

ANOMALY DETECTION BY ESTIMATING GRADIENTS OF THE TABULAR DATA DISTRIBUTION

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ABSTRACT

Detecting anomalies in tabular data from various domains has become increasingly important in deep learning research. Simultaneously, the development of generative models has advanced, offering powerful mechanisms for detecting anomalies by modeling normal data. In this paper, we propose a novel method for anomaly detection in a one-class classification setting using a noise conditional score network (NCSN). NCSNs, which can learn the gradients of log probability density functions over many noise-perturbed data distributions, are known for their diverse sampling even in low-density regions of the training data. This effect can also be utilized, and thus, the NCSN can be used directly as an anomaly indicator with an anomaly score derived from a simplified loss function. This effect will be analyzed in detail. Our method is trained on normal behavior data, enabling it to differentiate between normal and anomalous behaviors in test scenarios. To evaluate our approach extensively, we created the world’s largest benchmark for anomaly detection in tabular data with 49 baseline methods consisting of the ADBench benchmark and several more datasets from the literature. Overall, our approach shows state-of-the-art performance across the benchmark.

1 INTRODUCTION

Anomaly detection, the process of identifying data points that deviate significantly from expected patterns, is a critical task with applications spanning industries such as finance (Al-Hashedi & Magalingam, 2021), healthcare (Fernando et al., 2021), manufacturing (Gupta et al., 2013), and cybersecurity (Ahmad et al., 2021). While traditional machine learning techniques such as nearest neighbors and density-based methods have historically dominated the anomaly detection landscape, particularly in tabular data, their performance has shown limitations in high-dimensional, large-scale datasets. This is especially true as data complexity increases and the demands for scalability and real-time processing become more pressing. Despite advances, traditional methods often struggle to cope with the intricate patterns present in modern data, making them less suitable for complex applications (Ramaswamy et al., 2000).

The increasing availability of high-dimensional data has fueled research into more sophisticated methods, particularly generative models, which have emerged as powerful tools for capturing the underlying distributions of normal data. By learning the data manifold of normal behavior, generative models provide a promising mechanism for anomaly detection by modeling deviations from this manifold as potential anomalies. Among these approaches, score-based generative models, such as Noise Conditional Score Networks (NCSN) (Song & Ermon, 2019), have gained significant attention for their ability to learn the gradient of the log-likelihood functions across noisy data distributions. Unlike traditional generative models like GANs and VAEs, which often face challenges in computing exact probabilities, NCSNs excel at this task, making them a natural fit for detecting anomalies (Dhariwal & Nichol, 2021). NCSN are also closely related to Denoising Diffusion Probabilistic Models (DDPM) (Karras et al., 2022).

The anomaly detection problem is often framed as a one-class classification task, where the objective is to learn a model that characterizes normal behavior from training data and can distinguish between normal and anomalous observations during testing (Schölkopf et al., 1999). This is also often called semi-supervised learning (Livernoche et al., 2024). Unlike traditional supervised learning tasks, where labeled data is available for all classes, anomaly detection typically lacks labeled examples of

anomalous data. This makes the task more difficult, as the model must generalize from normal data alone and detect subtle deviations that indicate an anomaly. All the designations have in common that the training is unsupervised, i.e., without labels, and the preselection only takes place in data preprocessing.

In this paper, we propose a novel approach to anomaly detection in a Learning from Positive Unlabelled Examples (LPUE) or one-class classification setting that leverages the inherent strengths of score-based models. Our method introduces an NCSN-based diffusion network trained on normal data, which learns in the training to differentiate between normal and anomalous behavior during testing. The essential advantage of this approach lies in the ability of NCSNs to discriminate perturbed samples on the data manifold through a score-based error. The score variation between normal and anomalous samples provides a robust mechanism for anomaly detection. A well-trained network enables the output of a direct score on which a sample can be assessed as an anomaly or not, making this approach both intuitive and effective.

Our motivation for employing score-based models is rooted in the limitations of existing approaches. Traditional methods, such as reconstruction-based techniques, rely on the assumption that anomalies produce a higher reconstruction error. Still, these approaches often require external knowledge (Tack et al., 2020) or pre-trained models (Fort et al., 2021), which limits their transferability and scalability. Similarly, while embedding-based and synthetic anomaly-based methods have shown strong performance on industrial benchmarks, they depend on large datasets and leverage external knowledge, which may not always be available or transferable. In contrast, score-based models, particularly NCSNs, offer a self-contained and mathematically sound approach to anomaly detection that does not rely on external priors or complex architectures (Shin et al., 2023).

To demonstrate the effectiveness of our approach, we conduct extensive experiments on the largest benchmark for tabular anomaly detection, ADBench benchmark (Han et al., 2022), which includes 57 datasets spanning diverse domains such as finance, healthcare, and industrial applications. This benchmark contains 47 tabular datasets, as well as datasets consisting of extracted representations from images and of extracted embeddings of natural language tasks, with a total of 121 sub-datasets, providing a comprehensive evaluation of our method across different modalities. Moreover, we add 15 further frequently used datasets from other studies. In this new benchmark, we compare our approach against 49 baseline methods, including both classical and state-of-the-art techniques, and we show that our NCSN-based model, called noise conditional score-based anomaly detection (NCSBAD), outperforms existing methods in terms of detection accuracy and scalability.

Our key contributions are summarized as follows:

- We present a novel approach for one-class anomaly detection utilizing a score-based model with a simplified loss function, which operates without needing external knowledge such as external priors, pre-trained models or additional datasets.
- We perform the first empirical study of NCSN anomaly detection on tabular data, where our adaptation approach shows a high performance and interpretability.
- We demonstrate the inherent capability of the trained score model to effectively identify anomalies, and we provide a thorough analysis of how various parameters, including the network architecture, impact its performance.
- Through comprehensive experiments on well-established public benchmarks, including ADBench and other widely used tabular datasets, we demonstrate that our approach consistently achieves state-of-the-art results in tabular anomaly detection, outperforming existing methods across multiple metrics.

2 BACKGROUND

In anomaly detection, the unsupervised setting is particularly challenging because anomalies typically constitute only a small fraction of the overall data, and labels are unavailable during training. This scenario assumes that the data consists of a mixture of normal and anomalous samples without access to label information. Many methods in this category rely on assumptions about the underlying data-generation process, making techniques such as embedding models and deep generative models well-suited candidates. However, deep models often struggle with the tendency to inadvertently

model the anomalies within the input data, thus complicating distinguishing them. In contrast, one-class classification approaches within semi-supervised anomaly detection are specifically designed to address this issue (Ruff et al., 2021). This idea relies on LPUE, where anomaly detectors are trained on positive data only and then validated/tested on both normal and abnormal data (Golan & El-Yaniv, 2018; Sabokrou et al., 2019; Chen et al., 2020).

In this work, we focus on detecting anomalies without prior knowledge of their distribution, thereby avoiding reliance on labeled data for training. Various unsupervised methods aim to estimate the density of the data distribution $p(\mathbf{x})$ or its log-likelihood $\log p(\mathbf{x})$. Score matching, introduced by Hyvärinen & Dayan (2005), provides a way to estimate data density by circumventing the intractable computation of partition functions in parametric models. Vincent (2011) established a critical connection between the denoising auto-encoder and score matching, demonstrating that the denoising auto-encoder objective is equivalent to the score-matching objective. Building on this principle, we adopt the denoising score-matching approach to learn an approximation of the score introduced by Song & Ermon (2019), which forms the core of our method for anomaly detection.

The score of a probability density function $p(\mathbf{x})$, is defined as $\nabla_{\mathbf{x}} \log p(\mathbf{x})$. Score-based generative models estimate this score, $\nabla_{\mathbf{x}} \log p(\mathbf{x})$. Unlike likelihood-based models, score-based models do not require normalization and simplifying parameterization. A non-normalized statistical model has the form $p_{\theta}(\mathbf{x}) = \frac{e^{-E_{\theta}(\mathbf{x})}}{Z_{\theta}}$, where $E_{\theta}(\mathbf{x}) \in \mathbb{R}$ is known as the energy function, and Z_{θ} is an unknown normalizing constant that ensures $p_{\theta}(\mathbf{x})$ constitutes a valid probability density. In traditional likelihood-based training, calculating the normalizing constant Z_{θ} is intractable. Focusing on the score $\nabla_{\mathbf{x}} \log p_{\theta}(\mathbf{x}) = -\nabla_{\mathbf{x}} E_{\theta}(\mathbf{x})$, eliminates the need to compute the normalizing constant Z_{θ} .

While diffusion models can be represented through various mathematical formulations, either discrete or continuous, (Song et al., 2020b) offers a unified framework using Stochastic Differential Equations (SDEs). In this framework, the forward diffusion process is defined as follows: Let $\{\mathbf{x}_t \in \mathbb{R}^d\}_{t=0}^T$ represent a diffusion process indexed by the continuous time variable $t \in [0, T]$. This diffusion process is governed by an SDE, given by

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w}_t, \quad (1)$$

where $\mathbf{f}(\cdot, t) : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is the drift coefficient, $g(t) \in \mathbb{R}$ is the diffusion coefficient, and $\mathbf{w}_t$ represents Brownian motion or Wiener process.

The optimization problem is formulated as a weighted sum of Fisher divergences for all noise scales:

$$\min_{\theta} \mathbb{E}_{t \sim \mathcal{U}(0, T)} \left[\lambda(t) \mathbb{E}_{\mathbf{x}_0 \sim p(\mathbf{x}_0)} \mathbb{E}_{\mathbf{x}_t \sim p(\mathbf{x}_t | \mathbf{x}_0)} \left[\|S_{\theta}(\mathbf{x}_t, t) - \nabla_{\mathbf{x}_t} \log p(\mathbf{x}_t | \mathbf{x}_0)\|_2^2 \right] \right], \quad (2)$$

where $\mathcal{U}(0, T)$ denotes the uniform distribution over the interval $[0, T]$, and $p(\mathbf{x}_t | \mathbf{x}_0)$ represents the transition probability from $\mathbf{x}_0$ to $\mathbf{x}_t$. The weighting function $\lambda(t)$, is a positive, time-dependent function, $\lambda(t) \in \mathbb{R}_{>0}$. In this objective, the expectation over the initial data distribution p_0 can be efficiently estimated by computing empirical means over observed data samples. The expectation over $\mathbf{x}_t$ can be estimated by sampling from the transition probability $p(\mathbf{x}_t | \mathbf{x}_0)$ (Song & Ermon, 2019; 2020; Song et al., 2020b).

3 METHOD

Figure 1 provides a general overview of our approach. In this section, we first define the tabular data anomaly detection task and then describe the design of our method in detail. The algorithms for training and inference are included in Appendix B.

Problem Statement Given a dataset of N normal behavior samples $\mathbb{S} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$, where each sample $\mathbf{x}_n$ is a vector in $\mathbb{R}^d$, our goal is to develop a scoring function $y : \mathbb{R}^d \rightarrow \mathbb{R}$. This function should assign lower scores to samples drawn from the same distribution as $\mathbb{S}$, while higher scores are assigned to samples that deviate from this distribution. This enables the distinction between in-distribution and out-of-distribution samples. For interpretability purposes, we aim to ensure that the scoring function $y_i : \mathbb{R}^d \rightarrow \mathbb{R}^d$ can also provide direct, feature-wise access to the results.

Score Network for Tabular Anomaly Detection We modify the denoising score matching technique specifically for tabular data and introduce a noise-conditional score network that learns patterns from the training data. It maps samples from the target distribution $p(\mathbf{x}_0)$ to a prior distribution

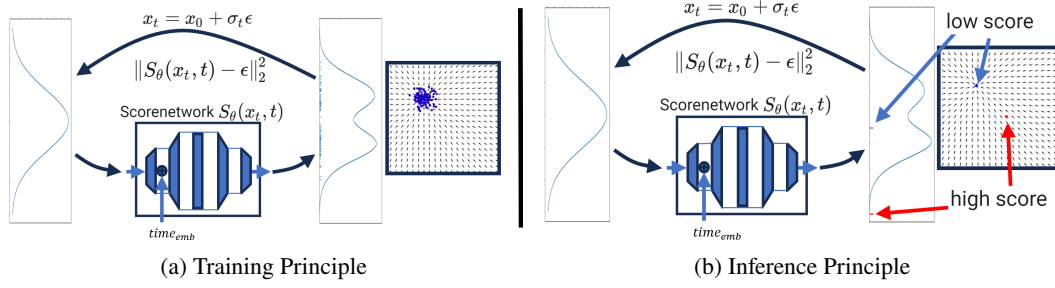


Figure 1: Overview of the proposed method. Each input data point x is transformed through a diffusion process from x_0 to x_T . During the training phase, the model learns a vector field (the score) that characterizes the underlying data distribution (shown on the right). In the inference phase, the trained model evaluates each sample, assigning an anomaly score based on its likelihood of residing within the learned vector field.

$p(x_T)$. To approximate the time-dependent score function $\nabla_{x_t} \log p(x_t)$, we train a score-based model $S_\theta(x_t, t)$ using a simplified denoising score matching. The parameters of the score network are trained by minimizing a simplified loss function where we directly predict the noise ϵ ,

$$\ell(\theta) = \mathbb{E}_{t \sim \mathcal{U}(0, T)} \mathbb{E}_{x_0 \sim p(x_0)} \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [\|S_\theta(x_t, t) - \epsilon\|_2^2], \quad (3)$$

where $t \sim \mathcal{U}(0, T)$ denotes the random drawn timestep, $x_t = x_0 + \sigma_t \epsilon$ the perturbed sample at timestep t and $\epsilon \sim \mathcal{N}(0, I)$ denotes the Gaussian noise. The derivation is outlined in Appendix C. Then $S_\theta(x_t, t)$ is a neural network that learns the denoising function to approximate the Gaussian noise using the perturbed data x_t and the time t . We use the standard L_2 loss for the denoising score matching, without adding any of the in Section 2 described weighting adjustments.

In general, every neural network that maps an input vector $x \in \mathbb{R}^d$ to an output vector $y \in \mathbb{R}^d$ with the same input and output dimensions can be used as a score-based model. This framework offers significant flexibility in choosing model architectures. To design our conditional score network, we use a simple multi-layer perceptron (MLP), a type of neural networks. While image-based approaches often use U-Net architectures, MLPs are more commonly used for tabular data, as shown in Section 6 and in the baseline methods. Our network architecture study, detailed in Appendix A, confirms that MLPs are a good fit for this task, working well with the datasets we evaluated.

Network Architecture The MLP, hereafter referred to as MLP2048, approximates the denoising function $\epsilon_\theta(x_t, t)$ and consists of three hidden layers, each using SiLU activation functions. Time-step embeddings, represented as $time_{emb}$, are created using Gaussian random features $[\sin(2\pi\omega t); \cos(2\pi\omega t)]$ (Tancik et al., 2020). These embeddings enable the network to capture the time dimension.

The MLP2048 takes two inputs: the current time step t and the input vector $x_t \in \mathbb{R}^{1 \times d_{in}}$, with $x_t = x_0 + \sigma_t \epsilon$. First, x_t is passed through a linear projection layer, which adjusts its dimension to d_{hidden} , with $h_0 = FC_{in}(x_t) \in \mathbb{R}^{1 \times d_{hidden}}$. Following the TabDDPM approach Kotelnikov et al. (2023), we add the time-step embeddings $time_{emb} \in \mathbb{R}^{1 \times d_{hidden}}$ to h_0 to create the input for the hidden layers $h_{hidden1} = h_0 + time_{emb}$.

The network has three hidden layers that process the input, and the final output score is calculated by the last linear layer $\epsilon_\theta(x_t, t) = h_{out} = FC_{out}(h_3) \in \mathbb{R}^{1 \times d_{in}}$. Specifically, the hidden layers of the MLP2048 are fully connected, and the dimension is doubled in the first hidden layer and halved in the last hidden layer to ensure the network can learn detailed patterns.

To avoid a reduction of the input dimensionality and, therefore, a compression after the input layer, we use a large hidden dimension of 2048, which is bigger than the maximum number of features in our datasets. This helps capture more information. More details about the network’s architecture, including ablation studies and parameter choices, can be found in Appendix A and E.

Noise Scale Selection The choice of noise scale is crucial in score estimation, as it determines how well low-density regions of the data distribution are captured. Therefore, it is the most crucial hyperparameter in our method. While larger noise scales can effectively cover these regions, they

tend to over-corrupt the data, distorting it significantly from the original distribution. On the other hand, smaller noise scales preserve the data’s structure but fail to adequately represent the low-density regions.

To strike a balance between these two extremes, we adopt a multi-scale noise perturbation approach inspired by previous work (Song & Ermon, 2020). Specifically, we perturb the data using isotropic Gaussian noise at timestep t increasing standard deviations, $\sigma_1 < \sigma_2 < \dots < \sigma_T$, where each σ_t introduces a different level of perturbation. The data distribution $p(x_0)$ is perturbed with Gaussian noise $\mathcal{N}(0, \sigma_t^2 \mathbf{I})$, resulting in noise-perturbed distributions $p(x_t) = \int p(y) \mathcal{N}(x_0; y, \sigma_t^2 \mathbf{I}) dy \approx \mathcal{N}(x_0; \mathbf{0}, \sigma_t^2 \mathbf{I})$.

Since we aim to model the original data distribution more accurately, especially for anomaly detection, we prioritize learning from lower noise scales. We ensure minimal distortion while capturing enough information from low-density regions by employing a moderate maximum noise scale. Therefore we define the multiscale variance σ_t^2 with $\sigma_t = \sqrt{(\sigma^{2T} - 1)/2 \log \sigma}$ and $t \sim \mathcal{U}(0, T)$ and set $\sigma = 0.01$. This results in a maximum of σ_t of $\sigma_T \approx 0.5$ and also a good approximation of low-density regions. Our optimized NCSN $S_{\theta^*}(x_t, t)$ estimates $\nabla_x \log p_t(x)$, such that $-S_{\theta^*}(x_t, t)/\sigma_t \approx \nabla_x \log p_t(x)$ in our simplified special case.

Anomaly Score Formulation We propose a novel anomaly score that is based on the simplified score-based loss function, which serves as a robust discriminative measure for detecting anomalies. The anomaly score evaluates how likely a perturbed sample matches the same data distribution as the training data. This provides an effective way to distinguish anomalous data points from the in-distribution samples.

Let $x_{t_{fix}} = x_0 + \sigma_{t_{fix}} \varepsilon$ represent the perturbed sample feed into the score-based model where $\varepsilon \sim \mathcal{N}(0, \mathbf{I})$. Here, the noise level t_{fix} is fixed during inference. To ensure that $x_{t_{fix}}$ is close to x_0 , the perturbations should be small. This ensures that the perturbation is not too large and still sufficient for a neural network. To determine an appropriate fixed t_{fix} , we make the following consideration, if we assume 1000 time steps for t , t_{fix} is chosen so that it corresponds to the first time step. The anomaly score for a sample x is defined as:

$$ADS = \mathbb{E}_{\varepsilon \sim \mathcal{N}(0, \mathbf{I})} [\|S_{\theta^*}(x_{t_{fix}}, t_{fix}) - \varepsilon\|_2^2], \quad (4)$$

which corresponds to the summed error of each output neuron. Since the noise scale t is fixed, the only randomness comes from ε . To reduce the influence, we perform the calculation with $NUM = 70$ randomly chosen values for ε .

In practical scenarios, especially for identifying anomalous regions within a sample $x \in \mathbb{R}^d$, we can skip the summation and use the feature-wise error measure directly. This error, denoted by ADS_i , is computed as:

$$ADS_i = \mathbb{E}_{\varepsilon \sim \mathcal{N}(0, \mathbf{I})} [\|S_{\theta^*}(x_{t_{fix}}, t_{fix})_i - \varepsilon_i\|_2^2], \quad (5)$$

where i refers to individual features of the data, and ADS_i captures the element-wise anomaly score for feature i . This feature-wise error provides an intuitive and interpretable measure for detecting localized anomalies, as demonstrated in a toy example in Section 5.

Benefit of Validation Data Due to the stochastic nature of the NCSN training, it can significantly benefit from using a validation dataset that is never used in training or inference. In general we train our NCSN for 200 Epochs however, since t and ε are randomly drawn from the respective distributions $t \sim \mathcal{U}(0, T)$ and $\varepsilon \sim \mathcal{N}(0, \mathbf{I})$, it cannot be guaranteed that this corresponds to the optimal training endpoint in terms of anomaly detection. Therefore, if a validation set is available as described in Section 4, a better training point based on the AUC-ROC on the validation data may be chosen and used for inference. This broadly corresponds to the idea of early stopping but is evaluated over the entire training process without causing a termination. We call this version NCSBADVAL.

Efficient Implementation and Inference Since we predict ε directly, it is important to highlight that the anomaly score proposed here differs from the score function used in Section 2 of the paper for denoising. Our anomaly detection framework is summarized in Algorithms 1 and 2, which outlines the steps for calculating the anomaly detection score. Despite some computational adjustments, the process is amenable to parallelization, as it does not require sequential operations. This is a significant advantage over DDPMs, whose calculations based on a Markov chain can only be performed sequentially and cannot be parallelized. This parallelism significantly accelerates

inference, making the method suitable for real-time anomaly detection applications. Further studies on the implementation can be found in Appendix A.

4 EXPERIMENTS

Datasets To ensure optimal comparable results in our study, we use all datasets that were used in the largest comparisons and parts of the code of previous works (Livernoche et al., 2024)¹, (Shenkar & Wolf, 2022)², (Bouman et al., 2024)³, (Han et al., 2022)⁴, (Zhao et al., 2019)⁵. In addition to ADBench benchmark (Han et al., 2022), which includes a collection of widely-used tabular anomaly detection datasets as well as newly generated datasets derived from images and natural language tasks we include datasets from ODDS (Ray), ELKI (Schubert & Zimek, 2019), ex-AE (Shin & Kim, 2020), the comparison from Goldstein & Uchida (2016) and from ICL (Shenkar & Wolf, 2022). In total, ADBench consists of 57 datasets with 121 sub-datasets, 47 from tabular datasets, five from extracted image representations, five from extracted embeddings from NLP areas, and 15 additional datasets. Please see Table 4 and the supplementary material for further information.

Experimental Setup In accordance with the previous approaches (Bergman & Hoshen, 2020; Shenkar & Wolf, 2022; Livernoche et al., 2024), the training set is constructed by randomly selecting 50% of the normal samples. The remaining 50% of normal samples and the full set of anomalies are divided into a test and a validation set at a ratio of 60% to 40%. In contrast to Livernoche et al. (2024), this is done to be able to carry out the experiments with validation data and allows a comparison between the choice of the optimal training time selected based on validation data never used in training and testing and a fixed number of training epochs. Consistent with prior work (Bergman & Hoshen, 2020), the decision threshold for the anomaly score is determined such that the predicted number of anomalies aligns with the actual number of anomalies present in the data. For each dataset, we apply a standardization based on the training samples.

Baseline Methods We compare our approach with a wide range of anomaly detection methods, including classical and deep learning-based models. We evaluate against the unsupervised trainable methods from PyOD (Zhao et al., 2019), ADBench benchmark, and from Bouman et al. (2024). The classical approaches encompass CBLOF (He et al., 2003), INNE (Bandaragoda et al., 2018), KPCA (Hoffmann, 2007), KDE (Latecki et al., 2007), GMM (Agarwal, 2007), SOD (Kriegel et al., 2009), ALAD (Zenati et al., 2018), COPOD (Li et al., 2020), ECOD (Li et al., 2022), FeatureBagging (Lazarevic & Kumar, 2005), HBOS (Goldstein & Dengel, 2012), IForest (Liu et al., 2008), kNN (Ramaswamy et al., 2000), LODA (Pevný, 2016), LOF (Breunig et al., 2000), MCD (Fauconnier & Haesbroeck, 2009), OCSVM (Schölkopf et al., 1999), PCA (Shyu et al., 2003), EIF (Hariri et al., 2019), Ensemble LOF (Breunig et al., 2000) (Bouman et al., 2024), GEN2OUT (Lee et al., 2021), DynamicHOBs (Goldstein & Dengel, 2012; Bouman et al., 2024), COF (Tang et al., 2002), ABOD (Kriegel et al., 2008), LMDD (Arning et al., 1996), ODIN (Hautamaki et al., 2004), CD (Cook, 1977), QMCD (Fang & Ma, 2001), and Sampling (Sugiyama & Borgwardt, 2013). Meanwhile, the deep learning-based models include methods such as LUNAR (Goodge et al., 2022), SOGAAL (Liu et al., 2019), AE (Aggarwal & Aggarwal, 2017; Ramaswamy et al., 2000), DeepSVDD (Ruff et al., 2018), DAGMM (Zong et al., 2018), GANomaly (Akçay et al., 2019), and MOGAAL (Liu et al., 2019). Additionally, we incorporate comparisons with other proposed deep learning methods such as DROCC (Goyal et al., 2020), GOAD (Bergman & Hoshen, 2020), ICL (Shenkar & Wolf, 2022), PlanarFlow (Rezende & Mohamed, 2015), VAE (Kingma, 2013; Zhou et al., 2020), SLAD (Xu et al., 2023b), and DIF (Xu et al., 2023a) from Livernoche et al. (2024). Furthermore, we benchmark our approach against the latest techniques including DDPM, DTE-IG, DTE-C, and DTE-NP, also proposed by Livernoche et al. (2024), as well as 3WNCROD (Zhang et al., 2023b) and MCM (Yin et al., 2024). To ensure the scope of our comparisons is robust, we include a dedicated evaluation of a Transformer-based model and NTP-AD proposed by Thimonier et al. (2023), which is detailed in Appendix D. These models demand specialized hyperparameter tuning for each dataset, making a direct comparison across all datasets infeasible in this work. Therefore, we provide results for overlapping datasets where hyperparameter tuning was performed, allowing for meaningful

¹Github: <https://github.com/vicliv/DTE>

²Code: Supplementary Material Zip https://openreview.net/forum?id=_hszZbt46bT

³Github: <https://github.com/RoelBouman/outlierdetection/tree/master>

⁴Github: <https://github.com/Minqi824/ADBench/tree/main>

⁵Github: <https://github.com/yzhao062/pyod>

comparisons. We deliberately exclude certain methods from PyOD, such as LOCI (Papadimitriou et al., 2003), due to their computational intractability $O(n^3)$, where n represents the number of data points. SOS (Janssens et al., 2011) was omitted due to its $O(n^2)$ memory requirements. These methods did not show significant improvements over the algorithms included in our study. Additionally, we exclude XGBod (Zhao & Hryniewicki, 2018), as it operates semi-supervised by incorporating partially labeled data, which deviates from the One-Class setting that is the focus of our work. Similarly, the methods presented in Pang et al. (2018) and Li et al. (2024) were not considered, as they perform single sample comparisons and thus do not align with the unsupervised and for the entire dataset automatic learning paradigm. The ATDAD method (Yang & Li, 2023) requires special hyperparameters for specific datasets, and due to the limited number of datasets in their experiments, a direct comparison with our method NCSBAD was not feasible. We provide further details in Section 6 and Appendix E.3.

