, namely about 1.3% in average. This is reasonable because the vanilla autoencoder already performed well on the MNIST dataset.

The comparison between SWAD and the vanilla autoencoder has empirically shown the benefit of the novel selection-and-weighting mechanism. This matches our expectation because the vanilla autoencoder trivially encodes all original features of the training data, while some information (e.g., background pixels or noise) can mislead the anomaly detection. By introducing the selection-andweighting in the learned latent space, we could further identify the most important latent dimensions and therefore achieved notable improvement.

In addition, the SWAD framework also achieved comparable or even better performance in comparison with the two reference methods on the benchmark datasets. On MNIST, SWAD outperformed the reference methods in nine of ten cases. On the more challenging CIFAR-10 dataset, the proposed framework still had comparable performance with DSVDD and significantly outperformed OCSVM. It should be noted that we only used shallow fully-connected networks on the benchmark datasets to illustrate the effectiveness, so further performance enhancement can be expected when more powerful backbone networks are used such as convolutional neural networks.

C. Case Study: Solar Cells

To automatically detect or identify defects on solar cells is an important use case for anomaly detection. In this experiment, we compared SWAD and a vanilla autoencoder on the solar cell image dataset [17]. The solar cell images were extracted from large-scale electroluminescence images. In total, 85513 normal solar cell images were used for training. Both validation and test sets consisted of 4737 normal and 189 abnormal images. Exemplary normal and abnormal solar cell images are shown in Fig. 3.

The solar cell images were more complex and had sizes of 120×120 , so the backbone networks in SWAD were replaced by convolutional autoencoders. In particular, the encoder consisted of 5 convolutional layers with 4, 8, 16, 32, 128 filters, respectively. The first four convolutional layers had filters with the size of 3×3 using a stride of 2 with the same padding, while the last convolutional layer used a 5×5 filter. Batch-normalization and Leaky-ReLU layers were used after each convolutional layer. The decoder used a mirrored structure with transposed convolutional layers. The learning network $g(\cdot)$ during the second training stage shared the same architecture with the decoder. As shown in TABLE III, the proposed SWAD framework improved the anomaly detection of an autoencoder moderately with respect to AUC.



Fig. 3: The first image from left is the normal solar cell, while the rest four images represent different defects.

D. Case Study: MVTec

MVTec [29] is a recently published real-world dataset for evaluating anomaly detection algorithms as shown in Fig. 4. The original MVTec dataset consists of images with high resolution (1024×1024) for 15 categories. In our experiment,

TABLE III: AUC on the solar cell dataset.

| | AE | SWAD (ours) | Gain |
|-------------|---------------------|--------------------|-------|
| Solar cells | $0.744 (\pm 0.001)$ | 0.754 (± 0.002) | 1.3%↑ |

the images were resized into 120×120 to spare training resources. In addition, as suggested in [29], we used data augmentation to increase the training data size to 4000 for each category. Both validation and test sets had tens of normal and abnormal images (varying from category to category). Specifically, for each category, defect-free products were considered to be normal, while the products affiliated with the same category but with defects were denoted as abnormal samples. Moreover, SWAD was implemented as the same as for solar cell images.

Fig. 5 illustrates the overall AUC on the test sets for different categories of MVTec. The SWAD framework outperformed the vanilla autoencoder for all 15 categories with more than 27% in average. In 10 of 15 cases, SWAD significantly improved the performance of a vanilla autoencoder with more than 5%, where the largest improvement was about 152% for the category *carpet*. It should be noted that the SWAD framework only had marginally improvement with the categories *wood*, *bottle* and *toothbrush*. One plausible reason might be the defect structure in these categories were too small and difficult to identify based on the current metric (MSE).



Fig. 4: Exemplary MVTec images. The first column from the left shows the normal images, while the rest columns illustrate the abnormal samples.



Fig. 5: AUC on the MVTec dataset.

E. Insight into SWAD

1) Hyperparameters k and τ : Fig. 6 shows the exemplary performance overview for the four datasets. In general, the



Fig. 6: AUC with respect to the two key hyperparameters k and τ on four exemplary experiments. The highest AUC is marked using a black point with dotted lines.

benchmark datasets are less challenging than the real-world datasets. Therefore, the resulting visualization of benchmark datasets is more homogeneous. On the contrary, the surface of the two real-world datasets is notably more bumpy. Furthermore, large τ cannot always guarantee the optimal anomaly detection performance. This matches our expectation that not all learned latent features can effectively contribute to detecting anomalies. In this case, the SWAD framework is essential to approach the optimal performance.

