Self-Supervised Anomaly Detection: A Survey and Outlook

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Abstract—Over the past few years, anomaly detection, a subfield of machine learning that is mainly concerned with the detection of rare events, witnessed an immense improvement following the unprecedented growth of deep learning models. Recently, the emergence of self-supervised learning has sparked the development of new anomaly detection algorithms that surpassed state-of-the-art accuracy by a significant margin. This paper aims to review the current approaches in self-supervised anomaly detection. We present technical details of the common approaches and discuss their strengths and drawbacks. We also compare the performance of these models against each other and other state-of-the-art anomaly detection models. Finally, we discuss a variety of new directions for improving the existing algorithms.

Index Terms—Anomaly Detection, Self-Supervised Learning, Contrastive Learning, Representation Learning.

I. INTRODUCTION

ANOMALY detection detection (AD) is the task of identifying samples that differ significantly from the majority of data and often signals an irregular, fake, rare, or fraudulent observation [1], [2]. In the literature, other terms such as outlier [1], novelty [3], out of distribution [4], and deviation [5] are also used instead of anomaly. Anomaly detection is particularly useful in cases where we are unable to define all existing classes during training. This makes AD algorithms useful to a broad range of application, including but not limited to, intrusion detection in cybersecurity [6], [7], fraud detection in finance and telecommunication [8]–[10], acoustic novelty detection [11], [12], stock market analysis [13], event detection in earth science fields [14], [15], physics [16], [17], astronomy [18], [19], medical diagnosis and disease detection [20]–[22], bioinformatics [23], and genetics [24].

Over the past few decades, a flurry of machine learning models are developed for anomaly detection. Kernel Density Estimation (KDE) [25], One-Class Support Vector Machine (OCSVM) [26], and Isolation Forests (IF) [27] are among the popular classical (non-deep) approaches in anomaly detection. These algorithms are still widely used for solving anomaly detection tasks, but their accuracy degrades in higher-dimensional problems.

In recent years, deep models have become popular and widely used in a wide range of applications. These methods can significantly outperform traditional non-deep learning based algorithms and achieve near-human-level accuracy in tasks such as object recognition and machine translation. A key strength of deep models is that they are capable of automatically learning lower-dimensional representations from raw data [28]. Because of this, they are commonly used instead of the manual feature extraction process employed in the traditional machine learning frameworks.

Deep-learning based models for AD can be roughly categorized into three groups: The first category includes the models that use deep neural networks for learning a lower-dimensional representation of the high-dimensional data, and then apply a classic anomaly detection algorithm (such as OCSVM [26]) to the obtained lower-dimensional representation [29]. By mapping the data into a lower-dimensional space, the traditional non-deeplearning AD approaches do not face the curse of dimensionality issue, hence can provide a fairly good detection accuracy. The second group of methods employs deep neural networks to reconstruct the input data and directly calculate an anomaly score based on the data reconstruction loss. The most commonly used network architectures are based on Autoencoders (AEs) [30] and Generative Adversarial Networks (GANs) [21], [31]. The underlying assumption is that if a network is trained to only reconstruct the normal data, a significant reconstruction error occurs when the network faces an anomaly. The third category includes algorithms that combine both of the above mentioned approaches [32], [33]. They jointly train a neural network for feature extraction and an anomaly detector on the latent space of the network. The anomaly detector provides an anomaly score for an input data.

Although the above methods use different approaches for AD, the concept remains the same, i.e. normal samples have similar feature distribution in the latent space of the trained network, and abnormal instances are not in line with the ordinary anticipated behaviour of normality².

Anomaly detection algorithms face unique challenges due to the nature of task they are dealing with. For instance, in many anomaly detection problems, we have an imbalanced dataset with a large volume of normal data and a few anomalies. This is due to the fact that anomalies are usually scarce or expensive to occur in real-world settings. Even in some cases, these small portion of abnormal samples are noise-contaminated, which makes the detection task more complicated. Another important issue is that anomalies cannot be considered as a single class of data, and a detection system might be exposed to new types of anomalies that it has never encountered during its training.

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²In the rest of the paper, the term normal has no relationship with the normal Gaussian distribution unless specified otherwise.
process. These challenges should be carefully considered for designing an appropriate algorithm.

In the literature, both supervised and unsupervised learning techniques are employed for anomaly detection [33], [34]. Self-supervised learning (SSL) is a subcategory of unsupervised learning. Recent studies show that self-supervised learning can achieve an excellent performance comparable to the fully-supervised baselines in several challenging tasks such as visual representation learning, object detection, and natural language processing [35], [36]. Inspired by this, several self-supervised methods are proposed for anomaly detection, which significantly improve the state-of-the-art [37]–[42]. SSL learns a generalizable representation from unlabelled data by solving a supervised proxy task which is often unrelated to the target task, but can help the network to learn a better representation. A diverse set of tasks such as denoising, rotation predicting, segmentation, or colorization can be used as the supervised proxy task.

There exist a number of survey papers that review and categorize existing anomaly detection models [43]–[45]. However, to the best of our knowledge, there is no survey paper that explores self-supervised anomaly detection methods. This paper aims to review the SSL-based approaches in anomaly detection for the first time and categorize the state-of-the-art techniques. We can summarize the contribution of our work as follows:

• We briefly review the current approaches in anomaly detection in order to locate the self-supervised anomaly detection in the context of anomaly detection research.
• We discuss the current approaches in self-supervised anomaly detection as well as its areas of application.
• We divide the existing self-supervised anomaly detection algorithms into two high-level categories based on their requirement of negative samples during training. SSL-based models are different from each other based on their proxy task and architecture. Hence, it is important to categorize these methods in a way that covers all of them. For each type of methods, we describe the techniques and assumptions and highlight the advantages and disadvantages.
• We discuss possible future directions in self-supervised anomaly detection research.

II. RELATED WORKS

In the past few decades, the anomaly detection problem is extensively explored in various research and application domains. Several survey articles attempted to group the anomaly detection algorithms into distinctive categories. Hodge and Austin (2004) [46] and Agyemang et al. (2006) [47] are two examples of the early studies that categorized the existing algorithms into four groups and extensively discuss the techniques that are used in each category. In another prominent work, Chandola et al. (2009) [1] surveyed the existing anomaly detection algorithms and divided them into six distinctive categories. In addition to describing the technical details of each method, Chandola et al. identified the underlying assumptions that are implicitly made regarding the anomalies. They also discussed the advantages, disadvantages and computational complexity of each technique. Furthermore, they extensively reviewed the application areas of the methods and highlighted the challenges face in each domain.

Recently, deep learning methods inspired anomaly detection researchers, and many new algorithms were proposed in this domain. In the recent years, deep anomaly detection is the topic of several review papers. Chalapathy and Chawla (2019) [43] was one of the first papers that presented a comprehensive review of deep anomaly detection methods. They categorized the existing methods based on their underlying assumptions and explained the pros and cons of each approach. Chalapathy and Chawla (2019) [43] also thoroughly explored applications of deep anomaly detection and assessed the effectiveness of each method. In another similar survey, Pang et al. (2020) [44] reviewed contemporary deep AD methods. They first discussed the challenges and complexities that anomaly detection faces, and then they categorized the existing deep methods into three high-level categories and eleven fine-grained subcategories. Pang et al. (2020) [44] described how each category of methods addressed the existing challenges in anomaly detection. In addition, they identified the key assumptions and intuitions of each model. Another important aspect of their work is that they gathered a list of publicly available codes and real-world datasets that contain anomalies and can be used to benchmark the existing algorithms.