Please note: For all methods used, we apply the default hyperparameters provided by the authors of the original publications and used their code directly, No additional hyperparameter tuning or other adjustments to the code were made. We recommend doing this additionally when using one of the baseline methods. A classification of which methods work in an inductive and which in a transductive setting and a further discussion of the baseline methods can be found in Appendix E.4.

Main Results Figure 2 presents the overall performance of all methods across our benchmark, each dataset constrained to a maximum of 50,000 data points; we provide more details for this in Appendix E.2. We show box plots of the AUC-ROC and F1-scores averaged over five different random seeds (0-4) used for the undersampling and data splitting over all datasets. Our proposed method demonstrates state-of-the-art performance across the benchmark, outperforming existing techniques on multiple metrics. Including a validation dataset further improves our approach, establishing it as

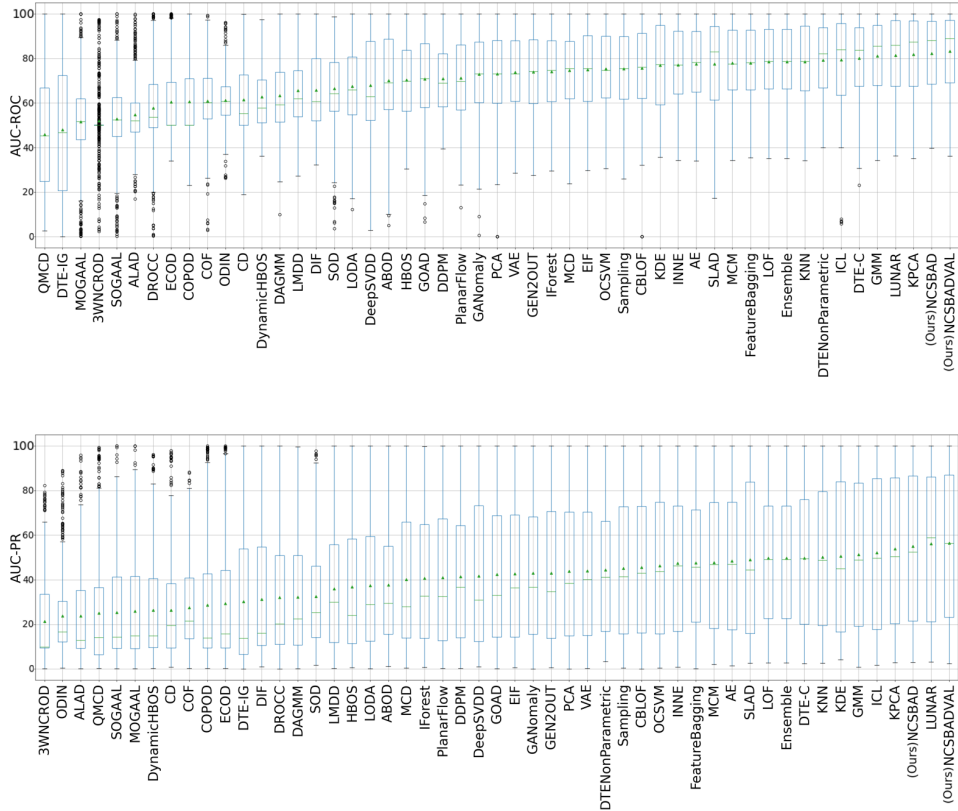


Figure 2: Box plots of AUC-ROC (top) and AUC-PR (bottom) across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green. Our proposed method NCSBADVAL outperforms all baseline models when validation data is used. Without validation data, NCSBAD still achieves the highest performance in AUC-ROC and secures the second position in F1-Score.

the top-performing model based on the mean values across all three evaluated metrics. Interestingly, while our NCSN with validation data, NCSBADVAL, ranks first for overall mean scores, the version without validation, NCSBAD, performs comparably, ranking just behind in AUC-ROC but falling slightly short in F1-score and AUC-PR against the LUNAR model. The notable performance of LUNAR, KPCA, and GMM—methods that are often overlooked in similar comparisons—should also be highlighted here. Due to space limitations, Figure 2 only presents the summarized results. Detailed results for the F1-Score, the performance on each dataset, and additional evaluation metrics proposed by Campos et al. (2016) as well as rankings are reported in Appendix F. Nevertheless, a closer inspection of the per-dataset results reveals a strong dependence on the specific dataset characteristics, with different algorithms outperforming others in various scenarios. This observation suggests that no single method universally dominates across all datasets. Consequently, we recommend practitioners evaluate multiple algorithms when confronted with a new dataset to identify the most effective approach. This highlights the importance of testing a diverse set of models to ensure optimal performance for any given application. Figure 14 in Appendix F.3 compares our method’s training and inference times against baseline models, alongside their computational requirements. Our model leverages a straightforward neural network architecture and parallelized inference, reducing inference time substantially. These results underscore the efficiency and robustness of NCSN for anomaly detection. Refer to Appendix D for further comparisons with Transformer-based models.

5 INTERPRETABILITY

In section 3, we mentioned that our proposed method possesses inherent and intuitive interpretability, providing a distinct advantage in anomaly detection tasks. The anomaly score generated by our model, initially aggregated as a single value for baseline experiments, can be flexibly evaluated at both the aggregate and feature levels. We present a toy example demonstrating feature-level anomaly localization to further illustrate this capability. We utilize the MLP2048 model and train it for this demonstration using a one from the MNIST-C dataset. MNIST-C also contains images with anomalies. Among other things, with an added zig-zag line. Given that the MNIST dataset comprises grayscale images $\mathbf{X} \in \mathbb{R}^{28 \times 28}$, each image is flattened into a vector $\mathbf{x} \in \mathbb{R}^{784}$ to conform to the model’s input requirements. Training and testing images are standardized according to training data distribution, as with all our experiments.

After training and inference, the resulting anomaly score—initially output as a vector $\mathbf{x} \in \mathbb{R}^{784}$ is reshaped into a matrix $\mathbf{X} \in \mathbb{R}^{28 \times 28}$ to correspond to the original image dimensions. This reshaped anomaly map is subsequently visualized as an image, as shown in Figure 3. The figure depicts the original training image, the test image (with an added anomaly), and the difference between the two. Additionally, the anomaly score heatmap, reshaped to mirror the original image structure, is plotted. As evident from Figure 5, the anomaly, represented by the added zig-zag line, is identified and exhibits strong alignment with the difference image.

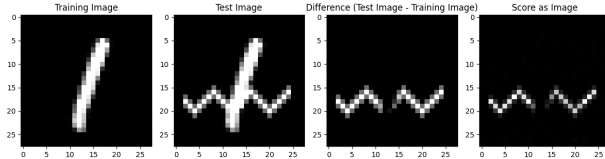


Figure 3: Interpretability of our method NCSBAD illustrated on MNIST-C and MNIST-C Zig-Zag datasets. The first image displays the training image, followed by the second image, highlighting the anomaly of the testing image. The third image presents the difference between the training and testing images. Finally, the last image visualizes the anomaly on the image, utilizing the feature-wise score output of the model reshaped into a 28x28 format.

The visualization highlights the model’s natural interpretability, showcasing its ability to detect outliers at the granular feature level. This approach offers a global anomaly score and facilitates fine-grained insight into the specific features contributing to the anomaly, providing a more transparent and interpretable anomaly detection process. While this is indeed a vision example, the flattened matrix is converted to a vector format akin to tabular data, meaning that no extended spatial patterns remain in 2D and also the MLP2048 is used. The visualization is merely a toy example selected for its illustrative potential. Providing an intuitive example in the context of tabular data is challenging, as noted by Shenkar & Wolf (2022). Beyond purely numerical statements we offer a tangible example.

The requirements for this example are using a grayscale image with a manageable dimension for ensuring comparability with tabular data. This example demonstrates that our method can localized anomaly detection at the feature level, enhancing its applicability for tasks requiring detailed anomaly diagnostics and offering robust interpretability.

6 RELATED WORK

Anomaly detection has seen considerable advances, particularly in tabular data, with several key studies focusing on method comparison (Bouman et al., 2024). The most comprehensive comparison of unsupervised methods, the development of new techniques (Bergman & Hoshen, 2020; Shenkar & Wolf, 2022; Livernoche et al., 2024; Thimonier et al., 2023; Li et al., 2024; Yin et al., 2024), and Zhao et al. (2019) or Han et al. (2022) offer detailed benchmarks on various datasets. Interestingly, high-performing GMM (Agarwal, 2007) and LUNAR (Goodge et al., 2022) are often omitted as baselines in recent works, along with KPCA (Hoffmann, 2007). For one-class classification anomaly detection, non-parametric methods are popular, like the historic kernel density estimation (Parzen, 1962) or the modern COPOD (Li et al., 2020). At the same time, parametric approaches include Gaussian-based methods (Agarwal, 2007) and adversarial learning (Zenati et al., 2018) or classical regularized classifiers, particularly kernel-based methods (Schölkopf et al., 1999), also offer an alternative to density estimation approaches by enforcing tighter fits around observed data. Recent developments have been driven by deep learning. Early models focused on autoencoders (Sakurada & Yairi, 2014; Aggarwal & Aggarwal, 2017; Kingma, 2013; Hawkins et al., 2002) and distance-based techniques (Ramaswamy et al., 2000), with later methods integrating deep learning and one-class classification (Pang et al., 2018; Sun et al., 2022). Many current methods adopt a self-supervised approach, leveraging task-specific loss functions to improve anomaly detection without labeled anomalies (Golan & El-Yaniv, 2018; Hendrycks et al., 2019; Li et al., 2023; Qiu et al., 2021; Schneider et al., 2022; Sohn et al., 2020). A comprehensive review is presented in the following surveys Ruff et al. (2021); Pang et al. (2021); Chalapathy & Chawla (2019); Chandola et al. (2009).

Score-based Models for Anomaly Detection There are two primary approaches for learning the score of a probability density function: Denoising Diffusion Probabilistic Models (Ho et al., 2020) and Noise Conditional Score-based Networks (Song & Ermon, 2019). While diffusion models have been extensively applied for anomaly detection in image and video data in one-class semi-supervised settings (Tur et al., 2023; Yan et al., 2023), their use in the context of tabular data and unsupervised settings was explored in (Livernoche et al., 2024). In Wolleb et al. (2022), a diffusion-based encoding method followed by a classifier-guided denoising procedure was proposed, and Zhang et al. (2023a) introduced the synthesis of anomaly samples for training denoising networks focused on anomaly repair. AnoDDPM (Wyatt et al., 2022) trains a denoising network using diffusion noise to reconstruct normal images, while Graham et al. (2023) extends this approach by combining reconstructions across multiple time steps to generate anomaly scores. On the other hand, NCSNs are less explored, and only closely related work exists. Shin et al. (2023) leveraged perturbation resilience from a geometric perspective for industrial image anomaly detection, while Cai & Fan (2022) perturbed normal data and trained a classifier to differentiate normal from anomaly samples. NCSN-based sampling has been applied to time-series anomaly detection Lim et al. (2023), combining reconstruction-based, density-based, and gradient-based anomaly scores. Energy-based models closely related to NCSNs have also been employed for manifold recovery in Yoon et al. (2023).

Score-based Models for Tabular Data Unlike image datasets, where pixel values typically follow Gaussian distributions, tabular data exhibits more complex, heterogeneous distributions across columns (Xu et al., 2019). This discrepancy for tabular data requires special consideration and suggests that score-based models that can learn complex data distributions are well-suited (Kim et al., 2022). Diffusion models have recently been adapted for this domain, such as applying DDPM to tabular data (Livernoche et al., 2024), where a modified ResNet (Gorishniy et al., 2021) architecture with time embeddings is incorporated before each block. Further advancements include TabDDPM (Kotelnikov et al., 2023), which utilizes a simple MLP to model the reverse diffusion process, adapted from prior work on diffusion models Gorishniy et al. (2021). Kim et al. (2022) employs an MLP architecture inspired by Grathwohl et al. (2018) for a score-based stochastic differential equation network tailored for tabular data synthesis. Additionally, Zhang et al. (2024) integrates variational autoencoder (VAE) embeddings to synthesize new tabular samples using an MLP-based network trained via denoising score matching.

7 CONCLUSION

This work introduces a new paradigm in anomaly detection in a LPUE setting by utilizing the power of score-based generative models with a general framework and a fixed architecture to effectively differentiate normal from anomalous behavior. By leveraging an anomaly score based on an NCSN only trained with normal behavior samples as a measure of anomaly, we present a robust, scalable, and interpretable approach to detecting anomalies in tabular data. Our extensive evaluations on ADBench and other widely used benchmarks validate the superiority of this method, positioning it as a compelling alternative to existing deep learning and classical anomaly detection techniques.

The improvement of our method over DDPMs warrants particular emphasis, as it addresses key limitations of DDPMs while enhancing both performance and efficiency. A major advantage of our approach lies in its inherent parallelizability, which is absent in DDPMs. DDPMs rely on a stepwise denoising process modeled as a Markov chain, requiring numerous sequential steps and significant computational time for anomaly detection in a reconstruction-based framework. In contrast, as detailed in Chapter 2, NCSNs learn SDEs that approximate the gradient of the log-likelihood. This enables direct anomaly scoring without the need for reconstruction and allows multiple predictions to be processed in parallel, drastically reducing inference times. Our method outperforms the DDPM and DTE-NP proposed by Livernoche et al. (2024) both in terms of anomaly detection results and computational efficiency. Additionally, we surpass the performance of DTE-IG and DTE-C, which employ time estimation during inference to generate anomaly scores. While these demonstrate faster inference times, they fall short of achieving the superior results delivered by our approach. Regarding interpretability, the methods presented in Livernoche et al. (2024) are comparable, with the restriction that they require an architecture specifically adapted to image data.

The significance of this work lies not only in its solid empirical results but also in its potential to address key challenges in the anomaly detection landscape. As the data manifold hypothesis (Song et al., 2020b) that data is supported on a lower-dimensional structure embedded in a high-dimensional space—becomes more widely accepted, score-based models offer a principled way to exploit this. While traditional methods such as locally linear embedding and manifold Parzen windows (Vincent & Bengio, 2002) aim to approximate local regions of the manifold and reconstruction-based methods like denoising autoencoders (Vincent et al., 2008) attempt to map between latent and data spaces, our NCSN approach directly leverages the score function to capture the structure of the manifold and its deviations. This makes it particularly suited for unsupervised one-class settings, where labeled data is scarce, and the goal is to detect anomalies by modeling the normal data distribution alone.

8 LIMITATION AND FUTURE WORK

While our approach NCSBAD, like other score-based models, demands substantial computational resources and time during training, it offers a distinct advantage regarding inference efficiency. Unlike traditional diffusion models such as DDPMs, our framework does not rely on a sequential Markov chain process for inference. This allows us to parallelize the inference step, reducing inference time compared to other diffusion-based techniques.

Our work is a foundational contribution to establishing NCSNs as a competitive method for anomaly detection in a LPUE or one-class classification setting. We have proposed a robust and generalizable framework, focusing on the fundamental principles, architectural design, and parameter settings necessary for effective anomaly detection using NCSNs. Future research could explore advanced training strategies, such as sliced score matching (Song et al., 2020a) and maximum likelihood weighting (Song et al., 2021), to optimize training efficiency and potentially enhance performance further.

9 REPRODUCIBILITY STATEMENT

To ensure full transparency and reproducibility of our results, we have made the experimental code available with detailed instructions in a README file, in the supplementary material zip file. Further information on models, hyperparameters, datasets, baselines, and experimental procedures can be found in Sections E.1, E.2, and E.3. Additionally, Section F includes an exhaustive listing of all results, including intermediate and partial outcomes, for further clarity and verification.

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A ABLATION, PARAMETERS AND ARCHITECTURE STUDIES

We perform extensive ablation studies, parameter tuning, and architectural analyses to evaluate the impact of various factors on our proposed method, thereby validating our theoretical assumptions. All experiments were carried out using the ADBench benchmark, employing seed 1 for consistency, and we report the mean AUC-ROC for the most influential parameters. The first shown experiments were conducted using the MLP2048 architecture, as presented in Section 3.

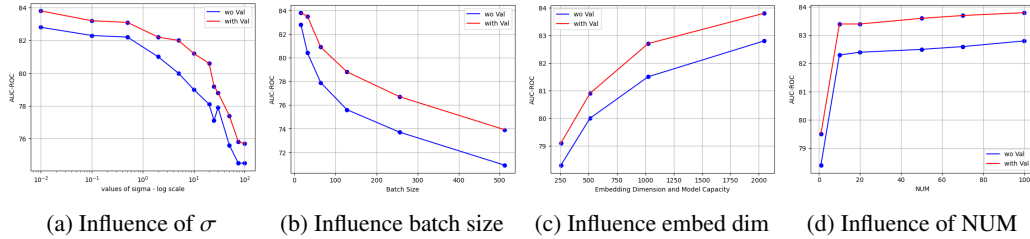


Figure 3: Mean AUC-ROC scores across the ADBench datasets using the MLP2048 model with seed 1, evaluated under various parameter configurations. Results are presented for both settings: without and using validation data.

Our first study investigates the effect of the noise **standard deviation** parameter σ . As predicted by theory, Figure 3a demonstrates our assumption that smaller σ values facilitate better learning of the underlying data structure. This confirms the theoretical insights discussed in Section 3. Note this is the parameter σ not σ_t .

Another critical parameter is the **batch size**, which, as shown in Figure Figure 3b, significantly affects both convergence speed and overall model performance. The model consistently benefits from a smaller batch size due to more frequent parameter updates and better adaptability to individual data distributions—a batch size of 16 yields optimal results, balancing training efficiency and performance. However, reducing the batch size further is not advisable as it may lead to unreasonably long training times.

The **embedding dimension**, which directly influences **model capacity**, is another key factor, particularly for datasets with high feature counts. To avoid compressing the data, we set the embedding dimension to be larger than the highest feature number across the benchmark. For example, since the InternetAds dataset has the highest number of features (input $x \in \mathbb{R}^{1555}$ for InternetAds dataset), we set the embedding dimension to 2048, as illustrated in Figure Figure 3c. This choice ensures sufficient capacity for all datasets in ADBench.

Finally, we explore the effect of multiple perturbations denoted by **NUM** in Algorithm 2 during inference. As shown in Figure Figure 3d, the random effects of perturbations stabilize after approximately ten repetitions, indicating that additional perturbations do not significantly improve performance beyond this point.

Additionally, we evaluate the impact of incorporating **validation data** across all experimental settings. As depicted in the accompanying figures, the mean AUC-ROC performance gain with validation data ranges from approximately 1% in optimal settings to up to 3% in sub-optimal settings, depending on the chosen hyperparameters and model configurations. This consistent enhancement underscores the advantage of validation-based training in our framework and highlights its effectiveness in achieving superior performance across various settings.

We have carried out a comprehensive analysis of various possible **architectures**. As mentioned in Section 3, the only constraint is that the input dimension must match the output dimension. Consequently, we included all models from our benchmark that satisfy this criterion: VAE, the tabular ResNet of DDPM, the model used in ICL, the model used in DTE-C, DiffWave (Kong et al., 2020), a reduced version of DiffWave, and TabSyn (Zhang et al., 2024). DiffWave is an

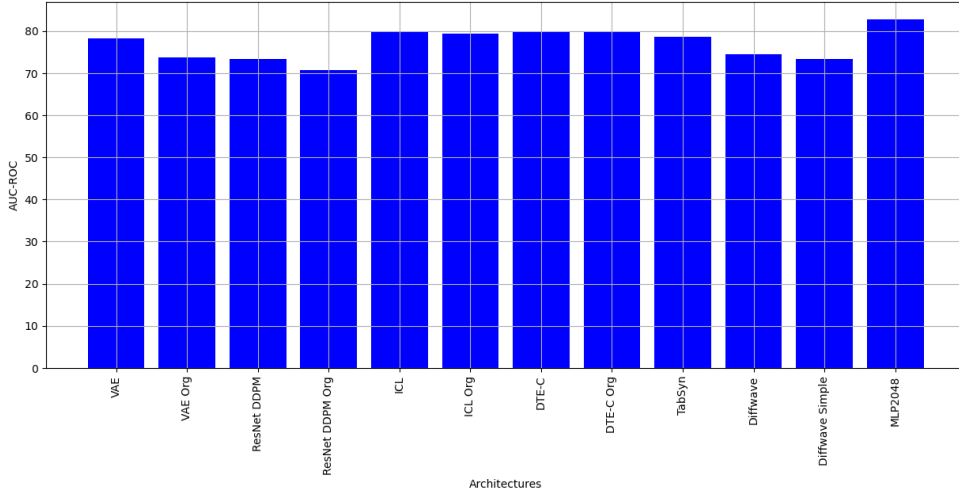


Figure 4: Comparison of various model architectures compatible with our proposed method, where the input and output dimensions must be identical. Additionally, the original performance of each architecture is included as a baseline (labeled as *Org*).

architecture frequently used in the literature, based on convolutional neural networks for diffusion models, primarily used to generate sound waves. TabSyn, on the other hand, is explicitly designed to generate tabular data. Additionally, our proposed MLP2048 architecture, as described in Section 3, was included for comparison.

The results of these evaluations are presented in Figure Figure 4. We also report the original benchmark results for each tested model for benchmarking purposes. The findings indicate that most architectures either achieve better AUC-ROC scores with our approach or are at least comparable to their original performances. Moreover, these results support our hypothesis that MLPs are particularly well-suited for handling tabular data, outperforming other architectures in this context. This is particularly evident in the results of the ResNet and DiffWave architectures. As we anticipated, models designed for tabular data benefit more from the MLP approach, which emphasizes capturing feature interactions, compared to convolutional neural networks (CNNs), which are better suited for detecting spatial correlations. The insights gained from these architectural studies culminate in the framework presented in Section 3, providing further validation of our proposed methodology.

B ALGORITHM

This section provides a detailed algorithmic illustration of the proposed method. **Algorithm 1** outlines the diffusion phases involved in the training process, where the model learns complex

underlying data distributions. **Algorithm 2** demonstrates the inference procedure for anomaly detection, where the anomalies are estimated based on the learned score model. This process leverages the training loss from multiple perturbed samples to identify anomalies.

Algorithm 1 NCSBAD: Training

Parameter: Variance scale parameters (σ, t) , Timestep T
Input: Batches of normal data $\mathbf{x}_0$
Output: Optimized score model S_{θ^*}

Initialization:
1: Get number of features $f \leftarrow$ features of $\mathbf{x}$
2: Get multiple scales of noise perturbations $\sigma_t \leftarrow \sqrt{(\sigma^{2t} - 1)/2 \log \sigma}$
3: **while** train **do**
4: Sample time steps t from $p(t) \sim \mathcal{U}(0, T)$ in interval $[0, T]$, get σ_t
5: Sample noise vectors $\varepsilon \sim \mathcal{N}(0, I) \in \mathbb{R}^{(f)}$
6: Get perturbed data $\mathbf{x}_t = \mathbf{x}_0 + \sigma_t \varepsilon$
7: Calculate loss $\ell(\theta) = \|S_{\theta}(\mathbf{x}_t, t) - \varepsilon\|_2^2$
8: Update the network parameter θ via AdamW optimizer
9: **end while**
10: **return** S_{θ^*}

Algorithm 2 AD Score Estimation

Parameter: Number of perturbations NUM , Variance scale parameter σ , Fixed timestep t_{fix}
Input: Optimized score model S_{θ^*} , Target sample $\mathbf{x}_0$
Output: AD Score ADS

Initialization:
1: Get number of features $f \leftarrow$ features of $\mathbf{x}$
2: Get fixed noise perturbations $\sigma_{t_{fix}} \leftarrow \sqrt{(\sigma^{2t_{fix}} - 1)/2 \log \sigma}$
3: Set initial AD score $ADS \leftarrow 0$
4: **for** $n = 1$ to NUM **do**
5: Sample noise vectors $\varepsilon \sim \mathcal{N}(0, I) \in \mathbb{R}^{(f)}$
6: Get perturbed data $\mathbf{x}_{t_{fix}} = \mathbf{x}_0 + \sigma_{t_{fix}} \varepsilon$
7: Calculate AD Score $ADS+ = \|S_{\theta^*}(\mathbf{x}_{t_{fix}}, t_{fix}) - \varepsilon\|_2^2$
8: **end for**
9: **return** ADS

C LOSS FUNCTION

Following Karras et al. (2022) the analytical solution for $\nabla_{\mathbf{x}} \log p(\mathbf{x}_t | \mathbf{x}_0)$ is:

$$\begin{aligned}
\nabla_{\mathbf{x}} \log p(\mathbf{x}_t | \mathbf{x}_0) &= \frac{1}{p(\mathbf{x}_t | \mathbf{x}_0)} \nabla_{\mathbf{x}} p(\mathbf{x}_t | \mathbf{x}_0) \\
&= \frac{1}{p(\mathbf{x}_t | \mathbf{x}_0)} \cdot \left(-\frac{1}{\sigma_t^2} (\mathbf{x}_t - \mathbf{x}_0) \right) \cdot p(\mathbf{x}_t | \mathbf{x}_0) \\
&= -\frac{1}{\sigma_t^2} (\mathbf{x}_t - \mathbf{x}_0) \\
&= -\frac{1}{\sigma_t^2} (\mathbf{x}_0 + \sigma_t \varepsilon - \mathbf{x}_0) \\
&= -\frac{\varepsilon}{\sigma_t}.
\end{aligned}$$

Final objective of the denoising score matching:

$$\min \mathbb{E}_{x_0 \sim p(x_0)} \mathbb{E}_{x_t \sim p(x_t|x_0)} \left\| S_\theta(x_t, t) + \frac{\varepsilon}{\sigma_t} \right\|_2^2$$

Because $S_\theta(x_t, t)$ learns $-\frac{\varepsilon}{\sigma_t}$, we can also train the neural network to directly predict the noise, this simplifies the optimization to:

$$\min \mathbb{E}_{x_0 \sim p(x_0)} \mathbb{E}_{x_t \sim p(x_t|x_0)} \|S_\theta(x_t, t) - \varepsilon\|_2^2$$

From a mathematical point of view, we then learn $\sigma_t \nabla_x \log p(x_t|x_0)$.

D COMPARISON OF RESULTS WITH TRANSFORMER MODELS

Since NPT-AD (Thimonier et al., 2023) utilizes distinct hyperparameters for training on each dataset and a comprehensive search for these parameters is beyond the scope of this work, we omit NPT in our comprehensive benchmark. Nonetheless, to provide a comparison against Transformer-based models, we compare our results with those reported in their study. Generally, their approach aligns with ours regarding training setup and evaluation protocol, following the methodology outlined in (Shenkar & Wolf, 2022). A key difference in their evaluation lies in their use of multiple 5% T-tests to calculate the mean and standard deviation rather than utilizing the entire test split across multiple random seeds as we do. Despite this variation, we believe the results are sufficiently comparable to be included here.