2) Study of Latent Dimensions: The proposed SWAD framework deals with the latent representation learned by an autoencoder. Accordingly, the latent dimensions can have impact on the final performance. We carried out experiments on the benchmark datasets with four different latent dimensions: 64, 128, 256 and 512. Fig. 7 and Fig. 8 present the results averaged over the ten classes for each dataset. kand τ were individually optimized for each normal class. Generally, latent dimensions have limited influence on the anomaly detection performance. On both datasets, it can be observed that the averaged AUC decreases with large latent dimensions. One reason might be that too large latent dimensions cannot well encode the input data and the subsequent selection and weighting can thus have limited contribution. On the other hand, for the more challenging dataset CIFAR-10, too few latent dimensions cannot perform well either. This suggests that some information of the normal data is not well preserved during the encoding due to the small latent dimension. Nonetheless, the proposed framework can still well work in a wide range of latent dimensions.



Fig. 7: Averaged AUC on MNIST under different latent dimensions of the autoencoder at the first training stage.



Fig. 8: Averaged AUC on CIFAR-10 under different latent dimensions of the autoencoder at the first training stage.

F. Discussion

In the proposed SWAD framework, the selection-andweighting is carried out in the learned latent space. Indeed, another intuitive alternative is to directly select and weight the features in the original data space, i.e., the pixel space for the image data. However, using pixels as features are less robust and more sensitive to the noise in the original images. Nonetheless, we argue that selection-and-weighting in the original data space can work if the data are structured. In addition, in this work, we used a fixed τ for a given dataset which was determined by a separate validation set. This design is intuitive and convenient for the implementation. Thereby, one natural future research is to include τ as a trainable parameter of the SWAD framework and the resulting framework is expected to be easier to use due to less hyperparameters.

As demonstrated in the previous subsections, SWAD has shown its ability of enhancing anomaly detection performance of autoencoder-based approaches. Nonetheless, we argue that our framework can also improve the representationlearning-based anomaly detection methods such as [19], [30]. Although these approaches do not utilize autoencoders, they finally output a latent representation for each sample and calculate certain distances based on the learned representation to determine the affiliation of the sample. Correspondingly, these methods often share the similar drawback with the autoencoder-based approaches: All original input dimensions or features are equally considered and transformed into a compact latent representation, so noise or redundant information can be also encoded and thus mislead the anomaly detection process. To apply the SWAD framework to representation-learning-based methods, we can simply replace the autoencoder by the targeting methods at the first training stage. The general pipeline stays the same. In this way, the final distance calculation can be carried out on the selected-and-weighted representations and better performance can be expected. This is also one of the on-going work of the authors.

V. CONCLUSION

This paper proposes a novel selection-and-weightingbased anomaly detection framework, namely SWAD. In contrast to existing autoencoder-based approaches, SWAD aims to select the most informative features of latent representations and to down-weight the non-selected features for better anomaly detection performance. Experiments on both benchmark and real-world datasets have shown its effectiveness. Furthermore, the study of the additional hyperparameters of SWAD is also practical for users. The future work may include applying the SWAD framework to other autoencoder-based anomaly detection approaches. Another future work might introduce adaptive weighting for individual latent dimensions for further enhancement. Finally, other learning objectives such as adversarial training can be considered to replace the canonical MES loss for better performance.

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REFERENCES

- Brian Paden, Michal Čáp, Sze Zheng Yong, Dmitry Yershov, and Emilio Frazzoli. A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on intelligent vehicles*, 1(1):33–55, 2016.
- [2] Mario Gerla, Eun-Kyu Lee, Giovanni Pau, and Uichin Lee. Internet of vehicles: From intelligent grid to autonomous cars and vehicular clouds. In 2014 IEEE world forum on internet of things (WF-IoT), pages 241–246. IEEE, 2014.
- [3] Ben Kehoe, Sachin Patil, Pieter Abbeel, and Ken Goldberg. A survey of research on cloud robotics and automation. *IEEE Transactions on automation science and engineering*, 12(2):398–409, 2015.
- [4] Jorge Posada, Carlos Toro, Iñigo Barandiaran, David Oyarzun, Didier Stricker, Raffaele De Amicis, Eduardo B Pinto, Peter Eisert, Jürgen Döllner, and Ivan Vallarino. Visual computing as a key enabling technology for industrie 4.0 and industrial internet. *IEEE computer* graphics and applications, 35(2):26–40, 2015.
- [5] Gian Antonio Susto, Andrea Schirru, Simone Pampuri, Seán McLoone, and Alessandro Beghi. Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, 11(3):812–820, 2014.
- [6] Baotong Chen, Jiafu Wan, Lei Shu, Peng Li, Mithun Mukherjee, and Boxing Yin. Smart factory of industry 4.0: Key technologies, application case, and challenges. *Ieee Access*, 6:6505–6519, 2017.
- [7] Shu-Kai S Fan, Chia-Yu Hsu, Du-Ming Tsai, Fei He, and Chun-Chung Cheng. Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. *IEEE Transactions on Automation Science and Engineering*, 17(4):1925–1936, 2020.
- [8] Raghavendra Chalapathy and Sanjay Chawla. Deep learning for anomaly detection: A survey. arXiv preprint arXiv:1901.03407, 2019.