In the past few years, most review papers in the field focused on specific sets of algorithms, such as deep or shallow methods. However, Ruff et al. (2021) [45] presented an extensive survey of anomaly detection methods. They unified classic shallow methods with recent deep approaches and highlighted the connections and similarities between these two types of algorithms. Ruff et al. (2021) [45] also provided an in-detail description and accurate taxonomy of common practices and challenges in anomaly detection.

In addition to the above mentioned studies, several other review papers are published in this research field that either focus on a specific domain of application or a particular type of method. For example, the two survey papers by Di Mattia et al. (2019) [48] and Xia et al. (2022) [49] are dedicated to reviewing the GAN-based anomaly detection methods. They discussed these models’ theoretical bases and practical applications and provided a detailed description of existing challenges and future directions in GAN-based anomaly detection. Both of the papers also carried out empirical evaluations to compare the performance of different algorithms. In another study, Villa-Perez et al. (2021) [50] empirically evaluated the performance of 29 semi-supervised algorithms for anomaly detection.

III. ANOMALY DETECTION: TERMINOLOGY AND COMMON PRACTICES

“Anomaly detection” is commonly used as an umbrella term for all algorithms that aim to identify samples that deviate from the normal patterns. Various anomaly detection models are developed depending on the availability of data labels, types of anomalies, and applications. In addition, the nomenclature
of anomaly detection is not consistent in the literature. To avoid confusion, in the following, we define and describe the relevant terminologies used throughout this paper.

A. Types of Anomalies

In the classic anomaly detection literature, anomalies are classified into three categories based on their nature [1], [44]:

1) **Point Anomalies:** A point anomaly is an individual anomalous sample, which often shows an irregularity or deviation from the standard pattern. A single cat image in the dataset of dog images or a fraudulent insurance claim are examples of point anomalies. Most studies on the anomaly detection literature focus on this type of anomaly [43].

2) **Contextual Anomalies:** A contextual anomaly, which is also known as a "conditional anomaly", is a data point that is considered anomalous in a particular context. The context should be defined as a part of the problem formulation. For example, a value of 120 km/h is considered an abnormal recording for the speed of a bike, whereas it is not considered an abnormal recording for the speed of a car.

3) **Collective Anomalies:** Collective or group anomalies are a subset of data points that are collectively anomalous with respect to the entire dataset. Each individual sample of a collective anomaly might not be an abnormal point by itself. For example, a series of high value credit card transactions that occur rapidly and subsequently might be an indicator of a stolen credit card, whereas each of those transactions might come across as normal.

With the rise of deep anomaly detection methods, in order to make distinction between different anomaly types that deep models aim to detect, two more anomaly types are suggested by Ruff et al. (2021) [45]:

4) **Sensory (low-level) Anomalies:** Low-level or sensory anomalies refer to the irregularities that occur in the low-level feature hierarchy, such as textures or edges of images. An example of a low-level anomaly is a fractured texture. Low-level anomaly detection is helpful in detecting defects and artifacts in industrial applications. The newly released MVTecAD dataset [51] contains numerous examples of sensory anomalies and defects in industrial application.

5) **Semantic (high-level) Anomalies:** High-level or semantic anomalies are samples that are coming from a different class comparing to the normal data. For instance, images of any object other than cats are considered a semantic anomaly when we train our network to detect cat images as normal samples.

It is important to note that both the sensory and semantic anomalies might overlap with other types of anomalies. However, it is still essential to distinguish between semantic and sensory anomalies to avoid confusion in our discussions throughout the paper.

B. Availability of Data Labels

For designing an appropriate algorithm, it is crucial to consider the availability of labels. Based on the label availability, we can divide AD algorithms into three settings:

1) **Unsupervised Anomaly Detection:** In this setting, which is arguably the most common in anomaly detection, we assume that only unlabeled data is available for training the model [45], [46]. In the simplified form of unsupervised learning, we commonly assume that the data is noise-free and its distribution is the same as the normal data, e.g. \( P = P^+ \). If noisy data or undetected anomalies are present in the training dataset, these assumptions are violated, hence the developed models are not robust. A more realistic approach can be to assume that the data distribution \( P \) is a mixture of normal data and anomalies with a pollution rate \( \eta \in (0,1) \), e.g. \( P = (1 - \eta)P^+ + \eta P^- \). In this approach, it is crucial to determine \( \eta \) and make a prior assumption about the distribution of anomalies \( P^- \), which may degrade the method generalization. Overall, the unsupervised settings for anomaly detection gained a great interest in learning commonalities of data from a complex and high-dimensional space without the need to access annotated training samples. Note that the self-supervised learning methods, that are the focus of this paper, can be considered as a subgroup of unsupervised learning techniques.

2) **Semi-supervised Anomaly Detection:** In this setting, we assume that the training dataset is partially labelled and includes both labelled and unlabeled samples. Semi-supervised algorithms are suitable for scenarios where it is costly to annotate the whole data. This setting is also prevalent in the anomaly detection field because usually both labelled and unlabeled data are present but labelling the data often requires expert knowledge, or in some cases, such as industrial and biomedical applications, anomalies are costly to occur. Incorporating a small set of anomaly examples during training could significantly improve the detection performance and maximize the robustness of a model [52]–[54], especially compared to the unsupervised learning techniques. However, due to the scarce availability of the labelled abnormal samples, semi-supervised setting is likely prone to overfitting. Therefore, making the correct assumptions about the distribution of anomalies, i.e. \( P^- \), is crucial for accurately incorporating the labelled anomalies in the training process.

Some existing papers refer to the task of “Learning from Positive and Unlabeled examples” (LPUE) as semi-supervised learning [1]. Note that based on the above definitions, LPUE is an unsupervised learning technique where the entire training data belongs to the normal class. LPUE is commonly used in the literature when benchmarking the anomaly detection algorithms using the popular datasets, such as CIFAR-10 and MNIST [33], [37]. In this task, the samples of one class of the dataset are deemed normal and are used during the training, and samples of other classes are considered to be anomalous [32]. "One-class AD" is another term which is used for referring to the LPUE task.

3) **Supervised Anomaly Detection:** In supervised anomaly detection, we assume that the dataset is fully labelled. When anomalies are easily annotated, it is more beneficial to adopt supervised methods [55]–[58]. At this point, it is essential to make a distinction between supervised anomaly detection and binary classification problems. One might claim that if the normal and abnormal data are available during the
training phase, the problem can be formulated as a supervised binary classification problem and will not be an anomaly detection task anymore. However, we should note that formally speaking, an anomaly is a sample that does not belong to the normal class distribution $P^\ast$. The anomaly class includes a broad range of data points that are not accessible/known during the training phase. The common practice in the AD methods is to assume that, in the training phase, there are enough labeled samples from the normal class that can reveal $P^\ast$ while the limited available abnormal samples can only partially reveal $P^\ast$. Hence, unlike binary classification which aims at learning a decision boundary that separates the two classes, the goal for AD is to discover the normal class boundaries.

Although the supervised settings can achieve higher accuracy and faster detection speed, they are rarely used to formulate the anomaly detection problems compare to unsupervised and semi-supervised models. This is because, in most real world applications, it is impossible to know and have access to all existing anomaly classes.

C. Anomaly, Outlier, Novelty, Out-of-Distribution Detection

Some studies use the terms anomaly, novelty, outlier and out-of-distribution interchangeably, while others distinct them. Although most of the algorithms for detecting these are similar, their significance and application might differ. In this paper, we follow the terminology that was suggested by Ruff et al. (2021) [45] and define each of the tasks as follows:

1) Anomaly Detection: If we denote the distribution of normal instances by $P^\ast$, anomaly detection can be defined as the task of identifying the samples that are drawn from any distribution other than $P^\ast$. For example, if we represent $P^\ast$ as the distribution of horses, a zebra is considered anomaly.