Method	Transformer	NPT-AD	NCSBAD (Ours)	NCSBADVAL (Ours)
wine	61.4 (6.7)	96.6 (0.5)	99.97 (0.07)	99.98 (0.02)
Lymphography	99.5 (0.4)	99.0 (1.1)	99.97 (0.06)	99.90 (0.13)
glass	61.2 (7.0)	82.8 (2.4)	98.16 (0.62)	97.48 (2.25)
vertebral	44.8 (5.2)	54.6 (3.9)	74.54 (2.28)	79.98 (3.97)
wbc	95.0 (1.1)	96.3 (3.3)	99.24 (1.04)	99.40 (1.03)
ecoli	84.8 (1.6)	88.7 (1.6)	93.95 (4.31)	94.10 (3.63)
Ionosphere	95.4 (1.9)	95.9 (0.8)	99.13 (0.09)	99.10 (0.12)
arrhythmia	81.7 (1.1)	91.5 (1.4)	93.58 (1.82)	93.41 (1.80)
breastw	99.6 (0.1)	98.6 (1.7)	98.72 (0.26)	98.60 (0.34)
Pima	67.2 (2.4)	73.4 (0.4)	78.42 (2.20)	75.85 (2.53)
vowels	78.4 (9.2)	99.3 (0.1)	88.20 (2.71)	89.98 (2.39)
letter	80.5 (4.8)	96.1 (0.2)	43.03 (1.52)	48.77 (2.88)
cardio	93.5 (1.3)	94.7 (0.4)	89.69 (1.07)	91.09 (1.54)
seismic-bumps	58.2 (7.9)	69.8 (3.0)	96.10 (0.86)	96.93 (0.52)
musk	100.0 (0.0)	100.0 (0.0)	100.00 (0.00)	100.00 (0.00)
speech	47.2 (0.7)	54.3 (0.3)	45.76 (3.42)	43.32 (5.89)
thyroid	93.8 (2.0)	95.7 (0.7)	93.63 (1.28)	95.59 (4.09)
abalone	88.3 (2.0)	91.6 (1.2)	74.46 (11.42)	90.03 (5.21)
optdigits	96.4 (4.7)	97.5 (0.3)	97.21 (0.35)	97.85 (0.72)
satimage-2	99.7 (0.1)	99.9 (0.1)	99.22 (0.38)	99.17 (0.37)
satellite	73.8 (2.5)	80.3 (9.0)	80.46 (0.66)	80.07 (0.89)
pendigits	93.8 (2.6)	99.0 (0.2)	99.82 (0.05)	99.79 (0.12)
annthyroid	65.4 (1.4)	86.7 (0.4)	87.03 (0.27)	86.11 (10.92)
mnist	93.2 (2.1)	94.8 (0.4)	92.60 (0.47)	92.37 (1.87)
mammography	77.6 (1.0)	88.0 (3.2)	81.48 (0.75)	84.98 (3.10)

Continued on next page

Method	Transformer	NPT-AD	NCSBAD (Ours)	NCSBADVAL (Ours)
mullcross	100.0 (0.0)	100.0 (0.0)	100.00 (0.00)	100.00 (0.00)
shuttle	97.2 (2.2)	99.9 (0.0)	99.99 (0.00)	99.98 (0.02)
cover	95.1 (0.8)	95.8 (4.7)	95.49 (1.19)	99.42 (0.26)
campaign	75.3 (2.1)	79.1 (0.3)	70.46 (0.52)	75.29 (7.18)
fraud	94.7 (0.4)	95.7 (0.4)	95.03 (1.49)	95.18 (1.48)
backdoor	95.1 (0.2)	95.2 (0.1)	96.26 (0.35)	96.62 (0.78)
mean	83.4 (2.4)	<u>89.8 (0.8)</u>	89,08 (1,33)	90.33 (2,13)

Table 1: Mean and standard deviation AUC-ROC performance comparison of Transformer and NPT-AD with our method across various datasets. The best performance is highlighted in **bold** and the second best with underline.

Method	Transformer	NPT-AD	NCSBAD (Ours)	NCSBADVAL (Ours)
wine	23.5 (7.9)	72.5 (7.7)	25.71 (2.80)	46.62 (3.61)
Lymphography	88.3 (7.6)	94.2 (7.9)	98.40 (3.20)	<u>95.79 (5.40)</u>
glass	14.4 (6.1)	26.2 (10.9)	80.79 (4.02)	<u>78.28 (10.61)</u>
vertebral	12.3 (5.2)	15.1 (6.9)	47.50 (4.97)	53.70 (6.86)
wbc	66.4 (3.2)	67.3 (1.7)	<u>88.27 (13.67)</u>	91.65 (8.10)
ecoli	75.0 (9.9)	77.7 (10.1)	86.12 (4.37)	85.05 (7.92)
Ionosphere	88.1 (2.8)	92.7 (7.0)	93.94 (0.72)	94.13 (0.58)
arrhythmia	59.8 (8.2)	72.7 (10.6)	76.35 (5.86)	75.24 (5.91)
breastw	96.7 (0.3)	95.7 (0.3)	95.85 (0.68)	<u>95.75 (0.61)</u>
Pima	65.6 (2.0)	68.8 (0.6)	73.52 (1.05)	<u>71.06 (3.01)</u>
vowels	28.7 (8.8)	59.7 (7.0)	44.00 (2.49)	<u>52.00 (3.40)</u>
letter	41.5 (6.2)	71.4 (1.1)	4.67 (2.45)	10.00 (2.98)
cardio	<u>68.8 (2.2)</u>	78.1 (1.0)	66.04 (1.98)	64.53 (4.49)
seismic-bumps	19.1 (5.7)	26.2 (7.0)	71.37 (5.86)	77.45 (4.16)
musk	100.0 (0.0)	100.0 (0.0)	100.00 (0.00)	100.00 (0.00)
speech	6.8 (1.9)	9.3 (3.8)	4.86 (3.15)	1.62 (2.16)
thyroid	<u>55.5 (4.8)</u>	77.0 (0.6)	60.00 (4.60)	67.50 (13.57)
abalone	42.5 (7.8)	59.7 (7.0)	27.78 (7.03)	<u>37.78 (12.86)</u>
optdigits	61.1 (4.7)	73.2 (8.4)	57.11 (2.69)	66.22 (5.78)
satimage-2	89.0 (4.1)	94.8 (5.0)	90.23 (1.74)	85.58 (4.00)
satellite	65.1 (3.3)	74.6 (7.0)	<u>72.18 (0.83)</u>	72.55 (0.95)
pendigits	43.4 (10.9)	92.5 (1.7)	91.28 (1.24)	90.00 (4.59)
annthyroid	29.9 (1.4)	77.0 (6.1)	45.50 (1.43)	52.06 (16.99)
mnist	56.7 (5.7)	77.7 (1.6)	70.19 (1.31)	<u>71.71 (1.65)</u>
mammography	17.4 (2.2)	32.6 (1.7)	29.49 (1.62)	35.00 (8.21)
shuttle	85.3 (9.8)	98.2 (0.4)	98.93 (0.08)	98.96 (0.08)
mullcross	100.0 (0.0)	100.0 (0.0)	100.00 (0.00)	99.99 (0.01)
cover	21.3 (3.1)	57.7 (7.8)	<u>78.80 (1.85)</u>	87.13 (6.45)
campaign	47.0 (1.9)	49.8 (8.8)	39.50 (0.75)	45.52 (7.75)
fraud	54.3 (5.2)	58.1 (3.2)	56.69 (7.70)	63.11 (8.12)
backdoor	85.8 (0.6)	84.1 (1.0)	88.32 (0.97)	<u>88.30 (0.94)</u>
mean	56.2 (4.3)	<u>68.8 (2.0)</u>	66,56 (2,93)	69,49 (5,21)

Table 2: Mean and standard deviation F1-Score performance comparison of Transformer and NPT-AD with our method across various datasets. The best performance is highlighted in **bold** and the second best with underline.

Overall, the NPT performance ends up between our proposed method with and without validation data. Notably, the baseline Transformer used in their work as a baseline ranks the lowest among the evaluated methods. The order of datasets presented follows their paper for consistency. We attribute the higher standard deviation observed in our results to a more extensive experimental setup.

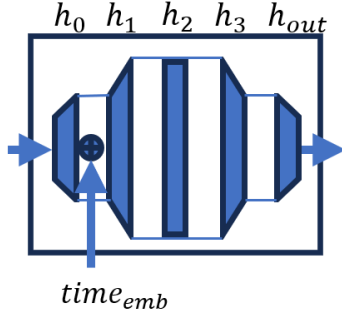
E IMPLEMENTATION DETAILS

E.1 HYPERPARAMETER AND NETWORK ARCHITECTURE

Hyperparameter	Value
Hidden layer size	[2048,4096,2048]
Time embedding dimensions	2048
Activation function	SiLU
Optimizer	AdamW
Learning rate	0.0001
Batch size	16
Number of epochs	200

Table 3: Hyperparameters for MLP2048

Scorenetwork $S_\theta(x_t, t)$



Input: $x_t \in \mathbb{R}^{1 \times d_{in}}$,

$$h_0 = \text{FullyConnected}_{in}(x_t) \in \mathbb{R}^{1 \times 2048}, \quad (6)$$

$$h_{in} = h_0 + \text{time}_{emb}. \quad (7)$$

$$h_1 = \text{SiLU}(\text{FullyConnected}_1(h_0) \in \mathbb{R}^{1 \times 4096}), \quad (8)$$

$$h_2 = \text{SiLU}(\text{FullyConnected}_2(h_1) \in \mathbb{R}^{1 \times 4096}), \quad (9)$$

$$h_3 = \text{SiLU}(\text{FullyConnected}_3(h_2) \in \mathbb{R}^{1 \times 2048}). \quad (10)$$

$$h_{out} = \text{FullyConnected}_{out}(h_3) \in \mathbb{R}^{1 \times d_{in}}. \quad (11)$$

Figure 5: Illustration of the network architecture of the MLP2048

E.2 DATASETS

We use all 57 datasets from the original ADBench benchmark (Han et al., 2022) benchmark as well as 15 additional datasets commonly used in the literature (Ray; Shin & Kim, 2020; Goldstein & Uchida, 2016; Shenkar & Wolf, 2022) for our experiments. Table 4 lists the names of the datasets, the origin, the number of samples, the number of features, the number of anomalies, the anomaly ratio, and the domain of the datasets.

Name	Origin	#Samples	#Features	#Anomaly (%)	Category
ALOI	ADBench	49534	27	1508 (3.04)	Image
Abalone	ICL	4177	9	29 (0.67)	Biology
annthyroid	ADBench	7200	6	534 (7.42)	Healthcare
arrhythmia	ODDS	452	257	66 (14.60)	Healthcare
backdoor	ADBench	95239	196	2362 (2.48)	Network
breastw	ADBench	683	9	239 (34.99)	Healthcare
campaign	ADBench	41188	62	4640 (11.27)	Finance

Continued on next page

Name	Origin	#Samples	#Features	#Anomaly (%)	Category
cardio	ADBBench	1831	21	176 (9.61)	Healthcare
Cardiotocography	ADBBench	2114	21	466 (22.04)	Healthcare
celeba	ADBBench	202599	39	4547 (2.24)	Image
census	ADBBench	299285	500	18568 (6.20)	Sociology
cover	ADBBench	286048	10	2747 (0.96)	Botany
donors	ADBBench	619326	10	36710 (5.93)	Sociology
Ecoli	ICL	336	7	9 (2.67)	Biology
fault	ADBBench	1941	27	673 (34.67)	Physical
fraud	ADBBench	284807	29	492 (0.17)	Finance
glass	ADBBench	214	7	9 (4.21)	Forensic
Hepatitis	ADBBench	80	19	13 (16.25)	Healthcare
hrss anomalous opt	ex-AE	19634	18	4517 (23.01)	Physical
hrss anomalous std	ex-AE	23645	18	5670 (23.98)	Physical
http	ADBBench	567498	3	2211 (0.39)	Web
InternetAds	ADBBench	1966	1555	368 (18.72)	Image
Ionosphere	ADBBench	351	32	126 (35.9)	Oryctognosy
landstat	ADBBench	6435	36	1333 (20.71)	Astronautics
letter	ADBBench	1600	32	100 (6.25)	Image
Lymphography	ADBBench	148	18	6 (4.05)	Healthcare
magic.gamma	ADBBench	19020	10	6688 (35.16)	Physical
mammography	ADBBench	11183	6	260 (2.32)	Healthcare
mi-f	ex-AE	25286	40	2161 (8.55)	Physical
mi-v	ex-AE	25286	40	3942 (15.59)	Physical
mnist	ADBBench	7603	100	700 (9.21)	Image
mulcross	ICL	286048	10	2747 (10.0)	Synthetic
musk	ADBBench	3062	166	97 (3.17)	Chemistry
NASA	ex-AE	4687	32	755 (16.11)	Astronautics
optdigits	ADBBench	5216	64	150 (2.87)	Image
PageBlocks	ADBBench	5393	10	510 (9.46)	Document
Parkinson	ELKI	195	22	147 (75.38)	Healthcare
pendigits	ADBBench	6870	16	156 (2.27)	Image
pen-global	Goldstein	808	16	90 (11.14)	Image
pen-local	Goldstein	6723	16	10 (0.15)	Image
Pima	ADBBench	768	8	268 (34.91)	Healthcare
satellite	ADBBench	6435	36	1333 (31.64)	Astronautics
satimage-2	ADBBench	5803	36	71 (1.22)	Astronautics
seismic-bumps	ODDS	2584	21	170 (6.58)	Physical
shuttle	ODDS	49097	9	3511 (7.15)	Astronautics
skin	ADBBench	245057	3	50850 (20.75)	Image
smtp	ADBBench	95156	3	30 (0.03)	Web
SpamBase	ADBBench	4206	57	1678 (39.9)	Document
speech	ADBBench	3686	400	31 (1.65)	Linguistics
Stamps	ADBBench	340	9	31 (9.12)	Document
thyroid	ADBBench	3772	6	93 (2.47)	Healthcare
vertebral	ADBBench	240	6	30 (12.50)	Biology
vowels	ADBBench	1456	12	50 (3.43)	Linguistics
Waveform	ADBBench	3442	21	100 (2.91)	Physics
WBC	ADBBench	223	9	10 (4.48)	Healthcare
WBC2	ODDS	378	30	5 (1.32)	Healthcare
WDBC	ADBBench	367	30	10 (2.72)	Healthcare
Wilt	ADBBench	4819	5	257 (5.33)	Botany
wine	ADBBench	129	13	10 (7.75)	Chemistry
WPBC	ADBBench	198	33	47 (23.74)	Healthcare
yeast	ADBBench	1484	8	507 (34.16)	Biology
yeast6	ODDS	1484	8	35 (2.36)	Biology
CIFAR10	ADBBench	5263	512	263 (5.00)	Image

Continued on next page

Name	Origin	#Samples	#Features	#Anomaly (%)	Category
FashionMNIST	ADBench	6315	512	315 (5.00)	Image
MNIST-C	ADBench	10000	512	500 (5.00)	Image
MVTec-AD	ADBench	5354	512	1258 (23.50)	Image
SVHN	ADBench	5208	512	260 (5.00)	Image
Agnews	ADBench	10000	768	500 (5.00)	NLP
Amazon	ADBench	10000	768	500 (5.00)	NLP
Imdb	ADBench	10000	768	500 (5.00)	NLP
Yelp	ADBench	10000	768	500 (5.00)	NLP
20newsgroups	ADBench	11905	768	591 (4.96)	NLP

Table 4: Summary of all multivariate datasets included in our benchmark: This table presents an overview of each dataset, including its colloquial name, source, number of samples, number of features, number of anomalies, and the corresponding application domain.

As described in Section 4 and following the ADBench Benchmark and previous work (Livernoche et al., 2024) we subsample some datasets to 50,000 data points. For further transparency, we carried out a statistical analysis for the data sets where the limitation to 50,000 samples applies. The study was carried out with the seeds 0-4 used in the benchmark.

Dataset	#Samples	#Anomalies	Anomalies %	Anomalies % full dataset	Abs difference
backdoor	50000.00	1238.40 (24.39)	2.4768	2.48	0.0032
celeba	50000.00	1101.40 (23.16)	2.2028	2.24	0.0372
census	50000.00	3094.80 (55.33)	6.1896	6.20	0.0104
cover	50000.00	491.00 (17.20)	0.9820	0.96	0.0220
donors	50000.00	2965.20 (39.84)	5.9304	5.93	0.0004
fraud	50000.00	84.00 (7.62)	0.1680	0.17	0.0020
http	50000.00	186.40 (10.13)	0.3728	0.39	0.0172
mulcross	50000.00	5067.80 (32.91)	10.1356	10.0	0.1356
skin	50000.00	10393.00 (69.09)	20.786	20.75	0.0360
smtp	50000.00	17.60 (2.80)	0.0352	0.03	0.0052

Table 5: Statistical evaluation of subsampled datasets

The preprocessed dataset (without anomalies) is then used in the training data at 50% as explained in Section 4. The remaining data is enriched with the anomalies and used as validation and test data in a ratio of 40% to 60%. If rounding is necessary, it is rounded in favor of the test data.

E.3 BASELINE METHODS

Clustering Based Local Outlier Factor (CBLOF) (He et al., 2003). CBLOF calculates an outlier score based on cluster size and distance to large clusters. Data points in small clusters are flagged as anomalies if far from large clusters. Weights based on cluster size are optional but disabled by default due to potential misbehavior. By default, K-means is used for clustering instead of the original Squeezer algorithm for efficiency.

Isolation-based Anomaly Detection using Nearest-Neighbor Ensembles (INNE) (Bandaragoda et al., 2018). INNE is a fast anomaly detector based on nearest neighbor ensembles, addressing weaknesses of isolation forests, such as detecting local anomalies and handling high-dimensional data. It achieves linear time complexity, making it significantly faster than traditional nearest-neighbor methods, especially for large datasets.

Kernel Principal Component Analysis (KPCA) (Hoffmann, 2007). KPCA extends PCA to non-linear spaces, using the reconstruction error in feature space as the anomaly score. Data is mapped into an infinite-dimensional space, and anomalies are detected based on their distance from the principal subspace, serving as a novelty detection method.

Kernel Density Estimation (KDE) (Latecki et al., 2007). KDE detects outliers by comparing the local density of a point to its neighbors. A robust local density estimate is calculated using a variable kernel, and the negative log probability density is used as the anomaly score.

Gaussian Mixture Models (GMM) (Agarwal, 2007). GMM detects anomalies by fitting a two-component Gaussian mixture to deviations in data over time. This approach reduces false positives by mitigating the multiple testing problem and is scalable for real-time monitoring of large datasets.

Subspace Outlier Detection (SOD) (Kriegel et al., 2009). SOD aims to identify outliers in varying subspaces of high-dimensional feature spaces. For each data point, SOD examines the axis-parallel subspace defined by the point’s neighbors and measures how much it deviates from them in this subspace.

Adversarially Learned Anomaly Detection (ALAD) (Zenati et al., 2018). ALAD leverages bi-directional GANs to derive adversarially learned features. Anomalies are detected through reconstruction errors of these features. ALAD ensures data-space and latent-space cycle consistencies to stabilize GAN training, significantly improving detection performance.

Copula-Based Outlier Detection (COPOD) (Hoffmann, 2007). COPOD models multivariate data distributions using copulas to estimate tail probabilities for each data point, which indicates its level of extremeness or anomaly. COPOD is parameter-free, computationally efficient, and highly interpretable. It has shown superior performance and offers a fast Python implementation for reproducibility.

Empirical-Cumulative-distribution-based Outlier Detection (ECOD) (Li et al., 2022). ECOD addresses challenges in unsupervised outlier detection, such as high computational cost and limited interpretability. ECOD estimates the empirical cumulative distribution per dimension of the data and computes tail probabilities. Outlier scores are then calculated by aggregating these probabilities across dimensions. ECOD is parameter-free, easy to interpret, scalable, and efficient.

FeatureBagging (Lazarevic & Kumar, 2005). Feature Bagging for outlier detection combines results from multiple outlier detection algorithms, each applied to different randomly selected feature subsets. The outlier scores from these algorithms are aggregated to improve the overall detection quality. This approach has shown non-trivial improvements.

Histogram-based Outlier Detection (HBOS) (Goldstein & Dengel, 2012). HBOS is an efficient algorithm that scores records in linear time. It assumes feature independence, which allows for much faster computations than multivariate methods, albeit at the cost of reduced precision. HBOS reliably detects global outliers, performing comparably to state-of-the-art methods. However, it struggles with local outlier problems. In experiments, HBOS is up to 5 times faster than clustering-based algorithms and 7 times faster than nearest-neighbor-based methods.

Isolation Forest (iForest) (Liu et al., 2008). Isolation Forest introduces a fundamentally different approach by isolating anomalies rather than profiling normal points. Isolation enables the method to leverage sub-sampling extensively, making the algorithm highly scalable with linear time complexity, low memory requirements, and favorable performance on large datasets.

k-th Nearest Neighbor (kNN) (Ramaswamy et al., 2000). This method identifies distance-based outliers by ranking each point based on its distance to its k-th nearest neighbor. The top-n points in this ranking are declared outliers. The algorithm uses classical nested-loop join and index join techniques but also introduces a highly efficient partition-based algorithm that prunes partitions that cannot contain outliers.

Lightweight Online Detector of Anomalies (LODA) (Pevný, 2016). LODA demonstrates that an ensemble of weak detectors can yield a robust anomaly detector, performing as well as or better than state-of-the-art methods. LODA is particularly useful for real-time processing of large datasets or in scenarios with concept drift, where the detector must update online. It operates efficiently even with missing variables and can highlight features responsible for anomalies, making it practical for sensor-outage domains.

Local Outlier Factor (LOF) (Breunig et al., 2000). The LOF algorithm assigns each object a score of being an outlier based on how isolated it is relative to its neighborhood. This local approach detects meaningful outliers that existing binary outlier methods cannot capture. LOF is practical and effective at identifying meaningful outliers that existing approaches would miss.

Minimum Covariance Determinant (MCD) (Fauconnier & Haesbroeck, 2009). The MCD covariance estimator is designed for Gaussian-distributed data but can also be applied to data from an unimodal, symmetric distribution. It is unsuitable for multi-modal data, where the algorithm will likely fail. For multi-modal datasets, projection pursuit methods are recommended. MCD fits a minimum covariance determinant model and then computes the Mahalanobis distance as the outlier score.

One-Class Support Vector Machine (OCSVM) (Schölkopf et al., 1999). The OCSVM estimates a function f positive on a subset S of the data and negative on its complement. The function is based on a kernel expansion from a subset of training data and is regularized by controlling the weight vector in the associated feature space. OCSVM extends support vector algorithms to the case of unlabeled data.

Principal Component Analysis (PCA) (Shyu et al., 2003). This approach utilizes a robust PCA classifier for intrusion detection in unsupervised settings. Anomalies are treated as outliers, and the intrusion predictive model is built using the major and minor principal components of normal data instances. The distance in principal component space between the anomalous and normal data determines the anomaly score.

Extended Isolation Forest (EIF) (Hariri et al., 2019). EIF addresses issues with anomaly score assignment in the original Isolation Forest. The problem is demonstrated using heat maps, where artifacts in anomaly scores result from binary tree branching operations. EIF resolves this by introducing two methods: (1) random data transformation before tree creation, which averages out bias, and (2) slicing the data using hyperplanes with random slopes, mitigating the artifacts. This approach improves the algorithm’s robustness, as shown by reduced score variance for data points along constant-level sets.

Ensemble LOF: (Breunig et al., 2000; Bouman et al., 2024). This is an ensemble version of the LOF algorithm.

GEN2OUT (Lee et al., 2021). GEN2OUT handles both point and group anomalies in one framework, ranking anomalies by suspiciousness. GEN2OUT’s main features include a principled anomaly scoring that adheres to detection axioms, a dual capability to detect and rank generalized anomalies, and scalability, as it runs in linear time concerning input size.

DynamicHOBS (Goldstein & Dengel, 2012; Bouman et al., 2024). A newer implementation of the HBOS algorithm.

Connectivity-based Outlier Factor (COF) (Hoffmann, 2007). COF improves the effectiveness of LOF when a pattern has a neighborhood density similar to that of an outlier. It is theoretical and empirical, providing more effective outlier detection.

Angle-Based Outlier Detection (ABOD) (Tang et al., 2002). ABOD and its variants assess the angle variance between the difference vectors of a point and the other points. A significant advantage of ABOD is that it does not rely on any parameter selection that could influence the ranking quality. ABOD performs exceptionally well on high-dimensional data.

Linear Method for Deviation Detection (LMDD) (Kriegel et al., 2008). LMDD approaches the problem from within the data, using implicit redundancy. It formalizes the problem and proposes a linear algorithm to detect deviations. The solution mimics human behavior. After observing a series of similar data, a deviating element is recognized as an exception.

Outlier Detection using Indegree Number (ODIN) (Hautamaki et al., 2004). The ODIN algorithm utilizes a k-nearest neighbor graph to detect outliers. It improves on existing kNN distance-based methods. ODIN shows competitive results on synthetic data and outperforms other methods on real datasets with smaller observation counts.

Cook’s Distance (CD) (Cook, 1977). CD identifies points negatively affecting a regression model. It combines each observation’s leverage and residual values. Higher leverage and residual values correspond to higher Cook’s Distance. This unsupervised method requires at least two features (for X) to calculate each data point’s mean Cook’s Distance.

Quasi-Monte Carlo Discrepancy (QMCD) (Fang & Ma, 2001). The Wrap-around QMCD is a uniformity criterion used to evaluate the space-filling properties of samples within a hypercube. It

measures the difference between the continuous uniform distribution on a hypercube and the discrete uniform distribution of sample points. Lower discrepancy values indicate better parameter space coverage. This kernel-based method assigns higher discrepancy scores to outlier candidates than the other samples.

Sampling (Sugiyama & Borgwardt, 2013). A simple sampling-based scheme is an alternative to distance-based approaches like k-nearest neighbor methods that are widely used in outlier detection as they avoid the need to model underlying probability distributions, which is particularly challenging in high-dimensional data and outperforms many techniques in both efficiency and effectiveness.

Learnable Unified Neighbourhood-based Anomaly Ranking (LUNAR) (Goodge et al., 2022). LUNAR unifies local outlier methods by demonstrating that they are special cases of the more general message-passing framework used in graph neural networks. This enables the introduction of learnability into local outlier methods, allowing for greater flexibility and expressivity. LUNAR uses a graph neural network-based anomaly detection technique that learns to leverage information from each node’s nearest neighbors in a trainable manner.

Single-Objective Generative Adversarial Active Learning (SOGAAL) / Multiple Generators with different Objectives (MO-GAAL) (Liu et al., 2019). The SOGAAL method for outlier detection directly generates informative potential outliers based on the mini-max game between a generator and a discriminator. To mitigate the mode-collapsing problem, SOGAAL must stop training at the correct point. MOGAAL is an extension to provide a reasonable reference distribution across the entire dataset.

Autoencoder (AE) (Aggarwal & Aggarwal, 2017; Ramaswamy et al., 2000). The AE method is based on reconstruction. In this context, an AE is trained to minimize reconstruction errors, which are used to measure anomaly detection.