- [9] Hongzhi Wang, Mohamed Jaward Bah, and Mohamed Hammad. Progress in outlier detection techniques: A survey. *IEEE Access*, 7:107964–108000, 2019.
- [10] Victoria Hodge and Jim Austin. A survey of outlier detection methodologies. Artificial intelligence review, 22(2):85–126, 2004.
- [11] Zhiwei Gao, Carlo Cecati, and Steven X Ding. A survey of fault diagnosis and fault-tolerant techniques—part i: Fault diagnosis with model-based and signal-based approaches. *IEEE Transactions on Industrial Electronics*, 62(6):3757–3767, 2015.
- [12] Bernhard Schölkopf, John C Platt, John Shawe-Taylor, Alex J Smola, and Robert C Williamson. Estimating the support of a highdimensional distribution. *Neural computation*, 13(7):1443–1471, 2001.
- [13] Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. Isolation forest. In 2008 eighth ieee international conference on data mining, pages 413–422. IEEE, 2008.
- [14] Markus M Breunig, Hans-Peter Kriegel, Raymond T Ng, and Jörg Sander. Lof: identifying density-based local outliers. In *Proceedings* of the 2000 ACM SIGMOD international conference on Management of data, pages 93–104, 2000.
- [15] Andrew Brock, Soham De, Samuel L. Smith, and Karen Simonyan. High-performance large-scale image recognition without normalization, 2021.
- [16] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics, 2019.
- [17] Alexander Bartler, Lukas Mauch, Bin Yang, Michael Reuter, and Liviu Stoicescu. Automated detection of solar cell defects with deep learning. In 2018 26th European signal processing conference (EUSIPCO), pages 2035–2039. IEEE, 2018.
- [18] Patrick Schlachter, Yiwen Liao, and Bin Yang. Deep one-class classification using intra-class splitting. In 2019 IEEE Data Science Workshop (DSW), pages 100–104. IEEE, 2019.
- [19] Lukas Ruff, Robert Vandermeulen, Nico Goernitz, Lucas Deecke, Shoaib Ahmed Siddiqui, Alexander Binder, Emmanuel Müller, and Marius Kloft. Deep one-class classification. In *International conference on machine learning*, pages 4393–4402. PMLR, 2018.
- [20] Mohammad Sabokrou, Mohammad Khalooei, Mahmood Fathy, and Ehsan Adeli. Adversarially learned one-class classifier for novelty detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3379–3388, 2018.
- [21] Patrick Schlachter, Yiwen Liao, and Bin Yang. One-class feature learning using intra-class splitting. In 2019 27th European Signal Processing Conference (EUSIPCO), pages 1–5. IEEE, 2019.
- [22] Chong Zhou and Randy C Paffenroth. Anomaly detection with robust deep autoencoders. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 665–674, 2017.
- [23] Yiwen Liao, Raphaël Latty, and Bin Yang. Feature selection using batch-wise attenuation and feature mask normalization. arXiv preprint arXiv:2010.13631, 2020.
- [24] Andrew P Bradley. The use of the area under the roc curve in the evaluation of machine learning algorithms. *Pattern recognition*, 30(7):1145–1159, 1997.
- [25] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.
- [26] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. Tensorflow: A system for large-scale machine learning. In 12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16), pages 265–283, 2016.
- [27] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings* of the IEEE, 86(11):2278–2324, 1998.
- [28] Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.
- [29] Paul Bergmann, Michael Fauser, David Sattlegger, and Carsten Steger. Mvtec ad-a comprehensive real-world dataset for unsupervised anomaly detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9592–9600, 2019.
- [30] Raghavendra Chalapathy, Aditya Krishna Menon, and Sanjay Chawla. Anomaly detection using one-class neural networks. arXiv preprint arXiv:1802.06360, 2018.