2) Outlier Detection: An outlier is a low-probability sample from $P^\ast$. In the example of horse detection, a Falabella is an outlier in horse breeds.

3) Novelty Detection: A novelty is a sample that is drawn from a new region of a non-stationary distribution of normal samples $P^\ast$. It is commonly a sample that the network does not encounter its counterpart during the training phase. For instance, a new breed of horses is considered a novelty in the horse detection task.

4) Out-of-Distribution Detection: In out-of-distribution (OOD) detection, the goal is to identify samples that do not belong to any of the training set classes. This problem, which is also referred to as "open category detection" [59], is often formulated as a supervised learning problem where we have the labelled data from $K$ classes during training. We treat all the $K$ classes as normal samples, and we aim to identify if a sample is not coming from these classes during the inference phase. Recent studies have shown that training a supervised classifier on $K$ classes and using Softmax probabilities for calculating the anomaly scores can yield state-of-the-art performance in the OOD detection task [60]. An example of the OOD detection task is using a classifier trained on an animal dataset to detect samples from other datasets, e.g. flowers.

Fig. 1 illustrates an example of normal sample versus anomalies, outliers, novelty and out-of-distribution data.

IV. SELF-SUPERVISED LEARNING FOR ANOMALY DETECTION

In the remainder of this paper, we describe the general methodology and contribution of the self-supervised anomaly detection papers. Furthermore, we describe the application domains in which these methods are employed. The key aspects of these papers are summarized in Table I. In this table, we identify the task that each paper tries to solve, the metric used for evaluation, and how the paper quantified the anomaly score from the representation. Also, in Fig 2, we illustrated the methodology that each group of methods uses. Moreover, in Fig 3, we illustrated the timeline of papers that concerns with the self-supervised AD models and their application. This figure indicates the rapid growth of this field and its widespread applicability in solving real-world problems.

A. Algorithms

Self-supervised algorithms can learn a proper data representation with the help of a defined pretext supervised task from an unlabelled dataset. The pretext task guides the model to learn a generic representation of the data, which can be helpful for the downstream task such as classification and anomaly detection.

A wide range of proxy tasks and models are proposed in the literature of self-supervised learning. They include, but are not limited to colorization [61], maximization of mutual information between low-level and high-level representations [62], and predicting geometric transformations [63]. These methods showed promising results in various tasks, such as speech representation learning [64], visual feature learning [65], and healthcare applications [66].

In recent years, contrastive learning methods [36] become one of the most important groups of self-supervised learning. In contrastive learning, the goal is to learn a proper data representation by pulling different views of the same sample close together and pushing them away from other samples. This objective can be achieved by defining a proper loss such as contrastive loss [67] or triplet loss [68]. Several variants of contrastive learning models are suggested that can even achieve accuracy close to a fully-supervised model in specific tasks [36].

Despite their recent success and broad applicability, self-supervised models suffer from several important shortcomings. One of their most significant problems is their computational inefficiency. Compared to a fully-supervised model, they need more time and data to train and get an accuracy comparable to their supervised counterparts.

Self-supervised models are also popular in anomaly detection in the past few years. Previous studies showed that the representation that is learned from self-supervision can be useful for anomaly detection if the anomaly score and the pretext task are defined appropriately [42] [37]. Inspired by earlier works [69], we categorize the self-supervised AD models based on their pretext task into two groups:

- **Self-predictive Methods:** These models create the pretext task for each individual sample. Commonly, they apply a transformation to the input sample and try to
Fig. 1. Normal samples are shown in green, anomalies in red, outliers in blue and novelties in purple. The dataset of animals is denoted by a light-blue dashed box while other out-of-distribution datasets are shown by a dashed dark-red box.

either predict the applied transformation or reconstruct the original input. These models are effective even if only “positive” samples, i.e. in-distribution (IND) samples, are available. They do not necessarily require samples from other distributions, also known as “negative” samples, during training.

- **Contrastive Methods:** Contrastive models define the proxy task on the relationship between pairs of samples. They commonly generate positive views of a sample by applying different geometric transformations. Then, they aim to pull together the positive samples while pushing them away from the negative ones. In contrastive learning, samples of the current batch other than the anchor sample and its augmentations are considered as “negative” while “positive” samples are the ones that are coming from augmentations of the anchor. Technically, contrastive models can also be considered as self-predictive models. In essence, they also need to learn to predict the transformations in order to associate the augmentations of the same sample to each other. However, recent fast growth of the contrastive learning algorithms encourages us to treat them as a stand-alone category.

Fig. 2 visually illustrates the representation learning process of these two different categories. As shown in this figure, unlike self-predictive algorithms, the contrastive learning methods use negative samples. This figure also depicts the pseudo-label generation process for different SSL methods. Self-predictive models apply the transformations on positive samples and try to either predict the applied transformation or reconstruct the original input. Contrastive methods, on the other hand, do not explicitly predict the transformations or reconstruct the input and instead, aim to distinguish between positive and negative samples. More details on the methods depicted in Fig. 2 are presented in Sections V and VI.

B. Assumptions and Evaluations

Based on the nature of the dataset and the availability of the data labels, the anomaly detection task is formulated differently in the past studies. The most common formulation is one-class anomaly detection (aka LPUE) [37] [70] [36], in which one class of the datasets is trained as the normal class, while the remaining classes are considered abnormal. An example of this task is taking a class of the CIFAR-10 such as Cat as normal, and the rest as anomalies. On the other hand, in multi-class anomaly detection tasks, multiple classes in the same datasets are considered normal during training, and one or multiple remaining classes are anomalous [42], [71].

Self-supervised models are capable of learning a good feature representation from the input data. However, this representation is not readily useful for anomaly detection. Defining a suitable scoring function to quantify the degree of abnormality from this representation is an essential step for designing an anomaly detection framework. Previous studies use different scoring functions based on the downstream tasks to detect anomalies. For example, for one-class anomaly detection, two widely used anomaly scores are normality score and reconstruction error. Normality score estimates the
normality of new samples at the inference time after applying different transformations [37], [72]–[74]. Examples of this type of score includes Dirichlet score [37] and rotation score [74]. Reconstruction error, which is typically measured by the Euclidean distance between the original and the reconstructed images, is another category of scoring functions. The assumption behind using this score is that the reconstructed features of anomalies from the latent space have higher reconstruction errors than normal samples [70], [75]. For multi-class anomaly detection, anomaly scores such as class-wise density estimation (negative Mahalanobis distance) [76] and data likelihood criterion [77] were also used. Finally, for tackling the out-of-distribution detection problem, several other measures including probability-based measures (rotation score [74], Confusion Log Probability (CLP) [78], Weighting Softmax Probability [38], and Mahalanobis distance [76] are used in the self-supervised anomaly detection literature.