Deep Support Vector Data Description (DeepSVDD) (Ruff et al., 2018). DeepSVDD is built on kernel-based SVDD and minimum volume estimation by finding the smallest data-enclosing hypersphere. In Deep SVDD, we learn helpful feature representations of the data and the one-class classification objective. A neural network is trained jointly to map the data into a hypersphere of minimum volume, capturing useful patterns for outlier detection.

Deep Autoencoding Gaussian Mixture Model (DAGMM) (Zong et al., 2018). DAGMM is a deep autoencoder that produces a low-dimensional representation and reconstruction error for each input. This output is further fed into a Gaussian Mixture Model (GMM). Instead of using a two-stage training process and the standard Expectation-Maximization (EM) algorithm, DAGMM jointly optimizes the deep autoencoder and the mixture model parameters in an end-to-end fashion, leveraging a separate estimation network to aid in parameter learning.

Deep Robust One Class Classification (DROCC) (Goyal et al., 2020). DROCC is a method that applies to standard domains without requiring side information and remains robust to representation collapse. The method assumes that points from the class of interest lie on a well-sampled, locally linear, low-dimensional manifold. DROCC builds on this assumption to better capture class structures.

GOAD (Bergman & Hoshen, 2020). GOAD is a method designed for generalization assumptions. GOAD extends the applicability of transformation-based anomaly detection methods to non-image data through random affine transformations.

Internal Contrastive Learning (ICL) (Shenkar & Wolf, 2022). ICL captures the internal structure of the single training class by learning mappings that maximize the mutual information between each sample and its masked-out portions. The mappings are optimized using contrastive loss, computed one sample at a time. During inference, ICL scores a test sample by determining whether the mappings result in small contrastive loss using the masked parts of the sample.

PlanarFlow (Rezende & Mohamed, 2015). Normalizing flows transform a simple initial density into a more complex one by applying a sequence of invertible transformations. This method unifies the finite and infinitesimal flow approaches, allowing for richer posterior approximations. PlanarFlow combines theoretically sound posterior matching with scalable variational inference.

Variational Autoencoder (VAE) (Kingma, 2013; Zhou et al., 2020). VAE trained on normal data is expected to reconstruct normal inputs accurately, while anomalies are detected through deviations.

GANomaly (Akçay et al., 2019). GANomaly is a Generative Adversarial Network (GAN)-based method for anomaly detection, using the reconstruction error of input instances as the anomaly score. Tabular data is modified with dense layers using tanh activation functions. The encoder-decoder-encoder structure of GANomaly is set to have a hidden size equal to half the input dimension, which allows for more suitable evaluation on tabular datasets.

Scale Learning-based Anomaly Detection (SLAD) (Xu et al., 2023b). The SLAD considers the relationship between the dimensionality of the original sub-vectors and their transformed representations. These scales serve as labels for converted representations, providing abundant labeled data for neural network training. SLAD learns to align the scale distribution, enabling it to model inherent regularities in the data.

Deep Isolation Forest (DIF) (Xu et al., 2023a). DIF is a representation scheme leveraging casually initialized neural networks to map raw data into random ensemble representations. Subsequently, random axis-parallel cuts are applied within these representations to partition the data. The synergy between random representations and partition-based isolation gives a more efficient separation of normal instances from anomalous ones.

Denosing Diffusion Probabilistic Models (DDPMs) (Livernoche et al., 2024). DDPMs utilize the diffusion process to implicitly learn the score function of the underlying data distribution. By simulating the reverse diffusion process, DDPMs reconstruct input samples and use the reconstruction distance as a metric to identify anomalies. It provides a mechanism for uncovering abnormal patterns in the data, leveraging the probabilistic framework to model intricate data distributions.

Diffusion Time Estimation (DTE) (Livernoche et al., 2024). DTE addresses anomaly detection by estimating the distribution of diffusion times for a given input, utilizing either the mode or mean of this distribution as the anomaly score. The analytical form for this density enhances inference efficiency through a deep neural network. The DDPM-based anomaly detection can be viewed as a distance estimation between an input and the denoised reconstruction. Given noisy inputs, the distribution of diffusion times follows an inverse Gamma (DTE-IG) distribution. This insight forms the foundation of the non-parametric (DTE-NP) method, which accurately predicts diffusion time and produces anomaly rankings comparable to kNN. Furthermore, a categorical (DTE-C) approach leverages a deep neural network for improved generalization and fast inference.

Three-Way Neighborhood Characteristic Regions Outlier Detection (3WNCROD) (Zhang et al., 2023b). 3WNCROD is an outlier detection approach that advances three-way neighborhood characteristic regions and corresponding fusion measurements. Building upon neighborhood rough sets, the method leverages three-way decisions to define neighborhood structures across model boundaries, inner regions, and characteristic regions. These structures are then used to drive information fusion and weight measurement across features and the development of a multiple neighborhood outlier factor. The method integrates various sources of neighborhood information to enhance the robustness and accuracy of outlier detection.

Masked Correlation Modeling (MCM) (Yin et al., 2024). MCM captures intrinsic correlations between features in the training set, with deviations from these correlations indicating potential anomalies. To generate multiple, diverse correlations, a masking strategy that learns to produce several masks is guided by a diversity loss that minimizes similarity between the masks. The model captures various feature correlations, increasing its robustness in detecting anomalous data points. Individual features and the relationships between them provide interpretability.

Transformer / Non-Parametric Transformers (NPT) (Thimonier et al., 2023). NPT is a model initially designed for supervised tasks to capture dependencies between features and samples. In a reconstruction-based framework, the NPT reconstructs masked features of normal samples, leveraging the entire training dataset during inference in a non-parametric manner. The model’s ability to accurately reconstruct masked features is then used to generate an anomaly score. For comparison, a baseline Transformer under similar conditions is stated.

E.4 DISCUSSION OF THE BASELINE METHODS

The baseline methods, as outlined in Chapter X, including their hyperparameters, were adopted exactly as implemented in the original code of their respective publications, as well as in the PyOD and ADBench libraries. This approach may introduce potential biases in the overall results. For

instance, in the case of the VAE model from the ADBench library, a sigmoid function is used as the output activation function. We attribute this choice to the similarity between anomaly detection and binary classification, which scales the output to a probability. However, to avoid restricting the model’s learned distribution, other activation functions, such as a linear activation function, could also be considered. This serves as an example of potential optimizations that could be applied to the baseline methods and is representative of other similar opportunities. Consequently, it cannot be ruled out that other models may also possess untapped optimization potential.

We strongly recommend optimizing baseline methods for the specific task at hand when applying them in practical scenarios. This recommendation applies to all baseline methods and encompasses all possible hyperparameters, including model architectures.

Furthermore, it should be noted that while the models from the ADBench library, as well as the deep learning baseline models, are suitable for an inductive setting in line with the LUPE or one-class classification framework described in this work, some models from PyOD or Bouman et al. (2024) operate exclusively in a transductive manner. This means that these models do not have access to the training data and make predictions solely based on the test data, which is not strictly in line with the one-class classification paradigm. This is particularly true for some purely mathematical models that do not involve training in the conventional sense. To avoid limiting the benchmark and to maintain its generalizability, these models were nevertheless included.

To assist in selecting appropriate models, Table 6 provides an overview distinguishing the inductive and transductive models and how they are included in the benchmark.

Model	Inductive	Transductive
IForest	X	
OCSVM	X	
COPOD	X	
ECOD	X	
FeatureBagging	X	
HBOS	X	
KNN	X	
LODA	X	
LOF	X	
MCD	X	
PCA	X	
DeepSVDD	X	
INNE	X	
KPCA	X	
KDE	X	
GMM	X	
CBLOF	X	
SOD		X
LUNAR	X	
SOGAAL	X	
ALAD	X	
AE	X	
CD	X	
MOGAAL	X	
QMCD	X	
Sampling	X	
EIF		X
Ensemble	X	
GEN2OUT	X	
DynamicHBOS		X
COF	X	
ABOD	X	
LMDD		X
DAGMM	X	

Continued on next page

Model	Inductive	Transductive
DROCC	X	
GOAD	X	
ICL	X	
PlanarFlow	X	
VAE	X	
GANomaly	X	
SLAD	X	
DIF	X	
DDPM	X	
DTE-IG	X	
DTE-C	X	
DTENonParametric	X	
MCM	X	
3WNCROD		X
ODIN		X
NCSBAD (Ours)	X	
NCSBADVAL (Ours)	X	

Table 6: Inductive and transductive methods

E.5 RUNTIME

The experiments on the first five seeds (0-4) of all 136 sub-datasets and 49 baseline methods, as well as one run each with score model with and without validation data, were performed on a server with 2x AMD EPYC™ GENOA 9654 processors, 2.40-3.70 GHz with 1.5TB RAM and 4x NVIDIA L40 GPUs with 48 GB GDDR6 VRAM on one GPU each. All benchmark results lasted a total of 702 GPU hours (stated over all methods. Note not all methods run on GPU).

F ADDITIONAL RESULTS

We present the complete results corresponding to the AUC-ROC and area under the precision-recall curve (AUC-PR) box plots in Section 4, detailed in Tables 9-16 and Tabela 23-32. We report all results from the 121 sub-datasets of the ADBench benchmark and the 15 additional datasets. Moreover, performance metrics, including the F1-Score, are provided in Tables 17-24, with the corresponding box plots shown in Figure 13. Furthermore, Figure 14 displays plots of the mean training and inference times. A particular emphasis is placed on improving inference performance compared to DDPM. Note that the y-axis is plotted on a logarithmic scale. Exact numerical values for the box plots can be found in Table 8. All results are averaged over five random seeds, and standard deviations are reported in parentheses for each dataset in our benchmark, ensuring a comprehensive and reliable performance comparison.

F.1 F1-SCORE, ADJUSTED F1-SCORE AND ADJUSTED AUC-PR

Campos et al. (2016) proposed adjusted metrics for AUC-PR and precision at n to account for biases in the different anomaly proportions of the test data. They defined: For a dataset DB of size N , consisting of outliers $O \subset DB$ and inliers $I \subset DB$ ($DB = O \cup I$), $P@n$ is formalized as:

$$P@n = \frac{|\{o \in O \mid \text{rank}(o) \leq n\}|}{n} \quad (6)$$

With the number of outliers n and $n = |O|$. Since in this work, following Bergman & Hoshen (2020), the decision threshold is chosen according to the number of actually existing anomalies, in this case the $P@n$ corresponds to the F1-score.

$$P@n = F1 - \text{Score} \quad (7)$$

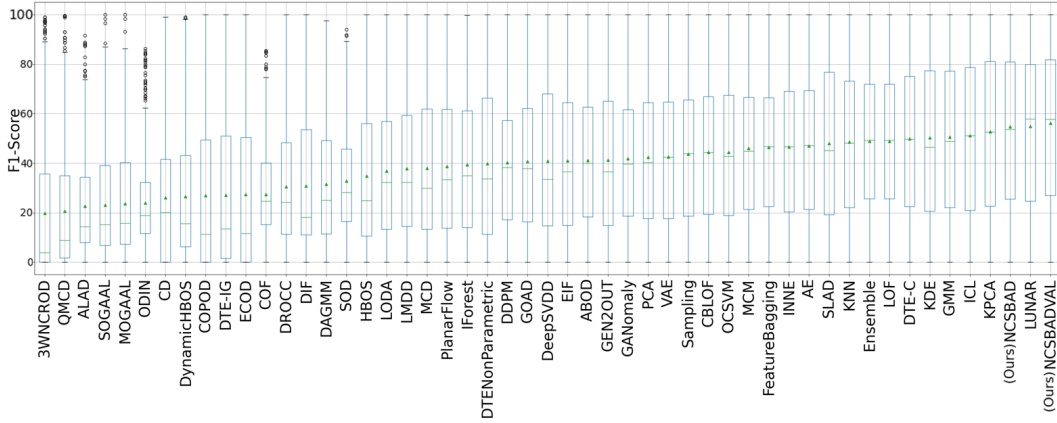


Figure 6: Box plots of F1-Score across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

They also use the average precision (AP):

$$AP = \frac{1}{|O|} \sum_{o \in O} P@rank(o). \quad (8)$$

This is called AUC-PR in our work.

Following Hubert & Arabie (1985), it is suggested to use the Adjusted Index:

$$\text{Adjusted Index} = \frac{\text{Index} - \text{Expected Index}}{\text{Maximum Index} - \text{Expected Index}} \quad (9)$$

From this, they derive the following equations for Adjusted $P@n$:

$$\text{Adjusted } P@n = \frac{P@n - |O|/N}{1 - |O|/N} \quad (10)$$

for consistency in the following denoted as ADJ F1-Score and Adjusted AP:

$$\text{Adjusted } AP = \frac{AP - |O|/N}{1 - |O|/N}. \quad (11)$$

for consistency in the following denoted as ADJ AUC-PR. We also report utilization of these metrics both in the form of the following boxplots for the overall performance and in the detailed results in this Appendix, Table 33-40 for the adjusted F1-Score and Table 41-48 for the adjusted AUC-PR.

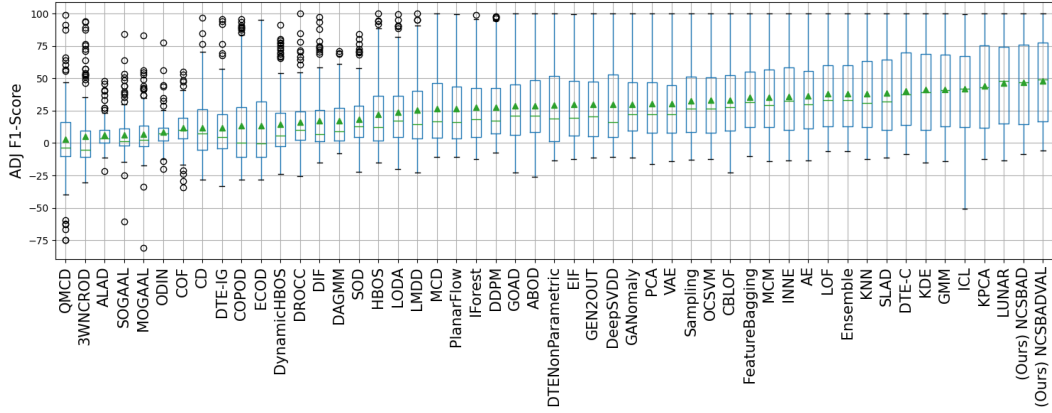


Figure 7: Box plots of ADJ F1-Score across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

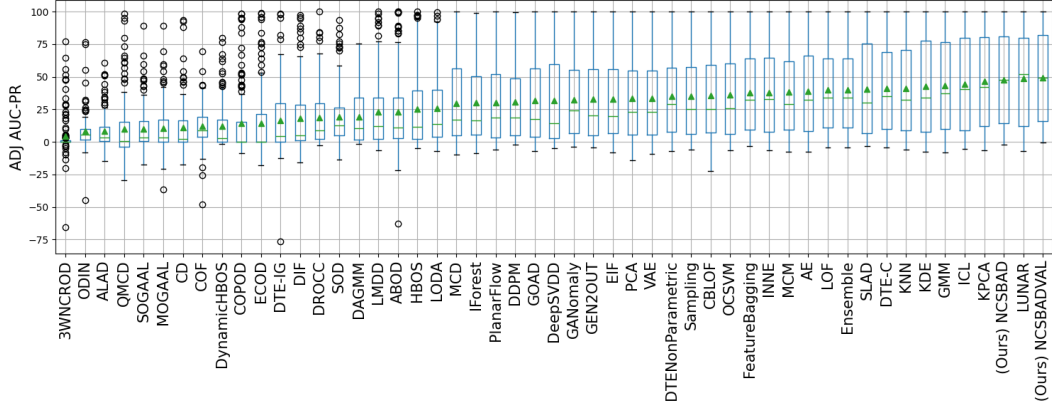


Figure 8: Box plots of ADJ AUC-PR across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

These adjusted metrics again confirm the superior overall performance of our method. While NCSBADVAL maintains its top positions in both metrics, NCSBAD overtakes LUNAR in the ADJ F1-Score. Regarding the ADJ AUC-PR, the result reported in the Main Results in Section 4 remains mainly unchanged for the best models.

F.2 RANKING OF THE ANOMALY DETECTORS

In order to take into account distortions of large outliers upwards and downwards, a ranking of the anomaly detectors is also created for the individual data sets. The following boxplots show the distribution of these rankings. The position is also listed in [...] in the tables 8-48.

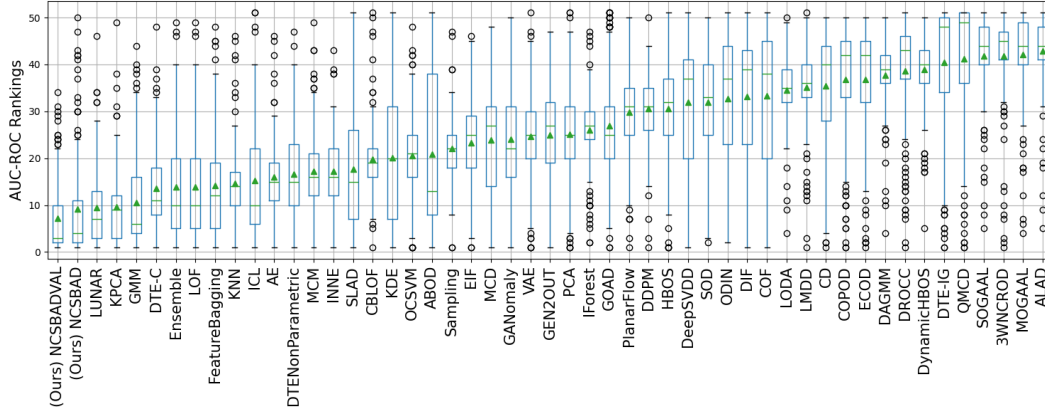


Figure 9: Box plots of rankings with AUC-ROC positions across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

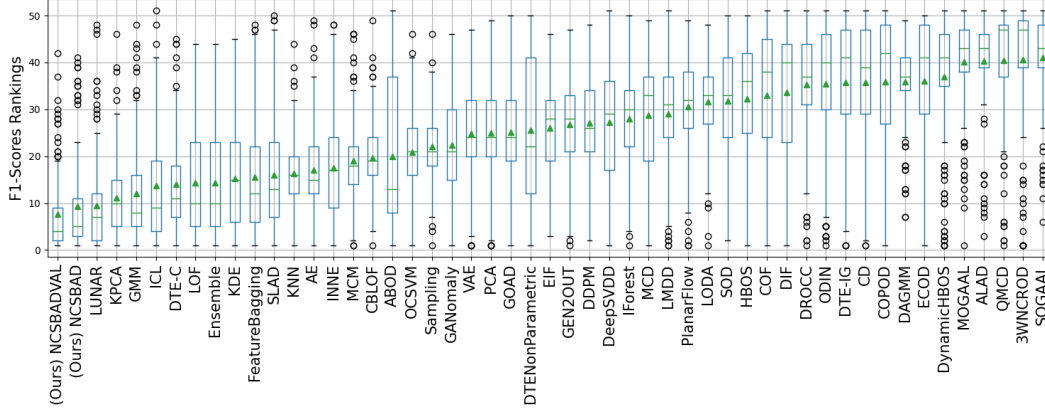


Figure 10: Box plots of rankings with F1-Score positions across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

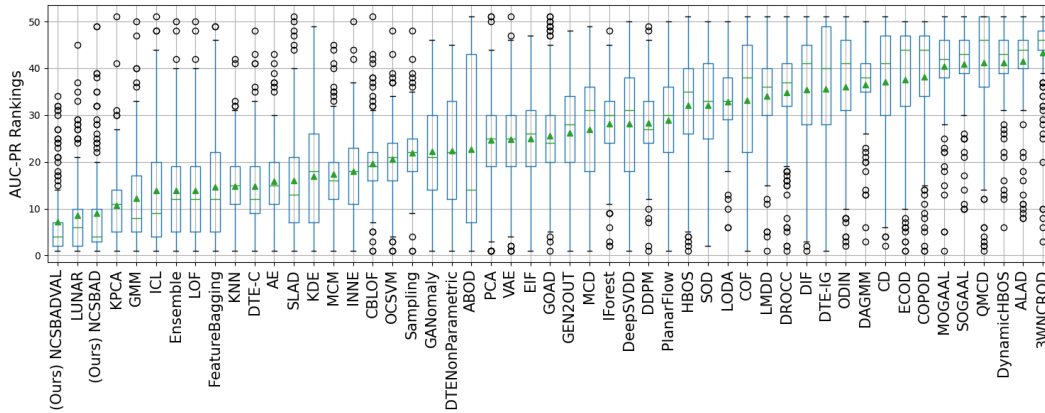


Figure 11: Box plots of rankings with AUC-PR positions across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

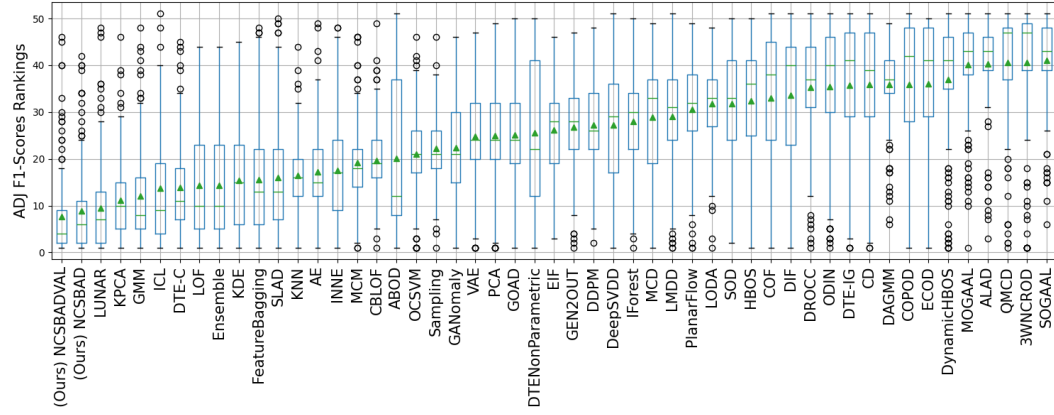


Figure 12: Box plots of rankings with ADJ F1-Score positions across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

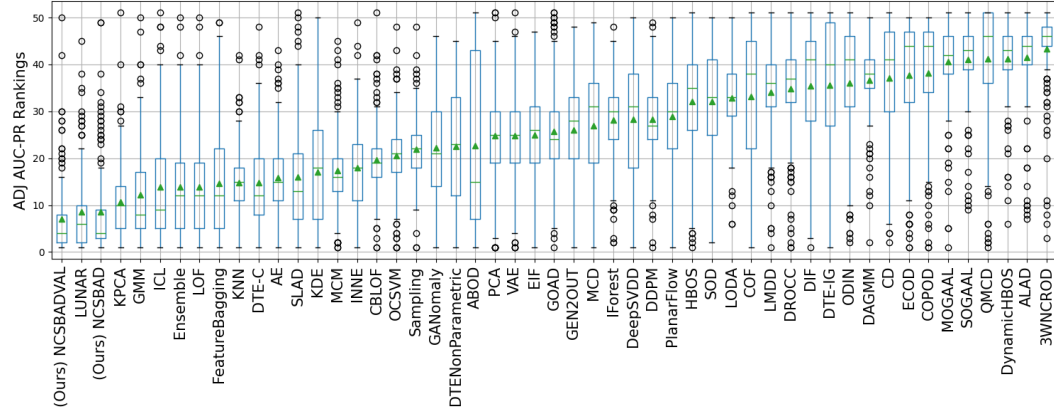


Figure 13: Box plots of rankings with ADJ AUC-PR positions across all datasets evaluated over five different seeds, utilizing only normal samples for training. The methods are ordered according to their mean performance, with the mean value highlighted in green.

This confirms the strong performance, with NCSBADVAL and NCSBAD at the top of the rankings for AUC-ROC, ADJ F1-Score, while NCSBAD has to admit defeat to LUNAR in F1-Score, AUC-ROC and ADJ AUC-ROC.