To evaluate the performance of an anomaly detector, several criteria are used. In practical applications, the cost of false alarms (type I error) and missed-detected anomalies (type II error) are usually different. Most anomaly detectors define the decision function as

\[
\text{Output} = \begin{cases} 
\text{normal}, & \text{if } \text{Score}(x) < \zeta \\
\text{abnormal}, & \text{if } \text{Score}(x) \geq \zeta
\end{cases}
\]

where \( \text{Score}(x) \) is the anomaly score for new sample \( x \), and the decision threshold \( \zeta \) is chosen to minimize the costs corresponding to the type I and II errors and to accommodate other constraints imposed by the environment [79]. However, it is common that the costs and constraints are not stable over time or are not fully specified in various scenarios. As an example, consider a financial fraud detector that receives anomaly alarms to investigate the potentially fraudulent activities. A detector can only handle a limited number of alarms, and its job is to maximize the number of anomalies containing these alarms based on the precision metric. Meanwhile, an anomaly alarm being wrongly reported can cause a credit card agency places a hold on the customer’s credit card. Thus, the goal is to maximize the number of true alarms given a constraint on the percentage of false alarms by using the recall metric.

Area Under the Receiver Operating Characteristic (ROC) Curve (AUROC or simply AUC) is known for its ability to evaluate the model’s performance under a broad range of the decision threshold \( \zeta \) [80]. The AUROC curve is an indicator for all sets of precision-recall pairs at all possible thresholds. This makes AUROC capable of interpreting the performance of models in various scenarios. As shown in Table I, most anomaly detection use the AUROC metric for evaluation. The random baseline achieves an AUC of 0.5, regardless of the imbalance between normal and abnormal subsets, while an excellent model achieves an AUC close to 1, concluding the robustness of the model in distinguishing normal from abnormal classes.

C. Application Domains

Anomaly detection systems are widely deployed in various domains, such as medicine, industry, infrastructure, social medical, financial security, etc. Despite the fact that self-supervised anomaly detection is a relatively new field, it is now
Self-supervised anomaly detection methods have been widely employed in practical applications along with other popular methods such as Semi-supervised learning [50], and GAN and its variants [49].

Self-supervised learning algorithms are commonly used in medical research for detecting irregularities in patients’ records. They are successfully employed for detecting epileptic seizures [81], pulmonary diseases [82], Parkinson disease [83], and retinal diseases [84]. In addition, they are applied to different modalities of medical data, including Computed Tomography (CT) scans [85], 3D volumetric CT data [41], X-ray scans [86], optical coherence tomography (OCT) [87], Spectral Domain - optical coherence tomography images (SD-OCT) [88], and MRI images [89], [90].

Self-supervised anomaly detection methods are also employed in industrial applications for defect detection, and failure prediction [91], [92], as well as for monitoring infrastructural facilities [93], [94].

The application of self-supervised AD is not limited to the aforementioned areas. Several fields such as financial fraud detection [95], [96], text anomaly detection [97], and splice detection [98] are also benefited from the SSL algorithms.

V. SELF-PREDICTIVE METHODS IN ANOMALY DETECTION

Self-Predictive methods can learn data embedding by defining the supervised proxy task on a single sample. This approach focuses on the innate relationship between a sample and its own contents or its augmented views. An example of a self-predictive task is masking a portion of an image and trying to reconstruct it using a neural network [75].

In most self-predictive approaches, the objective is to predict the label of the applied transformation, such as predicting the degree of rotation of an image. In this case, the anomaly score is commonly defined based on the Softmax probabilities of a supervised classifier. However, the objective of some methods is reconstructing the original input from its transformed version. Solving the Jigsaw puzzle and denoising autoencoders are examples of this approach. In this case, the reconstruction error of the model is used as the anomaly score. Geometric transformations were one of the earliest types of transformations that are used for visual representation learning. Doersch et al. (2015) [103] showed that predicting the relative position of image patches is a helpful pretext task for improving the representation for object detection. In a later work, Gidaris et al. (2018) [63] used rotation prediction for learning a better representation.

Geometric transformation models first create a self-labelled dataset by applying different geometric transformations to normal samples. The applied transformation is served as the label of each sample. Let $\mathcal{T} = \{T_1, T_2, \ldots, T_K\}$ be the set of geometric transformations. The new labelled dataset $S$ can be constructed from the original dataset $\mathcal{D}$ as below:

$$S := \{(T_j(x), j) | x \in \mathcal{D}, T_j \in \mathcal{T}\},$$

where $T_j$ represents the $j$th geometric transformation.
| Method | Author and Year | Task | Anomaly Score Indicator | Summary |
|--------|----------------|------|-------------------------|---------|
| **1.** Geometric Transformations (GODM) | Galan et al. 2018 [37] | One-Class AD | ROC | Anomaly score based on the similarity of the inlier and outlier datasets. |
| **2.** AE-based Neighborhood Relational Encoding (NRE) | Sabokrou et al. 2019 [70] | One-Class AD | Reconstruction Error | Besides learning a reconstruction scheme, AE preserves the local geometric manifold based on NRE that leads to identity-based self-supervised learning. |
| **3.** Rotation Prediction (SSL-OE) | Hendrycks et al. 2019 [74] | One-Class AD | AUROC | An auxiliary rotation loss is added to improve the robustness and uncertainty of the SSL model. |
| **4.** Classification-Based Anomaly Detection for General Data (GOAD) | Bergman et al. 2020 [99] | One-Class AD | Softmax Probability of the classifier | GOAD applies on all the given normal images and encourages learning the features that are useful for detecting novelties. |
| **5.** CL with Confusion Log Probability (CLP) | Winkens et al. 2020 [78] | OOD | ROC-AUC | A simple contrastive training-based approach for OOD detection is proposed. CLP captures the similarity of the inlier and outlier datasets. |
| **6.** A full-supervised classification training and a self-supervised OOD detection | Mohseni et al. 2020 [38] | One-Class AD | Softmax Probability of rejected classes | A 2-step training scheme is employed to learn the generalizable inlier- and outlier features. |
| **7.** Puzzle-AE: U-Net for puzzled inputs with adversarial robust training | Salehi et al. 2020 [75] | One-Class AD | Error Normalization Score (based on Reconstruction Errors) | U-Net solves the puzzled inputs. The quality of the reconstructed normal inputs is increased, and the robust adversarial training is used as an automatic shortcut removal. |
| **8.** Contrasting Shifted Instances (CSI) | Tack et al. 2020 [42] | One-Class AD | Maximizing cosine similarity and the norm of representation | A new detection score is introduced in the training phase that contrasts the sample with distributionally-shifted augmentations of itself. |
| **9.** SSD: a feature detector and cluster-conditioned detection | Sehwag et al. 2021 [76] | OOD | Mahalanobis distance | SSD: an outlier detector is based on only unlabeled in-distribution data. SSD uses SSL followed by a Mahalanobis distance in the feature space. |
| **10.** One-class AD by SSL: rotation prediction and CL (DROC) | Sohn et al. 2021 [72] | One-Class AD | Normality score (from OCSVM, KDE) | AUC | One-class AD emphasizes the importance of decoupling building classifiers for learning representations. |
| **11.** CutPaste augmentation | Li et al. 2021 [73] | One-Class AD | Gaussian density estimator (GDE) | AUC | CutPaste augmentation creates local irregular patterns during training and identifies these local irregularity on unseen real defects at the test time. |
| **12.** Masked Contrastive Learning (MCL) | Cho et al. 2021 [39] | Multi-Class AD | Class-wise density estimation (negative Mahalanobis distance) | AUC | MCL can shape dense class-conditional clusters by adding 2 components: class-conditional mask and stochastic positive attraction to boost both IN and OOD performance. |
| **13.** CL with Negative Data Augmentation (NDA) | Chen et al. 2021 [100] | One-Class AD | Reconstruction error | Negative augmentation generates negative samples closer to normal samples and helps separate normal and abnormal points. |
| **14.** SSL with Dynamic Local Augmentation | Yoa et al. 2021 [101] | One-Class AD | Regression Error and Uncertainty Score | SSL learns dynamic global and dense representations using only normal images. Local augmentation then generates pseudo-anomalous images and helps detect the anomalies. |
| **15.** SLA2P: Geometric Transformations and Adversarial Perturbation with Active Learning | Wang et al. 2021 [102] | One-Class AD | Uncertainty Based Scoring with Adversarial Perturbation | AUC | SLA2P designs a discriminative anomaly score by employing feature-level negative augmentation strategies based on self-supervised learning and adversarial perturbation. |
| **16.** NAF-AL: Neural Autoregressive Flows with Active Learning | Zhang et al. 2021 [77] | One-Class AD | Probabilistic scoring with majority voting | NAF-AL employs data transformations in the SSL setting and learns the data likelihood by using different data distributions and Adversarial Flows based Active Learning. |
| **17.** DAAD: SSL with an adversarial training | Zhang et al. 2022 [71] | One-Class AD | Probabilistic scoring with majority voting | DAAD includes an auxiliary classifier and a deep adversarial training model. DAAD captures different data distributions and makes an anomaly evaluation using majority voting. |
where the original data point is shown by \( x \). A multi-class network is trained over the dataset \( S \) to detect the transformation applied to the sample. During the inference phase, the trained models are applied to the transformed versions of the samples, and the distribution of the Softmax output is used for anomaly detection [37]. Unlike the Autoencoders and GAN-based methods, the geometric transformation models are discriminative. The intuition behind these models is that the model learns to extract important features of the input by learning to identify the applied geometric transformations. These features can also be helpful for anomaly detection.

The paper by Golan et al. (2018) [37] was the first work that used geometric transformation learning for anomaly detection. They named their method as GEOM and showed that it can significantly outperform the state-of-the-art in anomaly detection. They showed that their model can beat the top-performing baseline in CIFAR-10 and CatsVSDogs datasets by 32% and 67%, respectively.

To calculate the anomaly score of a sample from the Softmax probabilities, Golan et al. (2018) [37] combined the log-likelihood of the conditional probability of each of the applied transformations:

\[
    n_S := \sum_{k=1}^{K} \log p(y(T_k(x))|T_k)
\]

Then, they approximated \( p(y(T_k(x))|T_k) \) by a Dirichlet distribution:

\[
    n_S = \sum_{k=1}^{K} (\hat{\alpha}_k - 1) \log y(T_k(x)).
\]

An important issue of GEOM is that the classifier \( p(y(T_k(x))|T_k) \) is only valid for samples the network encountered during the training. For other samples which also includes anomalies, \( p(y(T_k(x))|T_k) \) can have a very high variance. To address this problem, Hendrycks et al. (2018) [104] proposed to use some anomalous samples during the training to ensure that \( p(y(T_k(x))|T_k) = \frac{1}{T} \) for anomalies. This method, which is also known as Outlier Exposure (OE), formulates the problem as a supervised task which might not be practical for some real-world applications as they do not have access to anomalies.

Even though self-predictive models showed promising results, their performance is still significantly poorer than fully-supervised models in out-of-distribution detection. However, some recent studies [74] hinted that using SSL models in conjunction with supervised methods can improve the robustness of the model in different ways. Therefore, even in cases where we have access to anomaly data and labels, using self-supervised proxy tasks can enhance the performance of the anomaly detector.

A significant downside of geometric models is that they only use transformations that are well-suited for image datasets and cannot be generalized to other data types, e.g. tabular data. To overcome this issue, Bergman and Hoshen proposed a method called GOAD [99]. In GOAD, the data is randomly transformed by several affine transformations \( T = \{T_1, T_2, \ldots, T_K\} \). Unlike the geometric transformations, affine transforms are not limited to images and can be applied to any data type. Also, we can show that the geometric transformations are special cases of the affine transforms, and the GEOM algorithm is a special case of GOAD.

In GOAD, the network learns to map each of the transformations into one hypersphere by minimizing the below triplet loss:

\[
    L = \sum_{i} \max_{m}(\|f(T_m(x_i)) - c_m\|^2 + s - \min_{m'\neq m}\|f(T_m(x_i)) - c_{m'}\|_2^2, 0),
\]

where \( f(.) \) is the network, \( s \) is a regularizing term for the distance between hyperspheres, and \( c_m \) is the hypersphere center corresponding to the \( m \)-th transformation. The above objective encourages the network to learn the hyperspheres with low intra-transformation and high inter-transformation variance. This is to provide a feature space, i.e. the last layer of \( f(.) \), in which the different transformations are separated. During the inference phase, the test samples are transformed by all transformations and the likelihood of predicting the correct transform is used as the anomaly score.

Although classification-based methods showed significant improvement in semantic anomaly detection on datasets such as CIFAR-10, their performance is poor on real-world datasets such as MV TecAD [75]. This is because these models can learn high-level features of data by learning the patterns which are present both in the original data and its augmented versions, e.g. rotated instances. However, these algorithms might not be well-suited for sensory-level anomaly detection tasks, e.g. detecting cracks in an object. This is because some types of low-level anomalies, such as texture anomalies, are often invariant to the transformations. To alleviate this issue, several other proxy tasks, that are more suitable for low-level anomaly detection, are proposed. For instance, Salehi et al. (2020) [75] used the idea of solving the jigsaw puzzle for learning an efficient representation that can be used for pixel-level anomaly detection. Their proposed method, which they named as Puzzle-AE, trains a U-Net autoencoder to reconstruct the puzzled input. The reconstruction objective ensures that the model is sensitive to the pixel-level anomalies, while the pretext task of solving the puzzle enables the network to capture high-level semantic information, as shown in Fig. 2. They further boosted the performance of their model by incorporating adversarial training.

More recently, Li et al. (2021) [73] developed a self-supervised method called CutPaste which significantly improves state-of-the-art in defect detection. CutPaste transformation randomly crops a local patch of the image and pastes it back to a different image location. The new augmented dataset is more representative of real anomalies. Thus, the model can be easily trained to identify and localize the local irregularity (shown by the white regions in the black background in Fig. 2). To detect the augmented samples from the un-transformed ones, the objective of the network is defined as follows:

\[
    L_{CP} = \mathbb{E}_{x \in \mathcal{X}} \{ \text{CE}(g(x), 0) + \text{CE}(g(CP(x)), 1) \},
\]

where \( CP(.) \) is the CutPaste augmentation, \( \mathcal{X} \) is the set of normal data, \( \text{CE}(\cdot, \cdot) \) is a cross-entropy loss, and \( g \) is a binary
classifier that can be parameterized by deep networks. In order to calculate the anomaly score from the representation, an algorithm like KDE or GDE can be used.

CutPaste can also learn a patch representation and compute the anomaly score of an image patch by cropping a patch before applying CutPaste augmentation. This facilitates localizing the effective area. In this case, the objective loss function is modified as:

$$E_{x \in X} \{ CE(g(c(x)), 0) + CE(g(CP(c(x))), 1) \},$$  \hspace{1cm} (6)

where $c(x)$ crops a patch at random location $x$.

In another similar work, Schlüter et al. (2021) [105], introduced a new self-supervised task, called Natural Synthetic Anomalies (NSA) to detect and localize anomalies using only normal training data. Their proposed approach creates synthetic anomalies by seamlessly cloning a patch with various sizes from a source image into a destination image. In particular, NSA selects a random rectangular patch in the source image, randomly resizes the patch, blends the path into the destination location from a different image, and creates a pixel-level mask. The new samples that NSA generates are different in size, shape, texture, location, color, etc. In other words, NSA dynamically produces a wide range of anomalies, which are more realistic approximation of natural anomalies than the samples that CutPaste creates by pasting patches at different locations. An example of NSA is shown in Fig. 2, where a random patch from a source cat image is seamlessly cloned onto another cat image. The NSA method outperforms the state-of-the-art algorithms on several real-world datasets such as MVTecAD.