F.3 TRAINING AND INFERENCE TIME

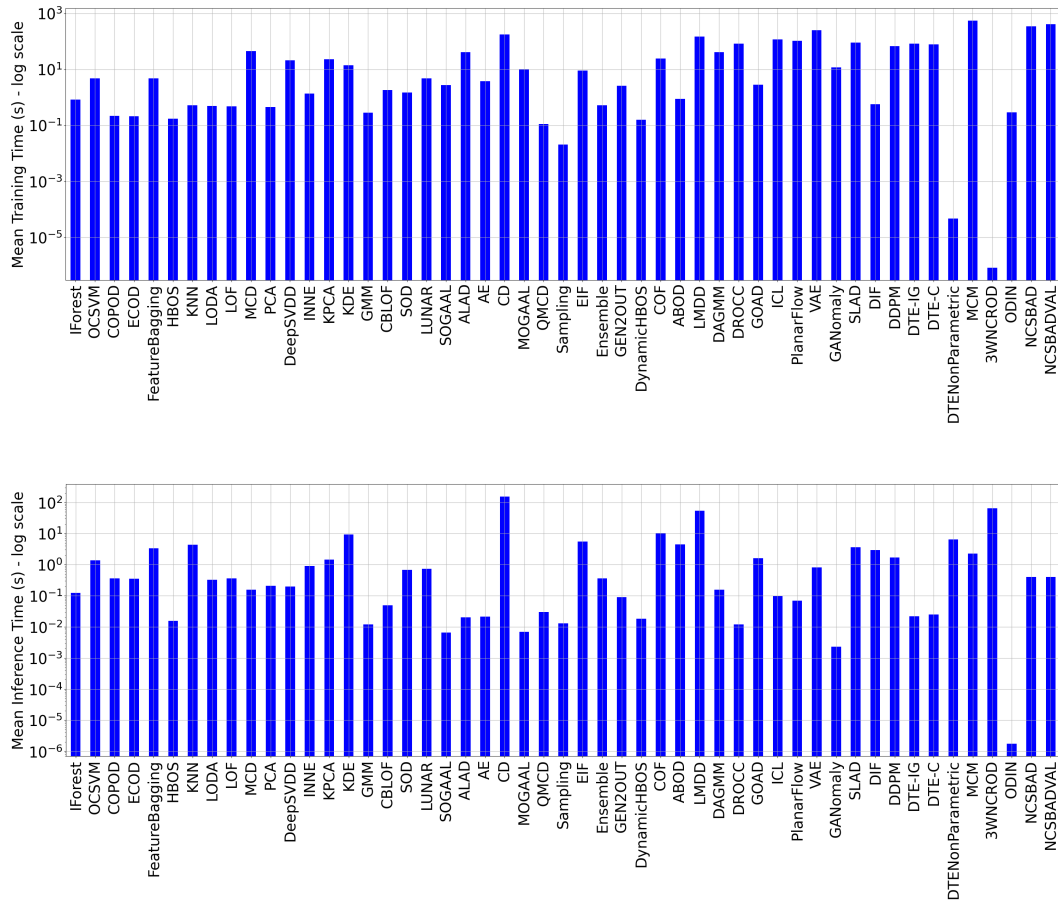


Figure 14: Mean training time (top) and mean inference (bottom) across all datasets and methods

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F.4 COUNTS BEST PERFORMANCE PER DATASET

Model	AUC-ROC	F1-Score	AUC-PR	ADJ F1-Score	ADJ AUC-PR
IForest	0	1	0	1	0
OCSVM	4	5	3	5	3
COPOD	2	6	2	6	2
ECOD	1	7	2	7	2
FeatureBagging	6	8	6	8	7
HBOS	3	1	1	1	1
KNN	3	4	3	4	3
LODA	0	1	0	1	0
LOF	7	7	6	9	7
MCD	4	3	3	3	3
PCA	3	4	5	4	5
DeepSVDD	2	2	2	2	2
INNE	3	3	3	3	3
KPCA	13	15	13	13	12
KDE	7	7	4	6	4
GMM	11	5	6	4	6
CBLOF	1	1	2	1	2
SOD	0	0	0	0	0
LUNAR	23	27	33	30	34
SOGAAL	0	0	0	0	0
ALAD	0	0	0	0	0
AE	3	4	2	4	2
CD	1	2	0	1	0
MOGAAL	0	1	1	1	1
QMCD	2	1	1	1	1
Sampling	0	1	2	1	2
EIF	0	0	1	0	1
Ensemble	7	7	6	9	7
GEN2OUT	4	1	3	1	3
DynamicHBOS	0	4	0	4	0
COF	3	2	2	2	2

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	1923	1924	1925	1926	1927	1928	1929	1930	1931	1932	1933	1934	1935	1936	1937	1938	1939	1940	1941	1942	1943	1944	1945	1946	1947	1948	1949	1950	1951	1952	1953	1954	1955
Model	AUC-ROC	F1-Score	AUC-PR	ADJ F1-Score	ADJ AUC-PR																												
ABOD	3	7	5	7	6																												
LMDD	1	2	1	2	1																												
DAGMM	0	0	0	0	0																												
DROCC	1	1	1	1	2																												
GOAD	2	1	1	1	1																												
ICL	7	10	11	10	11																												
PlanarFlow	1	2	1	2	1																												
VAE	3	4	3	4	3																												
GANomaly	1	2	2	2	2																												
SLAD	7	6	7	6	6																												
DIF	1	1	1	1	1																												
DDPM	1	0	1	0	1																												
DTE-IG	2	3	3	3	3																												
DTE-C	3	4	4	5	5																												
DTENonParametric	3	2	2	2	2																												
MCM	5	2	2	2	2																												
3WNCROD	1	6	0	6	0																												
ODIN	0	1	0	1	0																												
NCSBAD (Ours)	<u>29 (11)</u>	<u>26 (13)</u>	<u>23 (10)</u>	<u>24 (15)</u>	<u>19 (12)</u>																												
NCSBADVAL (Ours)	<u>36 (32)</u>	<u>27 (22)</u>	<u>26 (24)</u>	<u>22 (16)</u>	<u>23 (16)</u>																												

Table 7: Count of best performances in terms of AUC-ROC, F1-Score, AUC-PR, ADJ F1-Score and ADJ AUCPR of all methods in the benchmark. The best performance is highlighted in **bold** and the second best with underline. (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually, results if both are included in the same count are reported in parentheses)

F.5 METRICS PER METHOD

Model	Mean AUC-ROC	Mean F1-Score	Mean AUC-PR	Mean ADJ F1-Score	Mean ADJ AUC-PR
IForest	74.00 (16.62) [23]	39.41 (27.63) [30]	40.71 (29.50) [30]	27.62 (28.30) [30]	30.05 (30.55) [30]
OCSVM	75.31 (16.70) [20]	44.49 (28.64) [17]	46.27 (31.03) [17]	33.20 (30.47) [18]	36.38 (33.07) [17]
COPOD	60.55 (17.52) [43]	27.02 (31.26) [43]	28.72 (25.88) [42]	13.55 (31.65) [42]	14.04 (25.95) [42]

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	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Model	Mean AUC-ROC	Mean F1-Score	Mean AUC-PR	Mean ADJ F1-Score	Mean ADJ AUC-PR																												
ICL	79.30 (17.98) [7]	51.16 (30.03) [5]	52.20 (32.63) [5]	42.29 (33.04) [5]	44.35 (35.53) [5]																												
PlanarFlow	71.19 (17.32) [28]	38.73 (27.68) [31]	40.92 (29.78) [29]	26.91 (28.49) [31]	30.34 (31.07) [29]																												
VAE	73.73 (16.84) [25]	42.52 (27.97) [20]	44.03 (30.21) [21]	30.53 (29.69) [20]	33.56 (31.93) [21]																												
GANomaly	72.97 (15.68) [27]	41.83 (25.76) [22]	43.00 (28.49) [24]	30.03 (26.75) [22]	32.50 (29.84) [25]																												
SLAD	77.57 (18.40) [14]	48.04 (30.97) [12]	48.94 (33.21) [12]	38.92 (33.30) [9]	40.72 (35.79) [10]																												
DIF	65.72 (16.79) [36]	30.89 (25.85) [38]	31.31 (26.83) [39]	17.31 (24.46) [38]	18.06 (26.01) [39]																												
DDPM	70.86 (15.20) [29]	40.22 (26.34) [28]	41.43 (29.24) [28]	27.79 (27.40) [29]	30.40 (30.36) [28]																												
DTE-IG	47.95 (22.06) [50]	27.04 (24.74) [42]	30.21 (26.01) [40]	11.98 (23.77) [43]	16.21 (25.96) [40]																												
DTE-C	80.03 (15.76) [6]	49.91 (28.04) [8]	49.74 (29.74) [9]	40.45 (29.96) [8]	41.14 (31.77) [9]																												
DTENonParametric	79.18 (15.69) [8]	39.85 (30.84) [29]	44.49 (28.91) [20]	29.28 (31.90) [26]	35.06 (30.41) [20]																												
MCM	77.87 (15.92) [13]	45.99 (26.99) [16]	47.75 (30.02) [14]	35.40 (28.62) [15]	38.38 (32.08) [14]																												
3WNCROD	51.99 (13.37) [48]	19.79 (27.97) [51]	21.38 (18.51) [51]	5.01 (27.35) [50]	4.30 (15.56) [51]																												
ODIN	61.12 (11.34) [41]	24.02 (18.27) [46]	23.79 (18.31) [50]	8.31 (12.42) [46]	8.02 (13.22) [50]																												
NCSBAD (Ours)	82.19 (16.43) [2]	54.77 (29.54) [3]	54.99 (31.98) [3]	46.85 (32.02) [2]	47.83 (34.76) [3]																												
NCSBADVAL (Ours)	83.26 (15.25) [1]	56.17 (28.95) [1]	56.48 (31.33) [1]	48.29 (31.92) [1]	49.46 (34.45) [1]																												

Table 8: Mean, standard deviation and rank of AUC-ROC, F1-Score, AUC-PR, ADJ F1-Score and ADJ AUCPR performance comparison of all methods in the benchmark. The best performance is highlighted in **bold** and the second best with underline.

F.6 FULL RESULTS

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Table 9: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 1

Table 10: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 2

Table 10: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 2

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Table 11: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 3

[illegible]

Table 12: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 4

Model	FashionMNIST 0	FashionMNIST 1	FashionMNIST 2	FashionMNIST 3	FashionMNIST 4	FashionMNIST 5	FashionMNIST 6	FashionMNIST 7	FashionMNIST 8	FashionMNIST 9	MNIST-C brightness	MNIST-C camp edges	MNIST-C dotted line	MNIST-C fog	MNIST-C glass blur
IFnet	84.14 (0.66) [27]	95.47 (0.76) [27]	76.67 (1.89) [29]	86.75 (0.83) [27]	77.49 (1.53) [30]	93.54 (1.10) [28]	66.35 (1.25) [32]	95.94 (0.51) [21]	72.64 (1.17) [28]	95.05 (0.50) [26]	70.18 (2.10) [28]	74.65 (1.36) [23]	86.43 (2.34) [26]	94.73 (0.40) [27]	94.39 (0.40) [27]
OCSVM	88.19 (0.98) [21]	97.48 (0.23) [19]	84.06 (0.55) [21]	89.65 (0.56) [20]	83.81 (0.54) [19]	94.75 (0.64) [15]	73.95 (0.84) [21]	96.36 (0.46) [17]	77.80 (0.77) [20]	96.24 (0.49) [10]	74.07 (0.59) [22]	77.23 (0.77) [20]	81.33 (0.69) [23]	91.23 (0.46) [21]	96.74 (0.10) [20]
COPOD	50.00 (0.00) [46]	50.00 (0.00) [47]	50.00 (0.00) [44]	50.00 (0.00) [46]	50.00 (0.00) [46]	50.00 (0.00) [44]	50.00 (0.00) [42]	50.00 (0.00) [47]	50.00 (0.00) [44]	50.00 (0.00) [45]	50.00 (0.00) [44]	50.00 (0.00) [44]	50.00 (0.00) [44]	50.00 (0.00) [45]	50.00 (0.00) [45]
ECOD	50.00 (0.00) [46]	50.00 (0.00) [47]	50.00 (0.00) [44]	50.00 (0.00) [46]	50.00 (0.00) [46]	50.00 (0.00) [44]	50.00 (0.00) [42]	50.00 (0.00) [47]	50.00 (0.00) [44]	50.00 (0.00) [45]	50.00 (0.00) [44]	50.00 (0.00) [44]	50.00 (0.00) [44]	50.00 (0.00) [45]	50.00 (0.00) [45]
FeatureBagging	91.61 (0.90) [3]	98.51 (0.23) [4]	88.59 (0.49) [6]	92.85 (0.19) [5]	87.26 (0.75) [7]	95.29 (0.66) [6]	80.36 (1.20) [6]	96.92 (0.33) [6]	88.00 (0.73) [4]	96.79 (0.30) [1]	88.06 (0.45) [6]	92.54 (0.42) [4]	91.40 (0.24) [4]	97.92 (0.08) [5]	98.26 (0.10) [6]
HBOS	75.50 (1.23) [35]	87.83 (0.45) [36]	58.70 (1.01) [42]	79.19 (0.71) [33]	62.40 (0.62) [41]	90.51 (0.78) [33]	50.24 (0.84) [44]	94.45 (0.66) [31]	62.97 (1.56) [37]	92.68 (0.73) [31]	62.10 (0.51) [34]	69.86 (1.16) [32]	68.70 (1.09) [35]	71.39 (0.76) [35]	87.57 (0.23) [34]
KNN	90.16 (0.74) [14]	98.04 (0.23) [13]	86.77 (0.51) [11]	91.22 (0.43) [12]	85.78 (0.62) [12]	95.03 (0.65) [9]	77.61 (0.73) [13]	96.66 (0.40) [10]	81.82 (0.69) [16]	96.11 (0.51) [15]	82.59 (0.42) [14]	84.33 (0.53) [14]	87.66 (0.39) [13]	95.24 (0.20) [14]	97.85 (0.08) [10]
LODA	73.48 (5.31) [36]	92.51 (4.65) [32]	70.79 (5.42) [34]	77.49 (6.93) [35]	74.90 (4.06) [33]	90.33 (3.61) [34]	66.89 (1.74) [31]	92.25 (1.20) [33]	64.96 (8.78) [36]	88.98 (3.42) [36]	68.18 (8.74) [32]	57.31 (5.08) [40]	64.64 (6.65) [37]	83.25 (8.18) [31]	88.57 (5.97) [33]
LOF	91.47 (0.87) [6]	98.44 (0.22) [6]	88.61 (0.49) [4]	92.81 (0.21) [6]	87.30 (0.70) [5]	95.21 (0.67) [7]	80.32 (1.21) [7]	96.88 (0.30) [7]	87.83 (0.56) [6]	96.73 (0.37) [5]	87.74 (0.35) [9]	92.45 (0.23) [5]	91.19 (0.27) [5]	97.78 (0.15) [6]	98.18 (0.09) [7]
MCD	83.25 (1.14) [29]	91.11 (1.37) [34]	78.90 (2.12) [26]	85.14 (1.43) [29]	81.05 (1.48) [27]	93.00 (0.81) [31]	72.05 (0.55) [26]	93.07 (1.56) [32]	75.96 (0.28) [25]	92.52 (1.51) [32]	71.57 (0.63) [26]	71.54 (1.84) [29]	75.44 (2.20) [30]	83.87 (1.15) [29]	83.33 (1.97) [35]
PCA	87.77 (1.00) [22]	97.19 (0.24) [21]	83.21 (0.58) [23]	89.15 (0.57) [22]	83.23 (0.53) [23]	94.69 (0.66) [18]	72.87 (0.75) [23]	93.31 (0.49) [18]	76.16 (0.83) [23]	96.15 (0.50) [13]	72.37 (0.58) [23]	74.10 (0.88) [24]	79.64 (0.77) [25]	89.74 (0.52) [23]	96.37 (0.10) [22]
DeepSVDD	69.63 (4.42) [38]	90.13 (1.57) [35]	67.38 (1.70) [37]	73.26 (3.10) [37]	69.52 (2.86) [36]	90.79 (0.88) [32]	60.33 (1.51) [36]	91.84 (1.48) [34]	58.27 (5.15) [41]	90.12 (2.40) [34]	51.63 (0.47) [41]	58.44 (1.60) [37]	57.37 (4.63) [41]	66.17 (2.91) [37]	77.68 (0.41) [37]
INNE	90.32 (0.83) [12]	97.87 (0.31) [16]	86.55 (0.61) [12]	91.19 (0.49) [13]	84.69 (0.50) [17]	94.40 (0.63) [23]	77.38 (0.88) [15]	95.86 (0.40) [23]	82.65 (0.78) [13]	96.07 (0.35) [16]	78.99 (0.33) [17]	83.54 (0.53) [16]	85.67 (0.31) [16]	95.63 (0.43) [12]	97.83 (0.22) [11]
KPCA	90.43 (0.74) [10]	98.12 (0.21) [11]	87.09 (0.56) [9]	91.77 (0.41) [9]	86.36 (0.57) [10]	94.99 (0.61) [10]	78.34 (0.74) [11]	96.50 (0.41) [14]	83.22 (0.65) [12]	96.28 (0.49) [8]	83.93 (0.39) [11]	85.68 (0.49) [12]	88.26 (0.40) [10]	95.57 (0.27) [13]	98.09 (0.08) [9]
KDE	75.18 (1.59) [34]	92.63 (0.73) [31]	76.48 (0.47) [30]	82.57 (0.93) [32]	78.51 (0.68) [29]	93.76 (0.62) [27]	72.28 (1.42) [25]	95.42 (0.54) [29]	69.68 (0.90) [31]	93.19 (0.95) [30]	70.13 (1.37) [29]	70.13 (1.40) [31]	74.09 (0.60) [32]	83.44 (0.56) [30]	88.83 (0.78) [31]
GMM	91.53 (0.72) [5]	98.50 (0.22) [5]	98.15 (0.42) [1]	93.17 (0.30) [3]	98.70 (0.41) [1]	95.58 (0.55) [4]	80.50 (1.51) [5]	97.41 (0.37) [3]	87.92 (0.44) [5]	96.78 (0.42) [2]	89.11 (0.29) [4]	90.19 (0.30) [7]	90.92 (0.30) [7]	97.99 (0.16) [4]	98.73 (0.10) [4]
CBLOF	88.82 (0.93) [18]	97.90 (0.19) [14]	86.07 (0.51) [15]	90.37 (0.50) [17]	84.87 (0.55) [15]	94.78 (0.60) [14]	75.79 (0.97) [19]	96.57 (0.43) [12]	80.49 (0.54) [18]	96.03 (0.47) [17]	76.83 (0.47) [18]	79.82 (0.75) [19]	82.61 (0.49) [20]	93.02 (0.39) [19]	96.97 (0.08) [18]
SOD	83.45 (1.25) [28]	95.62 (0.27) [26]	78.82 (0.72) [27]	85.92 (0.49) [28]	81.40 (0.71) [25]	93.39 (0.47) [29]	69.67 (0.66) [28]	95.62 (0.48) [28]	73.77 (1.00) [26]	94.83 (0.47) [28]	71.63 (1.09) [25]	72.37 (0.56) [27]	83.39 (0.35) [19]	81.85 (1.23) [32]	92.90 (0.13) [30]
LUNAR	92.30 (0.43) [1]	98.84 (0.14) [1]	87.68 (0.85) [8]	93.11 (0.38) [4]	87.61 (0.64) [4]	95.44 (0.67) [5]	81.35 (0.72) [2]	97.31 (0.43) [4]	88.25 (0.67) [2]	96.60 (0.59) [7]	91.59 (0.37) [3]	94.03 (0.18) [2]	95.19 (0.19) [1]	99.26 (0.06) [1]	99.26 (0.06) [1]
SOGAAL	50.18 (3.51) [45]	61.41 (3.35) [45]	62.69 (2.29) [40]	55.22 (3.86) [44]	62.50 (5.24) [40]	41.93 (13.94) [50]	47.12 (6.24) [47]	56.27 (12.89) [46]	43.71 (5.70) [48]	59.57 (7.40) [43]	44.81 (7.34) [48]	28.74 (4.34) [49]	40.47 (3.32) [48]	58.90 (13.27) [38]	53.78 (4.52) [44]
ALAD	51.39 (3.65) [43]	53.46 (7.97) [46]	43.20 (5.73) [49]	47.33 (3.67) [49]	49.42 (8.85) [49]	57.53 (7.70) [42]	43.30 (3.94) [49]	58.24 (10.24) [44]	49.27 (8.92) [47]	61.29 (7.66) [42]	49.27 (8.92) [47]	46.64 (4.36) [47]	51.54 (6.93) [43]	53.08 (12.08) [43]	61.65 (7.74) [44]
AE	90.24 (0.82) [13]	97.88 (0.23) [15]	86.05 (0.57) [16]	91.07 (0.53) [14]	83.39 (0.66) [13]	94.69 (0.65) [18]	77.44 (0.81) [14]	96.81 (0.39) [9]	82.12 (0.65) [15]	98.28 (0.40) [8]	80.95 (0.36) [15]	84.27 (0.52) [15]	86.07 (0.49) [14]	95.05 (0.26) [15]	97.56 (0.08) [14]
CD	56.93 (13.85) [42]	63.51 (16.62) [42]	50.00 (0.00) [44]	65.15 (12.81) [41]	63.51 (11.38) [39]	50.00 (0.00) [44]	67.29 (3.58) [30]	50.00 (0.00) [47]	67.80 (4.57) [34]	50.00 (0.00) [45]	53.09 (3.87) [40]	58.04 (7.05) [38]	50.00 (0.00) [44]	52.54 (5.00) [44]	50.00 (0.00) [45]
MOGAC	50.00 (0.45) [44]	52.30 (3.57) [44]	60.89 (2.65) [41]	54.69 (5.10) [45]	61.69 (4.40) [42]	42.84 (13.93) [49]	46.98 (8.84) [48]	59.46 (12.75) [43]	41.50 (4.61) [49]	59.34 (6.75) [44]	41.94 (7.29) [49]	28.71 (3.16) [50]	38.71 (4.17) [50]	55.25 (10.88) [41]	47.39 (12.11) [49]
QAMC	11.45 (0.62) [51]	6.98 (0.26) [51]	18.62 (0.93) [51]	10.54 (0.37) [51]	21.25 (0.38) [50]	44.55 (1.09) [48]	25.49 (0.25) [51]	70.11 (1.97) [40]	20.92 (0.15) [51]	24.64 (1.34) [50]	14.60 (0.42) [51]	9.81 (0.39) [51]	7.21 (0.27) [50]	4.04 (0.15) [51]	
Sampling	88.56 (1.05) [19]	97.56 (0.44) [18]	83.80 (1.22) [22]	89.91 (0.73) [19]	83.59 (0.98) [20]	94.69 (0.88) [18]	74.90 (0.92) [20]	96.57 (0.55) [12]	77.46 (2.05) [22]	95.71 (0.60) [20]	75.73 (0.97) [19]	76.40 (1.66) [22]	81.96 (1.65) [21]	91.57 (0.62) [20]	97.00 (0.26) [17]
EIF	84.77 (1.10) [26]	96.16 (0.24) [25]	78.63 (0.75) [28]	87.57 (1.19) [25]	79.00 (2.04) [28]	93.96 (0.67) [26]	68.05 (1.39) [29]	96.02 (0.79) [20]	73.60 (0.59) [27]	94.76 (0.76) [29]	69.86 (1.88) [30]	72.62 (4.59) [26]	78.43 (1.75) [27]	86.11 (0.42) [27]	94.96 (0.95) [25]
Ensemble	91.47 (0.87) [6]	98.44 (0.22) [6]	88.61 (0.49) [4]	92.81 (0.21) [6]	87.30 (0.70) [5]	95.21 (0.67) [7]	80.32 (1.21) [7]	96.88 (0.30) [7]	87.83 (0.56) [6]	96.73 (0.37) [5]	87.74 (0.35) [9]	92.45 (0.23) [5]	91.19 (0.27) [5]	97.78 (0.15) [6]	98.18 (0.09) [7]
GENOUT	82.28 (0.41) [30]	94.80 (0.46) [29]	75.23 (1.33) [32]	84.32 (1.99) [30]	76.81 (2.20) [31]	93.27 (0.83) [30]	63.05 (2.19) [34]	95.76 (0.39) [24]	69.08 (2.32) [32]	94.88 (0.94) [27]	66.93 (4.68) [33]	72.23 (6.24) [28]	75.34 (2.19) [31]	83.92 (3.98) [28]	94.18 (2.31) [28]
DynamicHBOS	61.75 (0.11) [41]	71.11 (1.16) [40]	47.44 (0.20) [48]	60.88 (0.70) [42]	51.93 (0.68) [45]	82.63 (0.95) [37]	47.91 (0.50) [46]	88.26 (0.54) [36]	54.08 (1.65) [42]	86.67 (0.77) [37]	50.72 (0.73) [42]	54.98 (0.85) [43]	54.86 (0.75) [42]	53.74 (0.41) [42]	70.65 (0.76) [39]
COF	76.90 (2.04) [32]	77.30 (1.61) [38]	69.80 (2.40) [35]	77.93 (1.81) [34]	73.36 (1.12) [35]	79.81 (1.34) [38]	62.90 (1.77) [35]	76.56 (1.76) [38]	71.65 (1.31) [30]	89.11 (0.75) [35]	70.46 (1.07) [27]	69.75 (1.23) [33]	84.12 (0.27) [18]	55.65 (1.15) [40]	73.05 (1.13) [38]
ABOD	90.42 (0.73) [11]	98.27 (0.24) [9]	86.94 (0.52) [10]	92.47 (0.45) [8]	86.74 (0.77) [10]	94.94 (0.72) [11]	78.44 (0.77) [10]	97.05 (0.42) [5]	84.65 (0.71) [9]	95.87 (0.58) [18]	87.78 (0.33) [8]	89.44 (0.37) [8]	90.86 (0.27) [8]	97.47 (0.15) [8]	98.55 (0.09) [8]
LMMD	76.65 (3.05) [33]	91.88 (3.02) [33]	71.26 (2.52) [33]	77.40 (3.61) [36]	73.97 (2.58) [34]	86.67 (3.33) [36]	58.11 (3.96) [38]	72.69 (4.15) [38]	62.94 (5.34) [38]	75.03 (6.32) [39]	64.62 (5.29) [36]	70.67 (4.12) [34]	68.83 (2.56) [34]	74.82 (2.17) [34]	88.72 (2.99) [32]
DGMGM	69.23 (4.16) [29]	81.82 (2.24) [31]	69.03 (3.12) [36]	68.21 (3.12) [36]	68.21 (3.12) [37]	78.37 (3.64) [39]	57.00 (4.91) [40]	85.34 (2.37) [37]	71.34 (3.07) [39]	80.28 (3.26) [38]	58.62 (5.99) [36]	57.27 (5.58) [39]	60.46 (3.58) [39]	71.01 (2.96) [36]	73.77 (3.85) [36]
DBOCC	47.35 (8.88) [49]	62.71 (14.23) [43]	56.06 (8.55) [43]	57.01 (7.67) [43]	56.93 (7.85) [44]	55.35 (19.55) [43]	48.57 (8.13) [45]	65.64 (16.38) [41]	50.35 (9.57) [43]	48.77 (12.29) [49]	59.48 (10.42) [38]	59.20 (6.04) [36]	61.87 (10.41) [39]	57.15 (15.88) [39]	60.03 (17.90) [42]
GOAD	88.39 (0.81) [20]	97.40 (0.21) [20]	84.29 (0.66) [20]	89.63 (0.73) [21]	83.85 (0.64) [18]	94.75 (0.64) [15]	73.57 (0.66) [22]	96.38 (0.50) [16]	77.78 (0.54) [21]	97.17 (0.54) [12]	74.16 (1.09) [21]	78.16 (1.52) [21]	81.36 (0.83) [22]	91.14 (0.68) [22]	96.73 (0.27) [21]
ICL	91.01 (0.89) [8]	98.32 (0.27) [8]	88.17 (0.67) [7]	90.45 (0.97) [9]	84.57 (0.97) [9]	94.57 (0.73) [22]	80.66 (1.22) [41]	96.41 (0.46) [15]	84.03 (0.47) [16]	95.48 (0.41) [12]	88.30 (1.21) [5]	88.49 (0.20) [16]	90.85 (0.25) [11]	97.02 (0.10) [16]	97.73 (0.28) [12]
PlanerFlow	80.47 (1.03) [31]	94.88 (1.06) [28]	75.37 (1.83) [31]	84.31 (1.48) [31]	75.16 (1.18) [32]	94.16 (0.48) [25]	59.84 (1.57) [37]	95.76 (0.68) [24]	68.61 (1.20) [33]	95.45 (0.70) [24]	67.11 (1.80) [35]	57.99 (6.92) [39]	65.77 (9.17) [36]	77.98 (2.28) [33]	93.51 (1.27) [29]
VAE	87.77 (1.00) [22]	97.19 (0.24) [21]	83.21 (0.58) [23]	89.15 (0.57) [22]	83.23 (0.53) [23]	94.69 (0.66) [18]	72.87 (0.75) [23]	93.31 (0.49) [18]	76.16 (0.83) [23]	96.15 (0.50) [13]	72.37 (0.58) [23]	74.10 (0.88) [24]	79.64 (0.77) [25]	89.74 (0.52) [23]	96.37 (0.10) [22]
GANomaly	89.60 (0.66) [16]	98.09 (0.31) [12]	86.23 (1.03) [14]	90.19 (0.63) [18]	83.46 (0.75) [21]	95.68 (0.52) [3]	78.24 (0.51) [12]	95.74 (0.71) [26]	82.54 (1.21) [14]	95.05 (0.54) [21]	75.61 (1.00) [20]	81.02 (2.55) [18]	79.70 (1.82) [24]	93.73 (0.94) [17]	96.76 (0.48) [16]
SLAD	90.47 (0.62) [9]	98.21 (0.20) [10]	85.98 (0.68) [17]	90.86 (0.50) [15]	84.79 (0.89) [16]	94.90 (0.60) [12]	77.36 (0.90) [16]	94.69 (0.52) [17]	69.08 (0.48) [8]	95.26 (0.68) [25]	82.83 (0.52) [13]	86.78 (0.31) [15]	85.93 (0.13) [15]	96.78 (0.22) [11]	97.48 (0.10) [15]
DFP	68.67 (0.93) [40]	73.34 (0.87) [39]	66.26 (2.13) [38]	67.01 (1.25) [40]	60.12 (1.61) [43]	68.93 (1.10) [40]	57.79 (1.25) [39]	64.82 (0.64) [							