VI. CONTRASTIVE METHODS

The primary objective of contrastive self-supervised learning is to learn a feature space or a representation in which the positive samples are closer together and are further away from the negative points. Empirical evidence shows that contrastive learning models such as SimCLR [36] and MoCo [35] are particularly efficient in computer vision tasks. SimCLR, one of the most popular recent contrastive learning algorithms, learns representations by maximizing the agreement between different augmented versions of the same image while repelling them from other samples in the batch. Each image $x_i$ from randomly sampled batch $B = \{ (x_i, y_i) \}_{i=1}^{N}$ is augmented twice, producing an independent pair of views $\{ \hat{x}_{2i-1}, \hat{x}_{2i} \}$, and augmented batch $\tilde{B} = \{ (\hat{x}_i, \hat{y}_i) \}_{i=1}^{2N}$, where the labels of augmented data $\{ \hat{y}_{2i-1}, \hat{y}_{2i} \}$ are equal to the original label $y_i$. By performing independent transformation $T$ and $T'$ drawn from a pre-defined augmentation function pool $\mathcal{T}$, the augmented pair of views $\{ \hat{x}_{2i-1} = T(x_i), \hat{x}_{2i} = T'(x_i) \}$ are generated. Next, $\{ \hat{x}_{2i-1}, \hat{x}_{2i} \}$ are passed sequentially through an encoder and a projection head to yield latent vectors $\{ \hat{z}_{2i-1}, \hat{z}_{2i} \}$. SimCLR learns the representation by maximizing the following loss for a positive pair of examples $(m, n)$:

$$l(m, n) = - \log \frac{\exp(sim(z_m, z_n)/\tau)}{\sum_{i \neq m} \exp(sim(z_m, z_i)/\tau)}$$ \hspace{1cm} (7)

where $sim(z_m, z_n)$ represents the cosine similarity between the pair of latent vectors $(z_m, z_n)$, $1_{i \neq m}$ is an indicator function which is equal to 1 if $i \neq m$ and zero otherwise, and $\tau$ indicates the temperature hyperparameter which determines the degree of repulsion. The final objective is to minimize the contrastive loss, defined in (8), over all positive pairs in a mini-batch:

$$L_{SimCLR} = \frac{1}{2N} \sum_{i=1}^{N} \left[ l(2i - 1, 2i) + l(2i, 2i - 1) \right].$$ \hspace{1cm} (8)

Contrastive learning models established themselves as powerful representation learning tools. Still, they face crucial challenges for anomaly detection. Most widely-used contrastive learning algorithms, such as SimCLR and MoCo, need negative samples to operate. However, we either only have access to the samples from one class in many anomaly detection tasks, or the distribution of classes is highly imbalanced. In addition, the learned representation is not readily suitable for the anomaly detection task, and we need to define a proper anomaly score.

Despite these challenges, several contrastive anomaly detection models have emerged in the recent years. The CSI method proposed by Tack et al. (2020) was the first attempt for using contrastive learning in anomaly detection [42]. The CSI method is based on the idea of instance discrimination which considers every data point as a separate class and negative relative to other samples in the dataset [106]. This idea is proven to be practical in visual representation learning for classification, but its performance in anomaly detection is unexplored [36]. They also showed that if specific transformations are used for generating negative samples from a given point, the learned representation can be more appropriate for anomaly detection. These distribution-shifting transformations can be denoted by a set as $\mathcal{S}$. In contrast to SimCLR, which considers augmented samples as positive to each other, CSI attempts to consider them as negative if the augmentation is drawn from $\mathcal{S}$. A significant conclusion of the CSI method is that although using the shifted transformations does not improve and even in some cases hurts the performance of the representation in other downstream tasks such as classification, it can improve the performance for anomaly detection.

If we denote the set of shifting transformations by $\mathcal{S} = \{ S_0, S_1, ... , S_{K-1} \}$ with $I$ being the identity function and $K$ different (either random or deterministic) transformations, the CSI loss can be written as:

$$L_{con-SI} := L_{SimCLR} \left( \bigcup_{S \in \mathcal{S}} B_S : T \right)$$ \hspace{1cm} (9)

in which $B_S = \{ S(x_i) \}_{i=1}^{P}$, in simpler terms, the $L_{con-SI}$ is essentially the same as the SimCLR loss, but in the con-SI, the augmented samples are considered negative to each other.

In addition to discriminating each shifted instances, an auxiliary task is added with a Softmax classifier $p_{cls-SI}(y^S | x)$ that predicts which shifting transformation $y^S \in S$ is applied for a given input $x_i$. The classifying shifted instances (cls-SI) loss is defined as below:

$$L_{cls-SI} := \frac{1}{2B} \frac{1}{K} \sum_{S \in \mathcal{S}} \sum_{\hat{x}_S} - \log p_{cls-SI}(y^S = S | \hat{x}_S)$$ \hspace{1cm} (10)
The final loss of CSI is then defined as:

$$L_{CSI} := L_{con-si} + \lambda L_{cls-si}$$  \hspace{1cm} (11)

The authors of the CSI empirically showed that the norm of the representation $\|z(x)\|$ is indeed a good anomaly score, where $z$ is the representation vector and $\|\cdot\|$ denotes the second norm. This can be explained intuitively by considering that the contrastive loss increases the norm of the in-distribution samples to maximize the cosine similarity of samples generating from the same anchor. Consequently, during the test time, in-distribution samples are mapped further from the origin of the $z$ space, while the representation of other data points, i.e., anomalies, has a smaller norm hence are closer to the origin. This is an important observation as it helps to solve the problem of defining the anomaly score on a representation that is learned in an unsupervised fashion.

The authors also found that the cosine similarity to the nearest training point in $\{x_m\}$ can be another good anomaly score. They defined the score of their model as a combination of these two metrics as below:

$$s_{con}(x; \{x_m\}) := \max_n \sim(x_m), z_x) \cdot \|z(x)\|$$  \hspace{1cm} (12)

where $z_x$ is the representation vector of the test sample $x$ and $z(x_m)$ is the closest representation vector in the training set.

Parallel to Tack et al. (2020) [42], Winkens et al. (2020) [78] developed a contrastive model for detecting out-of-distribution instances. They evaluated their approach on several benchmark OOD tasks and showed that contrastive models are also capable in OOD. The paper’s key idea is that a fully supervised model might not be able to capture the patterns that can be useful for out-of-distribution detection. However, using contrastive learning techniques, the model learns high-level and task-agnostic features that can also help detect OODs. When we combine these techniques with the supervised learning techniques, the resulting model can learn more reliable features for both semantic classification and OOD detection.

The CSI algorithm shows that the task-agnostic representation learned through contrastive learning is suitable for anomaly detection. However, a task-specific approach can be more suitable for anomaly detection. (The task may be defined as the AD task itself or another downstream task such as data classification.) The contrastive models, such as SimCLR, are quite helpful in learning a representation for individual data points. They can also learn separable clusters for each class without having access to any labels. However, the resulting clusters may have blurry boundaries, and they commonly require fine-tuning for the downstream tasks.

To overcome this obstacle, Cho et al. (2021) [39] developed a contrastive model which is tailored for anomaly detection. Their model, which is called Masked Contrastive Learning (MCL), modifies the degree of repulsion based on the labels of the data points. In vanilla SimCLR, all other batch samples, regardless of their class label, are considered negative relative to the anchor sample and are repelled with equal magnitude. However, in MCL, the repelling ratio is defined by the following class-conditional mask (CCM):

$$CCM(m, n) = \begin{cases} \alpha & \text{if } \bar{y}_m = \bar{y}_n \\ 1 & \text{if } \bar{y}_m \neq \bar{y}_n \end{cases}$$  \hspace{1cm} (13)

where $0 < \alpha < \frac{1}{2}$. Basically, CCM adjusts the temperature $\tau$ for the same labelled views to a smaller value of $\alpha$. This means that if the negative sample has the same class as the anchor, it is repelled with less magnitude compared to other data points. The SimCLR loss function is modified according to this mask as follows:

$$L_{CCM} = \frac{1}{2N} \sum_{i=1}^{N} \left[ l_{CCM}(2i-1, 2i) + l_{CCM}(2i, 2i-1) \right],$$  \hspace{1cm} (14)

$$p_{CCM}(m, n) = \frac{\exp(\sim(z_m, z_n)/\tau)}{\sum_{i=1}^{2N} \mathbf{1}_{i \neq m} \exp(\sim(z_m, z_i)).CCM(m, i)},$$  \hspace{1cm} (15)

$$l_{CCM}(m, n) = -\log p_{CCM}(m, n),$$  \hspace{1cm} (16)

Although the proposed mask leads to a finer-grained representation space, the repulsive nature of the loss function may lead to the formation of scattered clusters. To prevent this phenomenon, the MCL algorithm stochastically attracts each sample to the instances with the same class label.

To further improve the MCL model in [39], an auxiliary classifier that predicts the applied transformation is also employed. The masking function is then modified based on the label of sample and its transformations. The repelling ratio is then smaller for the samples that simultaneously have the same class label and transformation labels, compared to the samples with the same class but different transformation labels. A sample with the latter property repels with a smaller magnitude than the negative points.

To score the anomalies in [39], the Mahalanobis distance [107], shown in (17), is employed.

$$MD(x) = (z_x - \mu)^T \Sigma^{-1} (z_x - \mu),$$  \hspace{1cm} (17)

where $z_x$ is the representation of $x$, $\mu$ is the sample mean, and $\Sigma$ is the sample covariance of features of the in-distribution training data. The Mahalanobis distance is a standard metric for scoring anomalies from their representation. It does not require any labelled data that makes it a common choice for many anomaly detection algorithms. In addition to this distance, the score of the auxiliary classifier is used to boost the model’s robustness.

In another similar work, Sehwag et al. (2021) [76] explored the applicability of contrastive self-supervised learning for out-of-distribution (OOD) and anomaly detection from unlabeled data, and proposed a method called SSD. They also extended their algorithm to work with labelled data in two scenarios: First is the scenario in which it is assumed that there are a few labelled out-of-distribution samples (i.e. a k-shot learning setting where $k$ is set to 1 or 5), and the second scenario is the case in which labels of the in-distribution data are provided during the training phase.
In SSD [76], the SimCLR is used to learn the representation and the Mahalanobis Distance is incorporated to detect anomalies. For the cases where the labelled data is present, the authors suggested using the SupCon loss, defined in (18), which is a supervised variant of the contrastive loss [108], to have a more effective selection of the positive and negative samples for each image. In SupCon, samples from the same class are treated as positive and other samples as negatives.

\[
L_{\text{SupCon}} = \frac{1}{2N} \sum_{i=1}^{2N} - \log \frac{\frac{1}{N_{y_m}} \sum_{j=1}^{N_{y_m}} 1(i \neq m)1(y_i = y_m)e^{u_i^T v_j}/\tau}{\sum_{j=1}^{2N} 1(i \neq m)e^{u_i^T v_j}/\tau},
\]

(18)

where \(N_{y_m}\) refers to the number of images with label \(y_m\) in the batch, and \(v_j = h(f(x_j)/\theta)\) with a projection head \(h(\cdot)\) and an encoder \(f(\cdot)\). Using SupCon loss yielded better performance compared to the contrastive loss throughout their experiments for the OOD detection from a labelled dataset. Overall, Sehwag et al. (2021) [76] showed that the contrastive approach can outperform other methods in OOD detection in both labelled and unlabelled settings.

Contrastive models are also used in conjunction with one-class models for anomaly detection. One-class classifiers are one of the most widely used models in anomaly detection. They can detect anomalies after learning from a single class of examples. Sohn et al. (2020) [72] employed a two-stage framework for detecting anomalies using self-supervised learning models. In this framework, an SSL-based neural network is used to learn the representation of the input. A one-class classifier, such as OCSVM or KDE, is applied to the learned representation to detect anomalies. The two-stage framework eliminates the need for defining an anomaly score and, as is empirically demonstrated in the paper, it can outperform other state-of-the-art methods.

Despite their promising empirical results, one-class classifiers suffer from a critical problem known as catastrophic collapse. This phenomenon happens when the network converges to the trivial solution of mapping all the inputs to a single point regardless of the input sample value \(x\), i.e. \(\phi(x) = c\) where \(\phi(\cdot)\) denotes the network output. This trivial solution is obtained when minimizing the center-loss defined as \(L = ||\phi(x) - c||^2\) [33], [109]. The features that the network learns in such case are uninformative and cannot be used for distinguishing anomalies from normal data. This issue is also known as “hypersphere collapse”.

To overcome the hypersphere collapse problem, Reiss et al. (2021) [40] proposed a new loss function, called Mean-shifted contrastive loss (MSCL). Unlike the conventional contrastive loss, where the angular distance is computed relative to the origin, MSCL measures the angular distance relative to the normalized center of the extracted features. An example of MSCL is shown in Fig. 2. Formally, for a sample \(x\), the mean-shifted representation is defined as:

\[
\theta(x) = \frac{\phi(x) - c}{||\phi(x) - c||}.
\]

The mean-shifted contrastive loss is then given by:

\[
L_{\text{MSCL}}(x', x'') = L_{\text{CONS}}(\theta(x'), \theta(x''))
\]

\[
= - \log \frac{\exp((\theta(x'), \theta(x''))/\tau)}{\sum_{i=1}^{2N} \exp((\theta(x'), \theta(x_i))/\tau) },
\]

where \(L_{\text{CONS}}\) is the typical contrastive loss for a positive pair, shown in SimCLR [36], and \(x', x''\) are the two augmentations of the input \(x\). One limitation of the MSCL loss is that it implicitly encourages the network to increase the distance of features from the center. Because of this, normal data lie in a region far away from the center. To solve this issue, the loss function is modified by adding the angular center loss, which shrinks the distance of normal samples from the center. Reiss et al. (2021) [109] showed that the overall loss, which is a combination of the MSCL and the angular losses, can achieve a better training stability and higher accuracy in anomaly detection than the regular center-loss.

In summary, recent papers suggest that the representation that is learned through self-supervised learning is indeed very useful for anomaly detection. An interesting observation is that even a simple scoring function such as the norm of the representation \(||z||\) can be used for detecting anomalies from the representations. This can be justified because, in CL-based models, the normal data is spread out on a hypersphere. This property can help to define the anomaly score as the distance of the representation from the center. A smaller distance means a higher probability of the point belonging to the anomaly class.

VII. COMPARATIVE EVALUATION AND DISCUSSIONS

To gain insight into the performance of the self-supervised algorithms, we present a comparative evaluation of the methods based on the results reported in their original paper.