		MVTe-AD grad	MVTe-AD hazelnut	MVTe-AD leather	MVTe-AD metal nut	MVTe-AD pill	MVTe-AD screw	MVTe-AD tile	MVTe-AD toothbrush	MVTe-AD transistor	MVTe-AD wood	MVTe-AD zipper	SVHN 0	SVHN 1	SVHN 2	SVHN 3	SVHN 4
iforest	66.29 (1.82) [32]	75.36 (2.52) [22]	98.97 (0.05) [24]	69.12 (7.72) [31]	67.38 (2.02) [37]	59.84 (3.21) [27]	84.94 (0.71) [22]	90.14 (2.87) [24]	76.33 (3.12) [28]	77.70 (1.19) [30]	82.51 (2.96) [27]	60.70 (1.64) [29]	65.37 (0.78) [24]	61.16 (1.39) [30]	58.84 (0.77) [32]	61.37 (1.23) [17]	61.37 (1.23) [17]
OCVM	67.27 (0.46) [26]	72.82 (2.70) [29]	99.05 (0.34) [26]	70.05 (8.08) [34]	66.57 (2.33) [30]	61.35 (1.68) [25]	83.65 (2.57) [26]	86.60 (2.85) [29]	76.35 (3.12) [26]	78.73 (1.32) [26]	80.56 (2.56) [24]	64.24 (1.70) [24]	63.87 (0.93) [12]	63.40 (0.94) [21]	61.22 (0.40) [19]	60.62 (1.90) [29]	60.62 (1.90) [29]
COPOD	50.00 (0.00) [46]	50.00 (0.00) [44]	50.00 (0.00) [44]	50.00 (0.00) [46]	50.00 (0.00) [46]	50.00 (0.00) [44]	50.00 (0.00) [47]	50.00 (0.00) [42]	50.00 (0.00) [42]	50.00 (0.00) [47]	50.00 (0.00) [47]	50.00 (0.00) [47]	50.00 (0.00) [45]	50.00 (0.00) [46]	50.00 (0.00) [46]	50.00 (0.00) [45]	50.00 (0.00) [45]
ECDD	50.00 (0.00) [46]	50.00 (0.00) [44]	50.00 (0.00) [44]	50.00 (0.00) [46]	50.00 (0.00) [46]	50.00 (0.00) [44]	50.00 (0.00) [47]	50.00 (0.00) [42]	50.00 (0.00) [42]	50.00 (0.00) [47]	50.00 (0.00) [47]	50.00 (0.00) [47]	50.00 (0.00) [45]	50.00 (0.00) [46]	50.00 (0.00) [46]	50.00 (0.00) [45]	50.00 (0.00) [45]
FeatureBagging	69.85 (1.31) [20]	75.70 (2.56) [19]	98.85 (0.23) [26]	73.05 (3.44) [19]	71.07 (6.16) [34]	66.97 (1.78) [15]	85.06 (0.68) [21]	92.80 (1.97) [18]	78.72 (3.02) [18]	82.97 (2.53) [16]	88.79 (2.50) [15]	68.59 (1.69) [13]	66.35 (0.70) [19]	66.74 (0.55) [14]	64.47 (0.65) [1]	62.76 (1.11) [8]	62.76 (1.11) [8]
HBO	59.95 (1.22) [37]	76.08 (2.09) [14]	98.42 (0.77) [32]	62.90 (2.04) [15]	67.51 (2.28) [26]	59.03 (2.50) [26]	84.57 (1.10) [26]	89.64 (2.42) [26]	74.61 (3.14) [21]	73.05 (1.89) [15]	80.40 (2.43) [31]	52.14 (1.94) [10]	63.81 (0.86) [27]	56.98 (1.12) [36]	54.81 (0.64) [29]	60.63 (1.13) [22]	60.63 (1.13) [22]
KHNS	74.90 (1.10) [14]	76.36 (2.24) [13]	99.32 (0.20) [15]	79.47 (1.94) [16]	73.12 (2.45) [17]	63.73 (2.67) [14]	85.78 (0.56) [17]	96.42 (1.62) [13]	74.67 (4.21) [15]	82.95 (1.93) [17]	87.79 (2.50) [18]	64.71 (1.91) [17]	66.97 (0.92) [11]	64.19 (0.70) [15]	61.78 (0.52) [14]	61.94 (1.00) [14]	61.94 (1.00) [14]
LODA	64.22 (3.32) [33]	69.46 (4.33) [35]	97.84 (0.67) [33]	64.78 (5.38) [34]	66.88 (0.90) [24]	57.14 (3.05) [36]	81.12 (2.29) [33]	71.72 (4.69) [36]	69.50 (4.05) [36]	73.94 (1.41) [34]	78.91 (4.41) [32]	54.00 (5.94) [32]	57.01 (3.82) [38]	53.52 (5.52) [39]	52.09 (2.93) [44]	55.96 (3.75) [39]	55.96 (3.75) [39]
LOF	69.55 (1.33) [21]	75.67 (2.46) [20]	98.69 (0.17) [20]	73.09 (2.04) [17]	70.91 (2.21) [17]	66.13 (1.62) [17]	84.88 (0.90) [23]	91.75 (1.90) [16]	78.81 (2.90) [16]	83.15 (2.26) [14]	88.25 (2.31) [16]	68.45 (1.76) [14]	65.94 (0.70) [20]	66.28 (0.52) [19]	64.28 (0.25) [21]	62.67 (1.41) [9]	62.67 (1.41) [9]
MCD	84.01 (0.46) [10]	81.53 (1.97) [11]	98.86 (0.61) [25]	82.56 (2.93) [12]	80.07 (2.97) [9]	73.84 (2.87) [12]	89.86 (1.24) [12]	94.37 (2.79) [15]	86.61 (3.20) [11]	90.12 (1.87) [11]	93.70 (1.44) [10]	62.59 (2.07) [28]	62.94 (1.29) [28]	61.69 (0.54) [28]	59.92 (1.46) [28]	60.30 (0.85) [29]	60.30 (0.85) [29]
PCA	66.51 (0.45) [30]	74.02 (2.39) [31]	99.15 (0.30) [31]	69.57 (2.69) [29]	66.40 (1.91) [31]	60.81 (1.20) [26]	83.81 (0.76) [29]	80.25 (1.63) [33]	75.66 (3.34) [29]	79.16 (2.12) [27]	82.21 (2.44) [28]	63.19 (1.70) [24]	67.06 (0.91) [18]	62.60 (0.51) [18]	60.92 (0.76) [28]	60.92 (0.76) [28]	60.92 (0.76) [28]
DeepSVDD	87.44 (3.41) [8]	84.94 (2.60) [10]	99.06 (0.37) [11]	86.66 (2.90) [11]	78.17 (3.85) [12]	60.11 (2.82) [8]	94.14 (1.62) [8]	90.76 (2.36) [12]	88.51 (0.94) [18]	93.69 (1.08) [19]	92.66 (1.53) [19]	55.12 (1.74) [23]	56.98 (0.65) [19]</				

Table 15: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 7

Model	SVHN 5	SVHN 6	SVHN 7	SVHN 8	SVHN 9	agnews 0	agnews 1	agnews 2	agnews 3	amazon	imdb	yelp	20news 0	20news 1	20news 2	20news 3	20news 4	20news 5
Ifcvec	60.77 (1.93) [28]	54.12 (1.92) [34]	65.43 (1.06) [24]	53.00 (1.80) [23]	53.00 (1.68) [36]	55.34 (0.70) [28]	58.69 (1.54) [27]	63.93 (0.44) [27]	56.14 (0.55) [30]	56.10 (1.22) [25]	48.60 (1.00) [32]	61.22 (1.51) [26]	67.33 (1.04) [28]	47.06 (1.89) [40]	66.46 (0.59) [26]	69.06 (0.59) [26]	52.01 (1.49) [32]	53.08 (1.78) [29]
OC5VM	63.09 (0.83) [28]	56.05 (1.02) [31]	67.53 (0.36) [33]	57.22 (1.96) [23]	57.17 (1.95) [19]	59.76 (0.65) [26]	59.77 (0.87) [24]	67.16 (0.58) [26]	60.21 (0.68) [32]	60.16 (1.21) [22]	48.29 (0.48) [36]	62.24 (1.33) [26]	66.42 (0.84) [23]	47.82 (0.10) [42]	57.46 (0.67) [40]	77.00 (1.00) [20]	54.04 (1.91) [23]	54.17 (1.43) [20]
COPOD	50.00 (0.00) [46]	50.00 (0.00) [45]	50.00 (0.00) [44]	50.00 (0.00) [43]	50.00 (0.00) [43]	52.68 (0.51) [34]	52.29 (0.64) [40]	61.51 (0.52) [35]	55.99 (0.92) [35]	56.90 (1.21) [19]	50.40 (0.52) [12]	50.79 (1.32) [27]	59.98 (0.65) [33]	46.82 (1.74) [45]	44.42 (2.86) [50]	60.34 (3.59) [31]	50.74 (2.37) [41]	51.79 (1.77) [36]
ECOD	50.00 (0.00) [46]	50.00 (0.00) [45]	50.00 (0.00) [44]	50.00 (0.00) [43]	50.00 (0.00) [43]	50.84 (0.60) [41]	50.47 (0.62) [36]	60.09 (0.51) [38]	55.50 (0.61) [36]	55.50 (1.40) [36]	46.38 (0.53) [50]	56.79 (1.30) [35]	59.25 (1.18) [36]	45.52 (0.84) [47]	48.15 (2.64) [32]	70.87 (4.29) [34]	52.42 (2.37) [28]	53.18 (2.47) [26]
FeatureBagging	65.97 (1.04) [31]	58.85 (0.72) [31]	67.66 (0.74) [41]	62.48 (1.60) [31]	60.22 (1.92) [31]	60.47 (0.47) [36]	80.41 (0.81) [31]	78.35 (1.08) [31]	72.98 (0.87) [41]	57.35 (1.03) [41]	49.19 (0.74) [26]	66.32 (1.14) [33]	79.62 (1.55) [35]	52.93 (3.24) [22]	72.99 (2.91) [19]	71.24 (7.11) [19]	54.78 (2.79) [16]	55.43 (1.69) [11]
HBO5	54.88 (2.13) [241]	49.07 (0.96) [49]	62.53 (0.61) [33]	47.71 (1.97) [50]	47.67 (1.19) [48]	52.03 (0.44) [36]	56.73 (0.63) [32]	60.52 (0.49) [37]	55.32 (0.79) [37]	56.61 (1.30) [29]	49.23 (0.56) [29]	60.36 (1.42) [29]	59.68 (0.70) [34]	46.82 (1.80) [42]	45.04 (2.94) [49]	67.71 (5.58) [32]	59.26 (2.27) [29]	54.17 (2.26) [20]
KNN	63.54 (0.99) [16]	57.02 (0.72) [18]	66.41 (0.40) [19]	58.39 (1.57) [19]	58.39 (1.57) [19]	62.84 (0.48) [12]	62.12 (0.87) [18]	65.84 (1.36) [16]	69.02 (1.09) [17]	67.95 (1.47) [16]	67.95 (1.68) [16]	73.10 (8.22) [14]	69.25 (8.22) [14]	52.20 (2.53) [34]	53.20 (2.53) [34]	52.20 (2.53) [34]	53.20 (2.53) [34]	52.20 (2.53) [34]
LODA	55.19 (2.06) [37]	52.14 (4.03) [42]	60.97 (3.59) [37]	55.60 (5.38) [31]	53.67 (5.59) [31]	58.85 (2.85) [22]	53.30 (4.72) [37]	62.52 (2.60) [31]	56.02 (2.65) [34]	53.88 (3.44) [35]	64.73 (2.45) [45]	58.37 (5.55) [34]	54.03 (3.00) [40]	47.76 (5.10) [33]	47.90 (2.04) [35]	68.84 (8.12) [27]	55.14 (4.49) [14]	50.87 (6.00) [46]
LOF	66.03 (1.11) [31]	58.85 (0.67) [31]	67.63 (0.76) [35]	62.38 (1.61) [21]	60.16 (1.87) [41]	61.57 (0.69) [41]	80.19 (0.86) [41]	78.28 (1.13) [41]	72.92 (0.95) [35]	57.84 (0.15) [42]	75.45 (0.73) [23]	66.46 (1.02) [11]	80.59 (1.11) [31]	53.51 (3.09) [13]	59.81 (0.98) [17]	70.94 (7.14) [21]	54.61 (2.88) [19]	55.01 (1.93) [13]
MCD	59.68 (1.64) [32]	54.93 (0.59) [30]	60.15 (1.09) [36]	56.24 (1.47) [30]	55.74 (2.38) [28]	64.13 (0.27) [10]	68.28 (0.57) [15]	74.96 (0.46) [14]	64.86 (1.08) [18]	60.57 (1.39) [81]	50.79 (0.57) [81]	66.69 (0.90) [10]	71.32 (1.41) [19]	55.96 (2.66) [81]	51.48 (1.95) [10]	73.85 (10.23) [13]	57.97 (2.74) [81]	66.56 (2.51) [31]
PCA	62.65 (0.97) [24]	56.30 (1.05) [23]	67.13 (0.33) [30]	56.25 (1.92) [28]	56.46 (1.94) [25]	52.03 (0.70) [36]	58.55 (0.70) [28]	62.00 (0.48) [32]	57.02 (0.55) [32]	54.91 (1.48) [31]	49.10 (0.39) [42]	59.41 (1.38) [31]	67.33 (1.04) [31]	46.37 (1.01) [43]	57.46 (2.73) [38]	68.49 (5.77) [29]	51.67 (2.14) [30]	53.88 (1.93) [24]
DeepSVD	52.94 (2.54) [40]	53.06 (1.07) [36]	62.52 (0.89) [41]	52.45 (2.08) [36]	53.16 (2.62) [34]	58.03 (0.22) [40]	46.72 (3.04) [50]	52.61 (4.50) [49]	58.71 (5.06) [49]	50.46 (3.36) [48]	46.66 (2.11) [46]	50.39 (3.14) [47]	56.64 (3.77) [48]	48.51 (5.09) [16]	71.46 (10.66) [17]	53.17 (2.46) [25]	54.84 (3.32) [15]	54.84 (3.32) [15]
INNE	64.61 (0.99) [8]	56.70 (0.78) [20]	67.41 (0.47) [9]	58.68 (1.77) [9]	57.56 (0.67) [10]	59.66 (0.70) [28]	65.75 (1.32) [19]	71.52 (0.85) [18]	62.97 (0.55) [19]	57.55 (1.60) [41]	48.74 (0.57) [13]	63.23 (1.17) [18]	71.41 (0.86) [18]	49.06 (1.69) [42]	45.03 (3.06) [43]	80.81 (7.78) [23]	54.75 (2.11) [17]	55.28 (1.69) [12]
KPCA	64.13 (0.94) [11]	57.13 (0.76) [9]	66.94 (0.48) [14]	59.03 (1.55) [15]	58.17 (1.98) [14]	63.35 (0.26) [17]	72.28 (0.72) [17]	81.17 (0.96) [14]	71.35 (1.25) [15]	50.20 (0.42) [14]	68.47 (1.58) [12]	55.57 (3.12) [10]	76.12 (1.58) [12]	55.57 (3.12) [10]	76.12 (1.58) [12]	78.82 (3.73) [10]	54.72 (2.43) [10]	58.16 (2.31) [8]
KDE	56.14 (0.58) [35]	55.59 (0.86) [28]	64.51 (0.78) [27]	57.80 (0.76) [22]	55.57 (2.02) [29]	52.88 (1.58) [33]	58.87 (0.94) [26]	60.94 (0.60) [36]	54.94 (0.99) [38]	52.37 (0.89) [40]	46.60 (0.62) [47]	56.27 (0.86) [37]	56.23 (0.94) [39]	53.37 (2.24) [20]	53.24 (2.03) [5]	83.72 (3.80) [5]	48.77 (0.95) [49]	51.47 (2.65) [30]
GMM	65.33 (1.00) [6]	59.30 (0.87) [4]	67.45 (0.59) [8]	60.95 (1.76) [8]	60.30 (2.03) [2]	67.48 (0.51) [3]	79.15 (0.28) [6]	81.96 (0.65) [3]	74.43 (0.94) [3]	61.37 (1.16) [14]	68.67 (1.09) [3]	72.84 (1.57) [6]	58.73 (2.45) [6]	54.58 (1.30) [5]	69.30 (3.95) [3]	62.28 (2.04) [5]	63.48 (2.83) [6]	63.48 (2.83) [6]
CBL0F	62.77 (0.84) [282]	55.72 (0.88) [287]	66.58 (0.45) [27]	57.15 (1.84) [26]	58.00 (2.22) [26]	60.59 (0.44) [27]	60.75 (0.94) [27]	70.01 (0.41) [24]	68.48 (1.28) [24]	58.36 (1.15) [41]	49.49 (0.67) [26]	67.56 (1.92) [21]	53.42 (2.21) [19]	64.35 (2.29) [47]	74.06 (7.94) [11]	52.83 (2.36) [26]	52.77 (2.06) [26]	52.77 (2.06) [26]
SOD	62.72 (1.28) [29]	55.93 (1.54) [26]	64.42 (1.02) [28]	57.87 (1.28) [21]	55.39 (1.96) [30]	60.85 (0.39) [24]	58.31 (0.79) [30]	70.71 (0.76) [20]	61.74 (1.63) [20]	58.61 (1.40) [29]	49.38 (0.62) [22]	65.21 (1.60) [15]	71.47 (1.38) [17]	54.91 (2.94) [13]	48.10 (0.79) [34]	57.48 (12.22) [42]	53.80 (2.63) [23]	49.34 (8.06) [40]
Lunar	64.26 (2.19) [10]	60.12 (0.71) [31]	67.40 (0.72) [31]	60.25 (1.89) [11]	59.87 (1.96) [7]	62.48 (0.44) [14]	69.06 (0.81) [14]	73.43 (0.61) [11]	67.38 (1.29) [13]	59.97 (1.36) [10]	49.75 (0.80) [18]	68.38 (1.37) [16]	74.55 (0.85) [18]	56.18 (3.70) [24]	80.97 (8.28) [46]	50.90 (2.76) [28]	50.90 (2.76) [28]	50.90 (2.76) [28]
SOGAAL	54.06 (3.31) [42]	51.56 (3.61) [44]	47.07 (5.48) [49]	52.05 (4.07) [38]	51.73 (3.72) [38]	47.39 (1.24) [49]	50.72 (1.15) [44]	53.81 (0.42) [45]	51.79 (0.78) [44]	50.93 (0.99) [46]	47.54 (0.34) [39]	54.78 (1.71) [42]	51.83 (1.41) [43]	45.07 (2.24) [48]	48.85 (2.54) [23]	65.48 (3.11) [37]	50.83 (1.57) [40]	51.07 (4.16) [41]
ALAD	46.87 (1.81) [30]	54.48 (0.60) [31]	48.71 (1.47) [47]	51.06 (2.58) [41]	51.59 (1.94) [39]	46.64 (0.82) [50]	51.04 (2.44) [39]	49.49 (1.95) [48]	48.13 (1.35) [50]	47.31 (2.59) [50]	45.74 (1.93) [51]	49.41 (2.51) [48]	51.45 (1.29) [50]	51.64 (2.94) [24]	51.46 (2.56) [12]	58.90 (7.40) [41]	46.59 (2.51) [40]	47.82 (5.24) [47]
AE	63.76 (0.95) [14]	56.39 (0.76) [19]	67.03 (0.58) [33]	58.80 (1.86) [16]	57.49 (2.02) [17]	62.15 (0.40) [12]	76.79 (0.92) [12]	66.52 (0.98) [12]	66.52 (0.98) [12]	66.56 (1.31) [15]	50.05 (0.60) [11]	66.96 (1.11) [19]	74.25 (1.17) [11]	54.44 (3.13) [14]	61.41 (1.69) [45]	71.26 (7.71) [18]	58.31 (2.13) [17]	54.57 (1.94) [17]
CD	54.68 (0.98) [6]	51.63 (2.07) [40]	51.68 (3.30) [42]	50.00 (0.00) [43]	50.81 (1.62) [42]	64.35 (0.37) [46]	60.07 (0.37) [16]	79.53 (0.61) [4]	59.34 (1.25) [9]	56.08 (1.47) [40]	46.46 (0.64) [48]	62.40 (0.92) [22]	62.09 (1.45) [40]	50.00 (0.00) [21]	50.00 (0.00) [21]	50.00 (0.00) [21]	50.00 (0.00) [45]	50.00 (0.00) [45]
MCGAL	53.74 (3.40) [43]	52.58 (3.62) [49]	47.12 (4.88) [48]	50.45 (2.80) [42]	51.24 (3.60) [41]	47.53 (1.63) [48]	50.76 (1.51) [43]	61.90 (0.61) [42]	51.11 (2.23) [44]	47.51 (0.21) [40]	55.35 (1.34) [40]	58.45 (1.41) [40]	64.56 (1.44) [46]	49.46 (2.32) [49]	68.48 (5.62) [24]	64.88 (3.57) [38]	54.02 (1.78) [37]	50.62 (4.00) [40]
QMCDD	41.23 (3.31) [51]	46.83 (0.77) [50]	37.80 (1.01) [50]	47.88 (1.87) [49]	46.57 (1.42) [50]	38.50 (0.50) [51]	35.92 (0.86) [51]	27.03 (0.70) [51]	35.24 (1.42) [51]	39.53 (1.21) [51]	49.90 (0.66) [47]	31.08 (1.45) [51]	27.45 (2.13) [51]	44.40 (3.50) [50]	52.12 (0.93) [48]	13.05 (4.32) [51]	51.17 (2.84) [38]	48.48 (2.15) [38]
Sampling	63.04 (1.49) [39]	63.04 (0.86) [17]	65.91 (0.60) [17]	64.96 (0.68) [22]	57.01 (1.77) [25]	56.64 (1.82) [23]	57.63 (1.58) [25]	57.81 (1.99) [31]	67.44 (1.30) [22]	59.69 (2.64) [26]	57.03 (2.18) [48]	48.54 (2.60) [33]	62.92 (1.74) [21]	66.16 (2.14) [25]	50.36 (3.47) [25]	71.36 (9.30) [30]	49.78 (2.07) [38]	47.17 (3.61) [39]
Emp	60.63 (1.30) [30]	53.70 (2.27) [35]	64.96 (0.68) [26]	53.02 (1.47) [32]	53.10 (2.44) [35]	55.27 (0.36) [29]	59.85 (1.65) [23]	64.95 (0.62) [27]	56.45 (1.29) [21]	56.45 (1.29) [21]	49.18 (1.06) [28]	61.29 (1.34) [24]	64.77 (0.51) [26]	67.42 (2.30) [34]	64.34 (2.65) [46]	71.51 (9.29) [16]	51.60 (2.14) [36]	54.21 (1.56) [38]
Ensemble	66.03 (1.11) [31]	58.85 (0.67) [31]	67.63 (0.76) [35]	62.38 (1.61) [21]	60.16 (1.87) [41]	61.57 (0.69) [41]	80.19 (0.86) [41]	78.28 (1.13) [41]	72.92 (0.95) [35]	57.84 (0.15) [42]	75.45 (0.73) [23]	66.46 (1.02) [11]	80.59 (1.11) [31]	53.51 (3.09) [13]	59.81 (0.98) [17]	70.94 (7.14) [21]	54.61 (2.88) [19]	55.01 (1.93) [13]
GENOUT	59.38 (1.60) [33]	53.02 (1.23) [37]	63.90 (1.87) [31]	51.34 (1.80) [39]	52.45 (1.80) [34]	53.35 (1.88) [31]	59.44 (0.46) [25]	63.48 (0.80) [28]	54.69 (2.53) [40]	57.74 (0.64) [29]	47.63 (0.61) [34]	60.45 (1.60) [46]	57.43 (0.94) [41]	53.45 (1.66) [46]	50.76 (2.43) [40]	57.17 (6.27) [15]	55.21 (2.32) [24]	54.41 (2.23) [18]
DynamicHBOS	50.84 (0.47) [45]	50.19 (0.67) [44]	56.94 (1.06) [44]	49.27 (0.62) [47]	48.86 (0.33) [47]	50.35 (0.72) [44]	48.61 (0.20) [47]	53.90 (0.47) [44]	51.84 (0.54) [44]	51.53 (0.77) [43]	48.36 (0.48) [35]	54.48 (0.99) [44]	48.87 (1.17) [47]	47.33 (0.47) [37]	47.84 (0.10) [37]	59.98 (2.94) [45]	51.10 (1.04) [39]	47.48 (0.50) [50]
COF	64.36 (0.81) [19]	57.55 (0.84) [11]	65.86 (0.88) [23]	61.32 (2.36) [46]	58.84 (1.90) [11]	60.36 (0.87) [11]	70.80 (1.22) [9]	73.05 (0.34) [11]	55.67 (1.82) [14]	60.79 (0.40) [37]	63.79 (1.12) [16]	73.93 (1.25) [14]	55.50 (3.55) [11]	58.96 (1.97) [19]	54.86 (1.33) [46]	57.06 (1.00) [11]	52.06 (2.46) [35]	52.06 (2.46) [35]
ABOD	65.20 (1.07) [17]	59.82 (0.42) [2]	68.37 (0.62) [2]	61.48 (1.71) [5]	59.27 (1.52) [9]	65.19 (0.19) [8]	70.25 (0.69) [10]	76.02 (0.82) [9]	69.61 (1.37) [8]	61.61 (1.15) [3]	50.72 (0.47) [10]	65.80 (1.19) [14]	76.73 (1.06) [10]	55.38 (1.89) [12]	51.06 (1.63) [15]	59.55 (4.66) [40]	54.73 (2.27) [18]	51.48 (0.95) [38]
LMMD	55.07 (0.11) [38]	54.14 (1.69) [32]	60.68 (0.89) [30]	52.20 (1.37) [35]	51.80 (1.70) [37]	50.15 (1.05) [42]	52.45 (1.40) [39]	55.98 (1.07) [42]	52.11 (0.81) [41]	52.52 (1.40) [41]	47.38 (0.89) [41]	55.13 (1.13) [41]	52.57 (1.18) [41]	47.77 (0.33) [32]	48.18 (1.69) [30]	60.32 (6.76) [39]	50.17 (1.64) [30]	50.75 (9.46) [40]
DMMGM	56.17 (3.14) [34]	52.60 (2.89) [38]	53.86 (2.60) [43]	51.77 (3.01) [43]	53.33 (2.54) [40]	53.45 (0.62) [47]	51.91 (4.61) [39]	51.42 (4.42) [47]	49.81 (3.31) [48]	51.00 (1.61) [45]	49.11 (1.17) [29]	51.18 (0.53) [42]	57.92 (4.38) [42]	47.38 (1.63) [37]	50.77 (2.59) [26]	50.47 (6.04) [42]	50.77 (6.04) [42]	50.77 (6.04) [42]
DBOCC	53.14 (0.69) [44]	51.15 (2.01) [43]	60.90 (0.26) [43]	49.10 (3.66) [48]	49.77 (3.50) [46]	49.47 (0.33) [46]	50.00 (0.00) [45]	49.77 (3.50) [46]	50.56 (1.12) [47]	49.41 (1.39) [47]	47.77 (0.91) [49]							

Table 16: Mean, standard deviation and rank AUC-ROC performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 8

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Table 17: Mean, standard deviation and rank F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 1

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Table 18: Mean, standard deviation and rank F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 2

	Model	Parkinson	pendgits	pen-globel	pen-local	Pima	satellite	satimage-2	seismic-bumps	shuttle	skin	smp	Spambase	speech	Stamps	svmcal	verbal	vowels	Waveform
Forest	92.04 (5.55) [22]	56.17 (6.54) [17]	69.76 (4.46) [26]	0.00 (0.00) [18]	70.99 (3.86) [14]	66.73 (1.39) [28]	71.16 (0.93) [10]	15.49 (3.79) [27]	96.65 (0.50) [22]	77.68 (1.26) [16]	0.00 (0.00) [40]	79.32 (0.92) [15]	3.78 (2.76) [14]	67.08 (7.29) [20]	82.86 (1.82) [1]	14.28 (1.98) [35]	14.67 (6.18) [13]	11.00 (2.26) [26]	
	OCVM3	95.99 (1.25) [28]	51.73 (3.20) [18]	79.45 (2.26) [18]	0.00 (0.00) [18]	68.84 (1.41) [21]	67.35 (0.81) [24]	92.56 (1.74) [31]	10.59 (0.69) [22]	90.69 (0.66) [25]	79.59 (0.36) [10]	76.18 (0.32) [1]	76.43 (3.07) [17]	68.05 (0.03) [29]	32.00 (6.07) [18]	12.67 (2.71) [26]			
CORO	87.47 (9.74) [37]	34.26 (2.64) [21]	43.95 (2.81) [42]	0.00 (0.00) [18]	64.85 (2.19) [32]	61.83 (0.57) [42]	82.33 (2.37) [48]	0.00 (0.00) [48]	96.61 (0.78) [23]	37.26 (0.48) [42]	0.00 (0.00) [40]	72.57 (0.39) [37]	3.24 (2.02) [22]	71.61 (3.95) [13]	35.71 (3.57) [45]	2.17 (4.34) [50]	4.00 (1.33) [45]	9.67 (6.16) [48]	
	ECOD	84.96 (0.97) [46]	44.26 (1.73) [21]	47.27 (3.84) [39]	0.00 (0.00) [18]	64.39 (2.16) [35]	57.86 (0.57) [42]	0.00 (0.00) [48]	93.90 (0.25) [32]	22.83 (0.38) [50]	76.18 (0.32) [1]	70.94 (0.58) [39]	43.32 (1.27) [37]	56.99 (0.57) [33]	63.21 (1.82) [29]	13.26 (1.86) [37]	23.33 (2.42) [39]	8.33 (1.49) [39]	
FeatureBagging	91.69 (1.44) [24]	87.27 (1.56) [8]	85.02 (6.61) [14]	33.33 (3.49) [4]	68.21 (2.33) [23]	72.70 (3.99) [6]	86.51 (0.93) [22]	21.57 (10.23) [21]	70.30 (0.72) [44]	59.41 (2.10) [28]	0.00 (0.00) [40]	70.88 (1.13) [40]	43.2 (3.12) [37]	70.42 (0.85) [12]	74.13 (4.79) [14]	29.23 (6.17) [12]	37.33 (3.89) [13]	28.67 (1.63) [3]	
	HMSB	96.09 (0.77) [12]	39.57 (3.50) [47]	20.85 (3.37) [20]	0.00 (0.00) [18]	70.85 (2.27) [10]	75.50 (0.46) [30]	82.59 (2.37) [28]	25.29 (1.50) [37]	94.92 (0.10) [51]	94.82 (0.28) [29]	74.82 (0.20) [31]	5.95 (2.65) [27]	78.93 (1.47) [33]	9.74 (3.87) [42]				
KNN	95.29 (0.38) [17]	90.64 (1.83) [5]	97.31 (1.14) [5]	33.33 (0.00) [4]	71.58 (2.22) [8]	71.70 (5.77) [14]	91.16 (0.93) [10]	13.14 (2.02) [36]	98.31 (0.15) [12]	96.34 (0.45) [21]	76.18 (0.32) [1]	80.54 (0.55) [12]	2.16 (1.00) [32]	79.45 (6.07) [7]	76.07 (2.67) [8]	20.45 (4.69) [28]	31.33 (6.43) [21]	26.33 (2.45) [9]	
	LODA	89.11 (1.78) [31]	44.26 (1.77) [21]	54.73 (8.13) [33]	0.00 (0.00) [18]	63.69 (5.21) [34]	64.91 (1.09) [36]	97.00 (2.08) [13]	7.45 (3.87) [47]	42.58 (3.57) [49]	53.18 (9.32) [32]	9.71 (6.54) [36]	74.48 (4.31) [32]	3.78 (2.16) [14]	63.01 (6.09) [42]	72.14 (3.30) [23]	41.00 (3.88) [48]	11.40 (6.46) [35]	
LOF	91.16 (3.30) [26]	79.14 (3.97) [10]	84.58 (3.08) [16]	20.00 (0.67) [8]	66.54 (2.88) [26]	72.68 (0.69) [37]	83.26 (1.74) [26]	11.26 (0.00) [38]	98.49 (0.18) [70]	74.18 (0.35) [34]	43.2 (3.12) [37]	1.96 (0.05) [26]	53.21 (4.29) [35]	29.26 (3.30) [18]	38.07 (4.78) [16]	27.65 (2.46) [6]			
	MCD	94.11 (0.53) [19]	15.32 (2.19) [40]	53.15 (5.14) [35]	0.00 (0.00) [18]	70.04 (2.04) [12]	63.04 (5.16) [40]	98.38 (0.00) [1]	42.35 (4.34) [14]	84.76 (0.43) [33]	76.71 (0.44) [18]	0.00 (0.00) [40]	77.52 (1.31) [28]	2.16 (1.02) [32]	33.16 (3.80) [43]	75.36 (2.08) [10]	13.15 (5.36) [34]	0.00 (0.00) [49]	
PCA	88.43 (1.10) [33]	42.98 (2.74) [24]	63.22 (5.28) [30]	0.00 (0.00) [18]	70.66 (1.15) [31]	62.47 (0.83) [41]	73.02 (0.83) [41]	88.37 (0.00) [48]	95.68 (0.10) [29]	37.70 (0.49) [41]	76.18 (0.32) [1]	78.53 (0.40) [23]	43.2 (3.12) [37]	64.72 (4.64) [22]	75.36 (1.30) [22]	14.26 (2.37) [39]	14.67 (6.13) [21]	10.97 (4.07) [27]	
	DeepSVD	98.10 (4.11) [9]	87.2 (5.65) [45]	74.0 (5.67) [25]	16.67 (0.54) [10]	53.19 (2.40) [43]	67.97 (2.42) [23]	73.49 (4.74) [33]	78.63 (0.66) [39]	98.22 (0.17) [33]	43.45 (3.14								

Table 19: Mean, standard deviation and rank F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 3

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Table 20: Mean, standard deviation and rank F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 4

Model	FashionMNIST 0	FashionMNIST 1	FashionMNIST 2	FashionMNIST 3	FashionMNIST 4	FashionMNIST 5	FashionMNIST 6	FashionMNIST 7	FashionMNIST 8	FashionMNIST 9	MNIST-C brightness	MNIST-C camy edges	MNIST-C doted line	MNIST-C fog	MNIST-C glass blur
IForest	36.08 (2.75) [10]	62.33 (2.83) [32]	26.03 (1.33) [17]	41.16 (4.22) [30]	29.84 (2.83) [16]	73.54 (2.57) [31]	13.33 (2.35) [40]	81.38 (1.44) [27]	23.17 (1.93) [20]	76.09 (1.03) [10]	18.67 (3.04) [34]	20.53 (1.24) [32]	38.87 (2.24) [32]	38.87 (4.97) [32]	57.40 (2.14) [30]
OCVM	49.01 (1.36) [26]	74.39 (1.40) [21]	46.45 (1.47) [21]	55.66 (0.40) [17]	48.57 (1.47) [19]	79.79 (1.40) [14]	30.02 (1.56) [20]	24.67 (2.55) [16]	25.61 (2.25) [23]	76.08 (1.07) [20]	24.67 (3.52) [23]	25.87 (1.15) [21]	39.20 (1.29) [19]	56.40 (1.06) [20]	70.00 (1.68) [19]
COPOD	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]
ECOD	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]
FeatureBagging	59.26 (3.38) [31]	78.52 (1.94) [7]	54.81 (2.63) [3]	61.48 (0.70) [4]	56.75 (0.62) [2]	79.15 (1.88) [21]	79.15 (1.88) [21]	82.96 (1.36) [16]	42.75 (2.15) [2]	79.15 (1.56) [3]	39.80 (1.67) [3]	51.47 (2.06) [3]	52.27 (1.34) [5]	73.40 (0.77) [5]	79.13 (0.96) [6]
HROS	27.72 (1.48) [37]	42.17 (1.00) [40]	4.55 (0.42) [45]	28.04 (0.58) [38]	12.06 (1.33) [45]	53.82 (0.75) [45]	73.76 (1.04) [33]	16.19 (0.30) [42]	66.98 (2.16) [32]	10.87 (1.24) [39]	17.27 (1.18) [34]	17.20 (1.19) [34]	15.20 (0.02) [42]	38.53 (1.72) [36]	
KNN	53.86 (2.27) [12]	76.72 (1.34) [13]	49.31 (1.69) [17]	56.51 (0.70) [13]	51.53 (0.86) [14]	79.89 (1.21) [11]	38.41 (1.85) [15]	83.17 (1.62) [14]	30.69 (1.74) [15]	76.83 (1.08) [14]	30.27 (0.77) [15]	31.47 (1.33) [16]	44.60 (0.69) [14]	60.53 (1.56) [14]	74.27 (0.80) [13]
LDA	36.51 (0.49) [20]	70.37 (0.95) [27]	34.29 (3.85) [26]	44.02 (6.69) [29]	38.20 (3.23) [28]	73.86 (4.57) [29]	26.88 (5.02) [26]	80.95 (1.89) [30]	21.38 (4.13) [32]	66.35 (3.35) [33]	25.75 (6.02) [30]	17.60 (3.42) [36]	23.93 (4.17) [35]	49.73 (12.06) [36]	56.73 (8.69) [31]
LOF	58.42 (3.40) [4]	73.77 (1.59) [9]	54.71 (2.28) [4]	56.61 (0.75) [3]	79.05 (1.48) [22]	82.96 (1.36) [16]	40.53 (1.28) [4]	71.16 (1.04) [37]	39.40 (1.72) [8]	50.80 (0.96) [5]	52.13 (1.24) [6]	72.53 (1.24) [6]	78.50 (0.96) [5]	79.13 (1.24) [6]	
MCA	28.25 (5.63) [36]	42.96 (6.56) [38]	20.95 (2.95) [39]	35.87 (4.53) [34]	32.59 (8.76) [34]	67.41 (7.20) [34]	21.80 (5.02) [28]	59.79 (6.71) [35]	18.41 (1.31) [39]	54.50 (6.30) [35]	15.27 (2.28) [38]	15.93 (2.73) [37]	18.60 (5.30) [39]	30.40 (6.69) [37]	19.57 (6.64) [41]
PCA	42.80 (2.92) [23]	73.76 (1.42) [22]	45.50 (2.39) [23]	54.81 (0.72) [21]	49.74 (1.09) [23]	79.79 (1.40) [14]	29.84 (1.23) [23]	82.86 (1.59) [23]	23.70 (1.98) [27]	53.75 (1.66) [23]	23.73 (0.98) [25]	22.77 (1.10) [24]	54.80 (1.19) [24]	69.47 (1.29) [24]	
DeepSVDD	34.92 (6.03) [31]	67.94 (4.05) [30]	31.85 (2.42) [30]	40.85 (3.20) [31]	39.15 (4.05) [26]	73.86 (1.48) [29]	22.54 (2.43) [27]	80.72 (1.75) [31]	21.38 (2.65) [32]	68.92 (2.99) [31]	21.00 (2.23) [30]	22.07 (6.66) [28]	25.60 (3.68) [29]	43.67 (1.40) [29]	52.20 (5.48) [31]
DNE	56.40 (3.77) [18]	76.40 (1.97) [14]	53.44 (2.66) [19]	58.20 (2.19) [10]	53.44 (0.89) [19]	79.84 (1.08) [32]	39.47 (3.74) [10]	78.94 (1.08) [32]	36.19 (3.91) [9]	33.40 (0.89) [27]	39.47 (2.14) [9]	49.07 (1.29) [9]	69.20 (2.31) [10]	76.60 (2.08) [10]	
KDCA	54.60 (2.51) [10]	77.67 (1.78) [8]	50.58 (2.36) [10]	57.88 (0.72) [11]	53.12 (3.16) [11]	80.42 (1.14) [4]	40.42 (1.19) [14]	83.49 (1.55) [10]	31.96 (2.16) [13]	77.67 (1.44) [10]	32.47 (				

Table 21: Mean, standard deviation and rank F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 5

Model	MNIST-C identity	MNIST-C impulse noise	MNIST-C motion blur	MNIST-C rotate	MNIST-C scale	MNIST-C shear	MNIST-C shot noise	MNIST-C spatter	MNIST-C stripe	MNIST-C translate	MNIST-C zigzag	MVTec-AD bottle	MVTec-AD cable	MVTec-AD capsule	MVTec-AD carpet
Fireext	7.73 (0.76) [42]	89.60 (2.95) [30]	37.53 (2.27) [33]	11.53 (0.81) [31]	15.87 (2.90) [35]	20.07 (1.53) [32]	25.33 (1.96) [33]	42.27 (3.22) [28]	83.73 (1.31) [30]	14.27 (0.25) [34]	35.87 (1.02) [30]	90.24 (1.50) [26]	57.80 (3.39) [32]	58.17 (2.70) [32]	58.88 (2.32) [31]
OCSVM	8.67 (1.07) [24]	97.80 (0.40) [11]	50.80 (1.44) [22]	12.80 (0.62) [21]	29.27 (1.14) [19]	22.73 (1.10) [25]	33.53 (1.96) [21]	47.93 (1.06) [19]	93.40 (0.44) [16]	19.27 (1.02) [24]	47.93 (1.42) [19]	90.73 (0.50) [23]	57.09 (2.97) [33]	57.05 (2.51) [36]	58.09 (4.05) [33]
COPOD	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [47]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [47]	0.00 (0.00) [47]	58.02 (5.96) [41]	71.80 (5.26) [11]	93.40 (1.79) [1]	68.41 (6.72) [10]
ECOD	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [47]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [47]	0.00 (0.00) [47]	58.02 (5.96) [41]	71.80 (5.26) [11]	93.40 (1.79) [1]	68.41 (6.72) [10]
FeatureBagging	8.53 (0.83) [30]	97.60 (0.33) [12]	64.53 (1.20) [8]	14.87 (0.50) [11]	40.80 (1.56) [7]	28.93 (1.12) [9]	47.87 (0.83) [4]	63.53 (1.71) [5]	95.20 (0.34) [8]	32.07 (1.88) [7]	61.67 (0.84) [7]	92.14 (0.55) [11]	60.07 (3.19) [25]	62.13 (3.25) [25]	61.20 (2.69) [19]
HBOS	7.67 (0.47) [43]	53.47 (1.50) [39]	26.20 (0.96) [39]	11.40 (0.49) [33]	6.20 (1.07) [43]	19.33 (1.92) [34]	19.87 (1.09) [38]	29.00 (1.41) [36]	66.27 (1.29) [36]	9.47 (1.22) [42]	21.93 (0.83) [40]	89.01 (1.80) [30]	60.24 (3.02) [24]	56.94 (1.71) [37]	61.75 (4.07) [18]
KNN	9.00 (0.60) [19]	97.27 (0.25) [18]	56.53 (1.09) [16]	13.87 (0.58) [18]	33.27 (1.47) [15]	26.20 (1.13) [15]	40.13 (2.35) [12]	53.80 (1.29) [14]	94.33 (0.42) [13]	22.67 (1.23) [19]	53.93 (1.29) [14]	91.53 (0.57) [16]	59.84 (3.34) [27]	62.94 (1.60) [22]	60.32 (2.46) [25]
LODA	8.13 (0.93) [39]	95.73 (3.34) [26]	42.00 (5.24) [30]	10.93 (1.54) [38]	16.33 (4.70) [33]	16.67 (2.92) [38]	24.93 (6.48) [34]	38.00 (6.21) [33]	83.93 (4.68) [29]	13.73 (2.48) [37]	31.47 (7.30) [34]	87.84 (2.80) [33]	52.84 (3.09) [39]	56.77 (3.32) [38]	54.34 (4.73) [37]
LOF	8.60 (0.77) [27]	97.20 (0.34) [22]	65.07 (1.10) [6]	15.20 (0.88) [9]	40.87 (1.61) [5]	29.07 (1.54) [6]	46.93 (1.53) [5]	63.07 (1.67) [6]	95.47 (0.16) [5]	32.13 (1.33) [5]	61.80 (1.20) [5]	91.67 (0.58) [14]	59.25 (3.37) [28]	62.25 (3.35) [23]	60.43 (3.02) [23]
MCD	9.20 (0.91) [16]	69.33 (8.61) [36]	30.07 (7.76) [37]	11.07 (1.42) [36]	16.93 (5.46) [32]	15.87 (1.89) [41]	18.47 (2.01) [39]	32.87 (2.75) [35]	72.20 (12.82) [31]	11.60 (1.34) [41]	24.87 (3.61) [38]	91.20 (0.67) [19]	65.44 (3.90) [16]	71.60 (2.31) [14]	61.10 (4.42) [20]
PCA	8.47 (1.56) [32]	97.27 (0.25) [18]	50.07 (1.82) [24]	11.93 (0.74) [29]	27.27 (0.98) [24]	22.73 (1.14) [25]	31.73 (1.69) [24]	46.60 (1.51) [23]	93.07 (0.39) [21]	18.47 (1.00) [28]	46.40 (1.47) [23]	89.18 (1.45) [28]	54.87 (2.68) [37]	56.07 (2.57) [39]	58.08 (4.47) [34]
DeepVDD	9.53 (0.62) [7]	92.27 (4.24) [27]	44.53 (1.90) [27]	12.47 (1.76) [25]	23.93 (3.68) [27]	17.13 (2.43) [37]	23.20 (3.98) [36]	34.93 (5.36) [34]	81.80 (1.59) [31]	15.13 (3.00) [31]	28.13 (6.51) [36]	92.30 (1.65) [19]	71.93 (4.09) [10]	64.97 (4.76) [20]	73.32 (3.13) [8]
INNE	9.00 (1.25) [19]	88.67 (1.17) [12]	61.67 (1.65) [10]	14.07 (0.74) [17]	36.00 (1.41) [11]	26.00 (1.96) [16]	42.33 (2.66) [10]	59.60 (2.89) [26]	88.73 (1.22) [10]	23.00 (1.35) [16]	59.73 (1.22) [10]	92.31 (1.13) [8]	58.92 (1.96) [26]	60.11 (3.73) [26]	
KPCA	8.60 (0.74) [27]	95.93 (0.39) [24]	58.53 (0.88) [12]	14.33 (0.70) [13]	35.47 (1.57) [12]	27.07 (1.04) [12]	42.60 (1.90) [9]	55.60 (1.29) [12]	95.40 (0.57) [7]	24.20 (1.53) [15]	56.40 (1.02) [12]	94.07 (1.63) [4]	80.29 (3.86) [1]	83.49 (2.54) [6]	76.08 (1.54) [2]
KDE	8.53 (0.30) [39]	98.20 (0.27) [5]	58.00 (1.14) [14]	14.20 (0.86) [15]	28.60 (1.29) [22]	23.33 (1.05) [22]	36.60 (1.32) [16]	45.93 (1.02) [25]	94.53 (0.86) [10]	22.87 (1.51) [18]	45.40 (1.22) [26]	92.62 (2.12) [7]	74.13 (3.69) [8]	82.82 (2.07) [7]	74.85 (2.01) [5]
GMM	9.60 (0.88) [5]	97.93 (0.33) [8]	62.87 (1.07) [9]	16.73 (0.57) [7]	41.80 (1.22) [4]	30.00 (0.79) [5]	46.33 (1.86) [7]	61.80 (1.36) [8]	94.67 (0.56) [9]	30.87 (1.53) [10]	61.67 (1.32) [7]	94.25 (1.43) [1]	78.12 (2.23) [5]	83.71 (2.76) [5]	75.50 (1.16) [4]
CHLOF	8.93 (1.22) [21]	97.33 (0.21) [14]	51.87 (1.48) [19]	12.53 (0.45) [24]	31.80 (1.20) [17]	24.67 (1.14) [19]	34.93 (2.26) [18]	48.27 (1.48) [18]	93.40 (0.44) [16]	19.13 (1.31) [25]	48.73 (1.32) [18]	90.79 (1.45) [22]	62.20 (3.64) [18]	61.41 (1.70) [26]	60.53 (4.34) [22]
SOD	7.27 (0.68) [46]	75.60 (1.32) [34]	46.73 (1.60) [26]	12.60 (1.44) [23]	11.13 (1.85) [39]	29.33 (1.75) [27]	45.40 (2.26) [26]	73.07 (1.81) [33]	25.93 (0.74) [13]	44.60 (2.24) [27]	28.70 (2.36) [34]	39.04 (2.36) [49]	47.90 (3.67) [50]	51.54 (3.77) [42]	
LUNAR	9.53 (0.75) [7]	99.33 (0.30) [1]	76.00 (0.79) [1]	21.73 (1.00) [1]	48.73 (1.06) [2]	35.20 (1.95) [1]	61.27 (2.61) [1]	71.20 (1.17) [1]	98.40 (0.80) [1]	37.40 (0.68) [3]	70.20 (0.96) [2]	93.91 (1.76) [5]	72.43 (4.55) [9]	71.07 (3.61) [16]	68.02 (4.08) [13]
SGAAL	9.27 (2.04) [14]	67.27 (20.98) [37]	25.80 (6.63) [40]	10.80 (0.96) [40]	7.93 (3.45) [41]	10.53 (1.67) [44]	10.13 (2.79) [45]	8.13 (1.67) [46]	23.67 (10.96) [41]	9.27 (1.85) [44]	8.07 (1.25) [46]	69.92 (5.76) [37]	40.56 (3.61) [47]	48.99 (3.91) [49]	43.24 (9.19) [49]
ALOD	10.07 (1.29) [13]	26.07 (14.29) [42]	18.40 (7.98) [43]	8.93 (1.81) [46]	11.87 (3.92) [38]	10.07 (1.91) [43]	11.60 (2.84) [43]	16.93 (7.40) [43]	24.87 (12.80) [40]	9.47 (1.31) [42]	16.13 (4.79) [43]	56.30 (12.25) [45]	39.34 (3.75) [48]	49.78 (5.50) [45]	43.18 (13.12) [48]
AE	9.47 (0.98) [9]	97.33 (0.21) [14]	55.20 (1.53) [17]	13.87 (0.58) [18]	33.87 (1.44) [14]	26.27 (1.10) [14]	37.93 (2.40) [15]	53.73 (1.69) [15]	93.80 (0.27) [14]	22.93 (1.02) [17]	53.80 (1.24) [15]	92.15 (0.38) [10]	60.66 (1.60) [23]	60.96 (2.55) [28]	59.28 (3.07) [28]
CD	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [48]	0.00 (0.00) [47]	0.00 (0.00) [48]	0.00 (0.00) [47]	14.87 (18.21) [45]	37.33 (19.34) [38]	0.00 (0.00) [47]	0.00 (0.00) [47]	58.02 (5.96) [41]	71.80 (5.26) [11]	80.69 (25.19) [11]	49.86 (21.57) [44]
MOGAL	9.47 (2.36) [9]	58.93 (25.49) [38]	25.00 (5.01) [41]	10.87 (1.53) [47]	7.33 (2.54) [42]	9.93 (0.61) [46]	8.80 (2.30) [46]	6.07 (1.06) [47]	17.67 (12.45) [45]	8.87 (0.83) [45]	8.20 (0.75) [45]	68.42 (5.56) [38]	40.60 (2.57) [46]	49.22 (3.97) [48]	44.75 (10.63) [47]
QMCD	17.80 (1.53) [1]	88.87 (1.33) [31]	67.33 (0.33) [47]	2.57 (0.21) [47]	0.00 (0.00) [47]	1.93 (0.57) [47]	0.00 (0.00) [48]	20.13 (0.62) [44]	0.00 (0.00) [47]	55.44 (1.86) [47]	0.26 (0.53) [51]	11.33 (3.77) [51]	13.18 (3.58) [51]		
Sampling	8.93 (1.16) [21]	97.33 (0.21) [14]	51.27 (1.10) [20]	12.33 (0.42) [28]	28.80 (2.07) [20]	23.47 (0.88) [21]	33.73 (1.68) [20]	47.93 (0.85) [19]	93.40 (0.33) [16]	19.60 (0.74) [21]	47.80 (0.91) [20]	90.87 (0.59) [21]	57.92 (2.39) [31]	62.98 (1.96) [21]	59.80 (5.60) [27]
EIF	7.53 (0.62) [45]	92.00 (2.12) [28]	38.73 (2.45) [32]	11.00 (1.53) [37]	18.67 (4.27) [29]	21.20 (1.71) [30]	27.47 (3.03) [29]	41.67 (3.39) [29]	88.67 (1.84) [27]	14.20 (0.69) [35]	38.07 (3.05) [28]	89.95 (1.77) [27]	55.60 (3.44) [36]	57.06 (1.98) [25]	59.01 (2.97) [30]
Ensemble	8.60 (0.77) [27]	97.20 (0.34) [22]	65.07 (1.10) [6]	15.20 (0.88) [9]	40.87 (1.61) [5]	29.07 (1.54) [6]	46.93 (1.53) [5]	63.07 (1.67) [6]	95.47 (0.16) [5]	32.13 (1.33) [5]	61.80 (1.20) [5]	91.67 (0.58) [14]	59.25 (3.37) [28]	62.25 (3.35) [23]	60.43 (3.03) [23]
GEN2OUT	6.87 (0.81) [47]	95.87 (1.24) [25]	41.67 (6.22) [31]	11.53 (1.45) [31]	15.07 (5.50) [36]	21.40 (2.47) [29]	26.87 (2.05) [30]	42.53 (4.96) [27]	87.60 (5.79) [28]	14.13 (1.47) [36]	34.40 (6.14) [32]	90.73 (1.20) [23]	61.01 (4.96) [22]	60.98 (0.73) [27]	57.94 (3.08) [36]
DynamicHBOS	7.60 (0.71) [44]	19.13 (3.93) [44]	16.40 (5.12) [44]	11.13 (0.16) [34]	5.87 (1.07) [44]	16.00 (3.29) [40]	18.33 (0.76) [40]	16.00 (4.23) [42]	20.40 (5.69) [43]	8.60 (1.12) [46]	19.87 (1.41) [42]	80.39 (6.27) [36]	63.96 (4.56) [17]	88.15 (2.19) [44]	62.81 (7.35) [16]
COP	8.13 (0.81) [39]	15.67 (0.92) [45]	35.27 (1.91) [35]	14.27 (1.10) [14]	5.00 (1.28) [45]	27.27 (0.68) [11]	26.07 (1.27) [32]	38.80 (2.22) [31]	16.13 (2.09) [46]	27.47 (1.07) [12]	45.67 (2.03) [25]	48.67 (4.21) [49]	41.09 (6.05) [45]	49.73 (1.41) [46]	49.03 (3.91) [45]
ABOD	9.87 (0.72) [4]	97.93 (0.25) [18]	67.20 (0.98) [5]	15.93 (0.57) [8]	36.27 (1.90) [9]	28.53 (1.67) [10]	46.27 (1.81) [8]	63.87 (1.13) [4]	94.47 (0.81) [11]	30.67 (1.52) [11]	63.07 (1.04) [4]	46.28 (6.17) [50]	47.15 (2.50) [42]	55.28 (1.79) [42]	51.04 (4.67) [43]
LMDD	8.67 (0.70) [24]	70.07 (29.33) [35]	42.53 (1.26) [29]	11.13 (0.65) [34]	18.47 (1.31) [30]	20.40 (0.83) [31]	26.20 (1.68) [31]	40.07 (0.68) [30]	80.33 (22.86) [32]	14.87 (0.72) [32]	36.20 (1.72) [29]	59.15 (5.64) [40]	61.92 (7.91) [20]	80.28 (10.23) [12]	66.12 (9.13) [15]
DAGMM	9.40 (1.27) [13]	48.00 (20.49) [40]	33.27 (6.61) [36]	9.87 (0.69) [42]	16.27 (14.86) [34]	16.20 (0.58) [39]	20.47 (3.70) [37]	29.00 (6.26) [36]	57.67 (19.32) [37]	12.53 (1.13) [40]	26.13 (6.92) [37]	68.14 (9.49) [39]	44.15 (5.30) [44]	49.39 (3.41) [47]	47.81 (12.18) [46]
DROCC	8.27 (1.95) [36]	80.40 (20.39) [33]	36.47 (6.45) [34]	14.20 (2.37) [15]	19.80 (8.93) [28]	18.60 (3.23) [35]	31.27 (7.51) [26]	27.93 (6.28) [38]	68.00 (4.77) [35]	18.53 (3.86) [27]	34.40 (12.60) [32]	80.92 (10.19) [35]	45.51 (1.77) [43]	51.16 (6.30) [44]	53.18 (9.14) [40]
GOAD	8.67 (0.99) [24]	97.33 (0.30) [14]	58.53 (1.67) [23]	12.67 (0.87) [22]	28.80 (1.13) [20]	23.27 (1.27) [23]	33.27 (2.30) [23]	47.87 (1.38) [21]	92.87 (0.62) [23]	18.93 (1.06) [26]	47.80 (1.93) [20]	91.21 (0.74) [18]	56.85 (2.58) [34]	57.15 (2.97) [34]	58.53 (4.67) [32]
ICL	8.40 (0.53) [44]	98.67 (0.47) [12]	68.87 (1.82) [4]	18.27 (1.02) [4]	36.27 (3.52) [9]	29.07 (1.62) [6]	39.07 (2.07) [14]	57.07 (0.83) [10]	96.07 (0.65) [2]	34.33 (1.05) [4]	60.00 (1.10) [9]	92.21 (1.68) [9]	76.89 (1.74) [7]	82.41 (0.44) [8]	77.51 (3.14) [1]
PlanFlow	8.20 (0.96) [37]	97.27 (0.53) [18]	43.73 (1.97) [28]	9.13 (1.71) [45]	17.87 (5.55) [31]	19.60 (2.35) [33]	24.27 (2.64) [35]	38.40 (1.98) [32]	91.27 (0.95) [25]	13.27 (1.62) [38]	29.80 (2.31) [35]	88.20 (1.35) [31]	50.94 (2.11) [41]	55.50 (2.26) [41]	54.20 (3.96) [38]
VAE	8.47 (1.56) [32]	97.27 (0.25) [18]	50.07 (1.82) [24]	11.93 (0.74) [29]	27.27 (0.98) [24]	22.73 (1.14) [25]	31.73 (1.69) [24]	46.60 (1.51) [23]	93.07 (0.39) [21]	18.47 (1.00) [28]	46.40 (1.47) [23]	89.18 (1.45) [28]	54.87 (2.68) [37]	56.07 (2.57) [39]	58.08 (4.47) [34]
GANomaly	9.47 (0.62) [9]	97.40 (0.13) [13]	58.47 (3.46) [13]	12.47 (1.13) [25]	29.47 (3.22) [18]	24.53 (2.38) [20]	35.93 (2.72) [17]	50.07 (3.47) [17]	93.13 (0.86) [20]	19.47 (0.69) [23]	52.13 (1.96) [17]	90.73 (0.84) [23]	62.10 (3.38) [19]	60.55 (2.14) [30]	61.87 (3.00) [17]
SLF	9.07 (1.02) [18]	98.47 (0.27) [3]	57.20 (1.45) [15]	14.80 (0.83) [12]	34.67 (1.17) [13]	27.07 (1.18) [12]	39.87 (2.09) [13]	55.60 (1.37) [12]	94.40 (0.57) [12]	25.47 (0.72) [14]	55.20 (1.00) [13]	93.77 (1.67) [6]	78.35 (2.97) [4]	79.67 (0.57) [13]	73.95 (1.76) [7]
DIP	10.27 (0.88) [2]	4.93 (0.49) [46]	12.07 (0.74) [46]	10.20 (1.07) [41]	8.93 (1.33) [40]	12.87 (									