A flurry of datasets is used to benchmark the self-supervised anomaly detection algorithms. CIFAR-10 [110], and MVTecAD [51] are two of the most common dataset that recent anomaly detection papers used. CIFAR-10 includes images of ten different objects. To benchmark an AD algorithm on this dataset, we assume that we only have access to the data from one of the classes during the training. During the test time, other classes are considered to be anomalies.

Table II presents the result of several state-of-the-art SSL models against the commonly-used shallow and deep baselines for one-class AD on the CIFAR-10 dataset. This task can evaluate the performance of algorithms in the semantic (high-level) anomaly detection. Looking at this table, we can readily confirm that the self-supervised approaches can outperform other shallow and deep anomaly detection algorithms by a significant margin. This remarkable improvement leads to the emergence of SSL algorithms as a key category of anomaly detection.

Besides semantic anomaly detection, self-supervised methods show satisfactory performance for defect detection and spotting sensory anomalies [113]–[115]. Fig. 4 shows the performance of the self-supervised models on the MVTecAD dataset against other widely-used algorithms including shallow models, deep models and generative models. More specifically,
the compared shallow models are Gaussian [45], MVE [45], SVDD [116], KDE [45], kPCA [45], patch-SVDD [117] and IGD [118]. The compared deep models are CAVGA [119], ARNet [120], SPADE [121], MOCCA [122], DSVD [33], FCDD [123], DFR [124], STFPM [125], Gaussian-AD [126], InTra [127], PaDiM [128] and DREAM [129]. The included generative models in Fig. 4 are AnoGAN [31], LSA [130], GANomaly [131], AGAN [45], Normalizing Flows-based DifferNet [132], CFLOW [133] and CS-Flow [134]. Looking at the figure, we can infer that SSL-based models can achieve a good performance on this dataset. However, the superiority of self-supervised algorithms over other baselines is less evident in this task than in one-class AD. Also, some algorithms such as GEOM, and CSI, which show state-of-the-art performance on CIFAR-10, achieve a weak accuracy in this anomaly detection task.

The above argument manifests the importance of choosing the right pretext task in self-supervised learning. Methods such as GEOM and RotNet which are based on geometric transformations, and CSI and SSD which are based on contrastive methods, work well for detecting semantic anomalies, but they are not well-suited for defect detection. On the other hand, SSL approaches that are based on pixel-level transformations, such as CutPaste, can achieve good accuracy on the MVTecAD dataset. Choosing the right proxy task, depending on the downstream objective and types of anomalies, is the key to the success of the SSL models. This allows researchers to improve the state-of-the-art by coming up with effective pretext tasks.

Out-of-distribution detection is another task in which SSL models are widely applied. Table III shows the experimental results of some SSL models (shown in the top 10 rows) against a supervised method, shown in the last row of the table. The supervised method is in fact a ResNet-50 network that is trained to classify the data available in CIFAR-10 from the other OOD dataset – i.e., ResNet-50 is trained as an eleven-way classifier, ten for CIFAR-10 and one for the OOD dataset. To benchmark an OOD algorithm, it is common to train a model on the CIFAR-10 dataset and test the model using another dataset. If the samples of the test datasets are similar to the CIFAR-10 to some extent, the task is called near-OOD detection (e.g. CIFAR-10 vs. CIFAR-100). Otherwise, it is referred to as far-OOD detection (e.g. CIFAR-10 vs. SVHN, or CIFAR-10 vs. LSUN). We observe that SSL can even achieve better performance than the supervised baseline. This manifests that it is not necessary to have access to the data ground truths for the OOD detection task.

The results reported in Table III shows that all the SSL-based methods can achieve an accuracy above 94% on far-OOD detection (i.e. CIFAR-10 vs. SVHN). It can suggest that the SSL models can learn meaningful features of the dataset. Almost all algorithms perform well in near-OOD detection, and some can even beat the supervised baseline.

VIII. FUTURE DIRECTIONS AND CONCLUSION

Although the self-supervised models have established themselves as state-of-the-art in anomaly detection, there is still much room for improvement in this research field. This
section briefly discusses some critical challenges that SSL-based anomaly detectors suffer from and presents some high-level ideas for addressing them.

A. Negative Sampling in Contrastive Models

In the recent years, contrastive models dominated self-supervised AD algorithms. To learn an efficient representation, CL algorithms require accessing negative samples. In the standard setting, it is assumed that other batch samples are negative, even though their class label is the same as that of the query sample. However, if the number of same-class samples increases, the quality of the learned representation degrades. In some anomaly detection tasks, where the training data comprises samples of one class, this negative sampling bias may turn into a big issue. This motivates researchers to design unbiased versions of the contrastive loss [136].

Interestingly, previous studies showed that even in the one-class setting, the instance discrimination contrastive learning can lead to a suitable representation for anomalies. This can be because all the training data are spread out on a hypersphere, and the anomalies are mapped to the center of the space, as we discussed in section VI.

Following the success of SimCLR, several other contrastive models are developed. These methods can be good candidates for one-class anomaly detection since they can be trained using only positive samples. Some recent models, such as BYOL [137] and Barlow Twins [138], do not require negative samples during training. To the best of our knowledge, there is no study that evaluates the performance of these models for anomaly detection.

B. Incorporating Labelled Data

In the most anomaly detection studies, it is assumed that no labeled anomaly is available during the training phase. However, in some applications, we might be able to have a few labelled anomalies. These labelled samples can significantly improve the algorithm if incorporated appropriately. Recently, Sehwag et al. (2021) [76] explored the problem of few-shot anomaly detection, where they assume a few labelled anomalies are present. They showed that even a few anomalies can significantly improve the detection accuracy. Zheng et al. (2022) [139] proposed an extended algorithm of multi-scale contrastive learning, called ANEMONE, by incorporating it with a handful of ground-truth anomalies.

Since the assumption of having access to a few anomaly samples during training time is feasible in many tasks, we believe that models with capability to incorporate them have a great potential to improve the detection performance. Such methods also have more application in the real-life problems.

C. Going Beyond Visual Anomaly Detection

Traditionally, self-supervised learning literature focused on visual representation learning. Even most recent anomaly detection algorithms are developed for visual anomaly detection. Hence, it is no surprise that visual anomaly detectors can dominate the self-supervised AD field. Inspired by the success of these algorithms, several papers have started to propose self-supervised frameworks for detecting anomalies in other data types. For instance, Zheng et al. (2021) [140] developed a SSL-based CL method to detect graph anomalies in two social network and four citation network datasets. In regard to speech data, Zhang et al. (2022) [141] proposed a self-supervised learning and an adaptive memory fusion module to
learn general normal patterns and rich feature representations, respectively. This supports detecting anomalies that are present in multivariate time series. Hojjati and Armanfard [142] also proposed a contrastive approach for detecting abnormal industrial sounds. Since anomaly detection’s application spans a vast area of application, exploring the idea of self-supervised learning for other input types, such as medical signals, is also important. Developing a suitable pretext task for these data types can be a significant challenge that researchers face.

D. Conclusion

In this paper, we discussed the state-of-the-art methods in self-supervised anomaly detection and highlighted the strengths and drawbacks of each approach. We also compared their performance on benchmark datasets and pinpointed their applications. In summary, we can argue that self-supervised models are well suited for tackling the problem of anomaly detection. Yet, there are still a lot of under-explored issues and room for improvement. Still, the significant success of SSL algorithms offers a bright horizon for achieving new milestones in automatic anomaly detection.

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