	Model	MVTrc-AD grid	MVTrc-AD handset	MVTrc-AD leather	MVTrc-AD metal nut	MVTrc-AD pill	MVTrc-AD screw	MVTrc-AD tile	MVTrc-AD toothbrush	MVTrc-AD transistor	MVTrc-AD wood	MVTrc-AD zipper	SVHN 0	SVHN 1	SVHN 2	SVHN 3	SVHN 4
Iforest	50.98 (0.68) [26]	52.81 (2.21) [20]	95.74 (1.61) [13]	60.22 (2.21) [34]	62.35 (2.54) [16]	45.15 (5.65) [41]	73.02 (2.41) [26]	76.61 (4.45) [31]	47.44 (5.90) [22]	60.68 (2.30) [27]	73.49 (4.34) [32]	15.00 (1.32) [27]	18.33 (1.28) [16]	19.60 (1.88) [30]	13.13 (6.50) [41]	20.00 (1.29) [6]	
	OCVM	52.00 (2.77) [26]	51.60 (2.84) [24]	95.74 (1.61) [13]	60.22 (2.21) [34]	62.35 (2.54) [16]	48.78 (3.38) [31]	73.12 (2.82) [25]	76.04 (2.33) [26]	60.68 (2.30) [27]	74.00 (4.34) [32]	15.51 (1.52) [22]	18.60 (0.96) [13]	21.20 (2.15) [22]	18.80 (0.61) [13]	19.32 (2.02) [41]	
COCO	31.14 (4.23) [44]	4.64 (8.11) [48]	76.68 (3.95) [39]	86.87 (1.57) [11]	96.80 (2.58) [11]	71.26 (6.32) [7]	70.80 (3.84) [32]	86.30 (1.85) [15]	0.24 (0.47) [48]	44.18 (7.07) [43]	94.43 (2.89) [11]	0.00 (0.00) [49]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [49]	
	ECOD	31.14 (4.23) [44]	4.64 (8.11) [48]	76.68 (3.95) [39]	86.87 (1.57) [11]	96.80 (2.58) [11]	71.26 (6.32) [7]	70.80 (3.84) [32]	86.30 (1.85) [15]	0.24 (0.47) [48]	44.18 (7.07) [43]	94.43 (2.89) [11]	0.00 (0.00) [49]	0.00 (0.00) [49]	0.00 (0.00) [48]	0.00 (0.00) [49]	0.00 (0.00) [49]
FusionBagging	53.37 (4.14) [21]	53.51 (3.67) [19]	94.57 (2.12) [27]	62.35 (1.99) [22]	65.14 (3.66) [21]	52.06 (5.08) [20]	73.97 (2.21) [19]	83.99 (5.42) [19]	45.22 (2.34) [32]	61.6 (2.28) [16]	79.29 (4.49) [20]	18.21 (1.44) [12]	14.93 (1.73) [33]	22.40 (1.55) [15]	21.04 (0.96) [6]	18.81 (1.24) [25]	
	HROS	37.25 (2.62) [39]	54.23 (5.53) [14]	93.24 (0.02) [32]	52.29 (1.69) [43]	63.13 (2.84) [32]	45.92 (5.43) [24]	72.91 (2.04) [28]	80.27 (3.49) [27]	46.67 (6.30) [27]	53.65 (2.04) [36]	72.07 (3.75) [35]	11.5 (21.37) [39]	17.67 (0.84) [21]	16.00 (1.28) [36]	8.58 (0.41) [46]	20.51 (0.91) [4]
KNN	56.73 (1.13) [18]	52.25 (2.16) [20]	95.74 (1.61) [13]	60.22 (2.21) [34]	62.35 (2.54) [16]	45.15 (5.65) [41]	73.02 (2.41) [26]	76.61 (4.45) [31]	47.44 (5.90) [22]	60.68 (2.30) [27]	73.49 (4.34) [32]	15.00 (1.32) [27]	18.33 (1.28) [16]	19.60 (1.88) [30]	13.13 (6.50) [41]	20.00 (1.29) [6]	
	LODA	44.09 (4.46) [23]	49.83 (2.93) [32]	95.23 (1.60) [31]	56.94 (4.13) [29]	61.95 (3.15) [37]	47.42 (5.28) [43]	68.41 (4.62) [37]	64.20 (5.31) [40]	47.49 (4.62) [34]	57.75 (5.54) [34]	71.26 (3.88) [38]	13.97 (3.73) [33]	17.00 (2.80) [25]	15.90 (2.69) [38]	13.73 (2.85) [37]	15.83 (2.00) [38]
LOF	53.19 (1.22) [23]	53.29 (1.56) [15]	94.31 (2.15) [28]	65.15 (1.91) [25]	65.14 (3.66) [21]	51.69 (4.29) [18]	73.97 (2.21) [19]	83.99 (5.42) [19]	45.47 (4.30) [30]	67.09 (5.15) [14]	71.26 (3.88) [38]	13.97 (3.73) [33]	14.80 (1.00) [34]	22.00 (1.70) [38]	21.27 (0.94) [3]	18.64 (1.30) [24]	
	MCD	62.07 (4.14) [11]	55.69 (1.07) [11]	93.05 (2.26) [33]	70.48 (3.04) [17]	70.48 (2.75) [13]	58.33 (6.22) [17]	76.54 (2.86) [12]	87.06 (2.79) [14]	61.06 (5.38) [11]	71.49 (2.60) [11]	85.54 (3.40) [15]	13.46 (1.40) [15]	14.47 (3.45) [36]	17.87 (2.24) [33]	13.73 (2.79) [37]	16.43 (1.76) [34]
PCA	50.86 (1.59) [29]	50.00 (2.97) [30]	95.07 (2.67) [22]	61.96 (2.15) [36]	64.16 (1.93) [30]	45.58 (2.66) [36]	73.13 (2.66) [23]	80.23 (2.72) [35]	47.20 (3.84) [25]	59.03 (3.91) [31]	72.77 (2.78) [33]	14.62 (0.63) [21]	18.67 (1.01) [19]	21.60 (1.81) [12]	17.31 (1.50) [26]	18.98 (0.02) [1]	
	DeepSVD	67.7 (4.00) [9]	61.11 (4.94) [10]	96.09 (1.42) [10]	73.71 (3.52) [14]	68.57 (0.07) [14]	64.58 (0.07) [14]	81.59 (2.96) [8]	70.81 (4.72) [15]	64.66 (7.03) [10]	78.81 (2.09) [9]	82.76 (2.32) [16]	14.62 (1.48) [28]	16.60 (1.33) [28]	17.60 (1.29) [34]	14.21 (1.25) [40]	18.98 (0.02) [1]
IPNE	52.79 (4.48) [25]	53.75 (1.84) [17]	93.07 (6.09) [6]	60.82 (2.22) [33]	64.07 (2.83) [49]	48.90 (4.18) [28]	74.52 (2.47)										

Table 23: Mean, standard deviation and rank F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 7

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[illegible]

Table 25: Mean, standard deviation and rank AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 1

	2615	2614	2613	2612	2611	2610	2609	2608	2607	2606	2605	2604	2603	2602	2601	2599	2598	2597	2596	2595	2594	2593	2592	2591	2590	2589	2588	2587	2586	2585	2584	
Model	hsv anomalies cpt	hsv anomalies sd	hnp	InternetAds	homosphere	landut	letter	Lymphography	magic gamma	mnemography	ml	mtv	maist	mlcires	mask	nasa	optdigits	PageBlocks														
Iforest	43.66 (0.31) [20]	43.29 (0.70) [40]	56.48 (9.43) [29]	28.86 (1.12) [48]	92.71 (1.64) [30]	47.47 (3.22) [14]	8.35 (0.22) [42]	93.22 (3.07) [28]	80.28 (1.00) [22]	37.31 (0.37) [19]	34.98 (2.21) [21]	45.36 (1.36) [13]	54.13 (6.26) [29]	99.15 (0.44) [27]	50.33 (20.17) [41]	35.06 (6.21) [23]	15.20 (3.30) [19]	44.46 (1.17) [40]														
OC5VM	43.51 (0.42) [20]	46.97 (0.54) [21]	99.80 (0.38) [16]	48.06 (1.34) [21]	97.72 (0.39) [15]	36.87 (0.37) [32]	8.31 (0.10) [43]	92.93 (0.29) [21]	79.23 (0.29) [21]	40.26 (2.33) [13]	34.54 (0.36) [17]	46.64 (1.51) [14]	66.94 (1.83) [19]	32.98 (0.56) [22]	64.62 (1.21) [17]	32.98 (0.56) [22]	6.92 (0.09) [34]	64.62 (1.21) [17]														
ECOD	46.88 (0.33) [17]	48.05 (0.46) [16]	47.95 (5.96) [34]	44.11 (1.55) [33]	80.64 (0.26) [41]	34.66 (0.54) [36]	8.67 (0.41) [38]	95.59 (0.11) [23]	72.62 (0.34) [17]	54.62 (1.36) [21]	15.75 (0.00) [47]	26.97 (0.00) [48]	16.86 (0.00) [49]	77.68 (0.02) [38]	94.67 (2.36) [30]	34.70 (0.39) [37]	5.99 (0.00) [37]	41.74 (1.20) [41]														
UPPO	50.69 (0.27) [6]	52.24 (0.39) [8]	29.18 (1.34) [40]	41.15 (1.54) [32]	78.07 (2.25) [14]	31.87 (0.40) [46]	10.04 (0.70) [23]	94.58 (0.25) [25]	68.52 (0.34) [25]	55.08 (1.32) [11]	15.75 (0.00) [47]	26.97 (0.00) [48]	16.86 (0.00) [49]	72.68 (0.02) [38]	99.17 (0.00) [29]	26.20 (0.18) [38]	5.90 (0.00) [37]	59.91 (1.42) [30]														
Fontenblugging	45.15 (0.60) [11]	42.49 (1.94) [17]	43.83 (8.06) [44]	51.33 (0.27) [14]	95.81 (1.11) [34]	61.45 (0.75) [11]	11.93 (1.12) [14]	67.79 (0.28) [18]	86.79 (0.28) [8]	29.95 (2.86) [27]	25.99 (0.42) [21]	41.67 (0.54) [23]	70.14 (1.13) [16]	100.00 (0.00) [1]	100.00 (0.00) [1]	35.71 (0.79) [19]	40.73 (3.28) [18]	70.83 (0.56) [44]														
HB05	42.14 (0.52) [19]	54.86 (0.31) [15]	37.29 (9.56) [38]	31.01 (1.51) [46]	64.91 (2.55) [46]	60.32 (0.67) [4]	8.78 (0.19) [43]	96.75 (0.19) [21]	77.22 (0.28) [12]	21.31 (1.67) [34]	34.76 (0.20) [15]	41.63 (0.54) [23]	22.16 (0.48) [44]	97.87 (0.88) [30]	100.00 (0.00) [1]	24.47 (0.40) [14]	43.99 (1.46) [44]	22.49 (0.69) [48]														
KNN	45.43 (0.41) [22]	49.51 (0.29) [13]	100.00 (0.00) [1]	49.51 (0.31) [20]	98.06 (0.55) [12]	54.96 (1.03) [8]	8.78 (0.12) [33]	98.95 (0.93) [13]	85.96 (0.15) [12]	40.30 (3.10) [12]	21.70 (0.48) [31]	47.50 (0.59) [6]	73.13 (1.42) [18]	100.00 (0.00) [1]	100.00 (0.00) [1]	40.00 (0.54) [12]	29.12 (1.56) [33]	67.93 (1.13) [10]														
LOF	41.56 (2.63) [44]	42.29 (2.76) [46]	7.81 (8.73) [45]	41.27 (2.48) [36]	85.20 (0.17) [23]	33.82 (1.54) [38]	8.07 (0.15) [49]	28.86 (1.96) [45]	75.96 (0.88) [31]	43.85 (5.68) [6]	34.67 (7.19) [6]	28.67 (4.78) [45]	34.79 (7.75) [41]	99.81 (0.21) [26]	91.99 (10.38) [12]	34.38 (3.55) [26]	4.27 (0.64) [46]	42.72 (2.30) [35]														
LDA	47.94 (0.58) [12]	52.51 (0.47) [12]	91.18 (3.50) [10]	50.09 (1.15) [16]	94.81 (1.23) [16]	61.30 (0.71) [12]	11.60 (1.30) [12]	74.86 (1.72) [33]	94.81 (0.34) [17]	34.12 (3.24) [26]	26.80 (0.18) [40]	24.71 (1.10) [30]	71.99 (1.00) [24]	100.00 (0.00) [1]	100.00 (0.00) [1]	35.51 (0.62) [20]	42.80 (0.36) [46]	71.09 (0.18) [4]														

Model	Parkinson	perisylla	pen-global	pen-local	Pima	satellite	satimage-2	sonnet-humps	shuttle	skin	libras	Spambase	speech	Stumps	thyroid	vertebral	vowels	Wormform
Boost	97.02 (0.50) [24]	57.17 (7.18) [16]	90.30 (3.50) [23]	1.16 (0.09) [31]	75.58 (1.48) [13]	81.94 (1.12) [24]	95.25 (0.55) [16]	16.87 (1.64) [30]	98.54 (0.37) [14]	64.28 (1.25) [21]	1.18 (0.10) [45]	87.18 (0.93) [3]	3.73 (1.14) [12]	64.00 (6.25) [21]	80.57 (5.33) [13]	19.52 (2.00) [30]	12.85 (3.47) [24]	11.09 (1.70) [24]
OCVM	97.51 (0.38) [21]	51.24 (4.08) [20]	91.46 (0.76) [17]	0.57 (0.08) [31]	70.26 (2.67) [14]	80.70 (0.59) [4]	90.70 (0.59) [4]	16.14 (1.13) [32]	97.10 (0.28) [20]	70.26 (6.14) [52]	82.20 (0.48) [19]	83.01 (0.73) [4]	70.21 (6.86) [13]	79.86 (6.01) [24]	80.89 (2.15) [17]	30.52 (3.37) [21]	11.61 (0.82) [22]	
COPROD	97.07 (0.84) [19]	31.79 (3.01) [1]	92.04 (3.02) [44]	0.38 (0.03) [43]	72.21 (1.25) [19]	74.72 (3.34) [19]	91.00 (1.09) [29]	12.35 (0.00) [47]	98.46 (0.15) [29]	38.48 (0.25) [19]	1.17 (0.14) [46]	75.84 (0.73) [3]	2.94 (3.48) [47]	61.03 (3.23) [25]	35.53 (1.46) [45]	15.00 (1.92) [56]	6.56 (0.42) [47]	10.74 (0.75) [26]
ECOD	83.78 (1.24) [46]	42.41 (3.49) [21]	42.74 (3.24) [43]	0.40 (0.04) [41]	68.7 (1.58) [31]	70.90 (0.47) [43]	83.94 (1.06) [43]	12.35 (0.00) [47]	96.31 (0.20) [29]	31.16 (0.21) [46]	75.58 (0.11) [1]	73.86 (0.80) [35]	3.37 (0.59) [47]	54.96 (4.71) [26]	20.54 (5.68) [28]	12.81 (0.88) [47]	8.18 (0.69) [46]	
FeatureBagging	97.18 (0.66) [23]	83.00 (0.96) [29]	94.66 (2.42) [15]	42.13 (4.27) [2]	69.19 (2.89) [25]	85.78 (0.38) [49]	91.79 (1.61) [22]	25.44 (1.07) [18]	45.54 (23.74) [49]	49.39 (1.27) [31]	0.27 (0.05) [49]	67.51 (1.43) [41]	3.48 (5.51) [42]	70.44 (6.87) [12]	37.86 (17.83) [44]	29.52 (3.21) [42]	37.21 (3.14) [44]	30.87 (4.42) [2]
HROS	98.98 (0.23) [13]	47.14 (4.19) [23]	42.71 (4.06) [37]	0.81 (0.12) [37]	77.70 (1.75) [24]	86.23 (0.21) [47]	94.64 (2.25) [21]	18.66 (0.55) [21]	97.47 (0.07) [21]	52.99 (0.04) [28]	1.39 (0.20) [42]	75.96 (0.84) [31]	3.83 (9.92) [10]	55.58 (2.93) [31]	88.57 (0.53) [20]	17.57 (2.44) [44]	8.57 (0.28) [40]	
KNN	98.63 (0.41) [15]	96.48 (0.64) [4]	99.09 (0.21) [7]	29.30 (5.87) [7]	77.16 (1.76) [10]	83.92 (0.53) [41]	97.12 (0.69) [3]	18.48 (0.88) [26]	98.04 (0.39) [29]	98.25 (0.36) [2]	57.95 (0.63) [8]	83.36 (0.42) [13]	3.19 (0.46) [32]	75.56 (8.29) [8]	82.77 (1.83) [2]	24.53 (2.86) [19]	31.33 (2.58) [19]	26.15 (2.59) [7]
LORA	95.11 (1.43) [34]	40.49 (9.76) [24]	53.85 (1.39) [33]	0.39 (0.06) [42]	62.47 (4.37) [26]	74.98 (0.98) [30]	94.19 (0.92) [18]	9.55 (2.48) [50]	43.35 (3.62) [40]	52.05 (6.95) [29]	9.39 (7.71) [34]	83.49 (3.46) [12]	3.47 (1.11) [23]	59.32 (7.45) [27]	68.6 (6.01) [28]	16.00 (1.71) [47]	12.20 (3.97) [2]	8.12 (1.36) [4]
LOF	98.68 (0.58) [26]	76.67 (2.34) [10]	94.92 (0.56) [13]	31.49 (7.99) [4]	60.67 (2.28) [3]	80.36 (0.41) [5]	89.61 (1.40) [29]	19.31 (0.94) [19]	99.81 (0.11) [4]	61.68 (1.82) [26]	57.36 (0.18) [43]	73.26 (0.43) [13]	69.45 (9.12) [94]	61.93 (3.11) [23]	79.78 (6.66) [12]	29.26 (2.76) [4]	9.26 (0.38) [2]	
MCD	98.38 (0.89) [30]	31.84 (1.04) [41]	53.08 (4.61) [34]	0.51 (0.03) [49]	69.31 (2.49) [24]	79.79 (3.04) [19]	92.21 (0.42) [1]	37.16 (5.28) [15]	62.34 (0.40) [43]	1.26 (0.20) [44]	81.87 (0.49) [26]	3.16 (0.39) [40]	43.80 (5.74) [9]	81.78 (9.12) [9]	19.82 (2.34) [37]	43.7 (0.09) [48]	8.32 (0.79) [38]	
PCA	96.39 (0.50) [29]	38.18 (2.97) [26]	56.60 (4.90) [26]	0.33 (0.03) [44]	73.06 (2.43) [16]	77.72 (0.54) [36]	92.26 (0.67) [21]	0.00 (0.00) [51]	96.41 (0.37) [27]	36.24 (0.22) [42]	3.17 (0.17) [47]	82.62 (0.44) [20]	82.69 (1.24) [49]	17.78 (1.40) [43]	12.21 (2.88) [36]	9.26 (0.82) [33]	9.26 (0.82) [33]	
DeepSVD++	99.01 (0.06) [1]	81.23 (5.99) [46]	91.67 (5.33) [22]	11.51 (12.15) [16]	80.67 (2.49) [41]	79.17 (1.74) [33]	97.37 (1.45) [3]	61.47 (5.36) [3]	98.13 (0.25) [18]	42.49 (1.29) [35]	43.45 (2.54) [25]							

Table 27: Mean, standard deviation and rank AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 3

[illegible]

Table 28: Mean, standard deviation and rank AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 4

Table 29: Mean, standard deviation and rank AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 5

Model	MNIST-C identity	MNIST-C impulse noise	MNIST-C motion blur	MNIST-C rotate	MNIST-C scale	MNIST-C shear	MNIST-C shot noise	MNIST-C spatter	MNIST-C stripe	MNIST-C translate	MNIST-C zigzag	MVTec-AD bottle	MVTec-AD cable	MVTec-AD capsule	MVTec-AD carpet
IResnet	9.15 (0.00) [40]	90.28 (3.77) [31]	32.23 (2.18) [36]	10.70 (0.30) [35]	15.20 (1.80) [32]	16.39 (0.71) [32]	24.63 (1.55) [30]	38.62 (3.91) [30]	87.41 (1.63) [30]	12.23 (0.39) [36]	31.25 (1.13) [30]	96.63 (1.05) [21]	61.14 (4.37) [28]	68.04 (2.67) [29]	68.66 (4.97) [31]
OCSVM	9.22 (0.22) [31]	97.81 (0.39) [24]	56.52 (2.00) [21]	11.66 (0.39) [24]	23.85 (0.85) [19]	19.07 (0.97) [23]	31.07 (1.83) [21]	47.04 (1.61) [19]	97.98 (0.50) [20]	14.99 (0.56) [25]	45.25 (1.68) [21]	96.60 (1.02) [23]	62.46 (4.36) [23]	68.55 (2.06) [27]	70.81 (4.22) [24]
COPOD	9.52 (0.00) [6]	9.52 (0.00) [46]	9.52 (0.00) [47]	9.52 (0.00) [46]	9.52 (0.00) [41]	9.52 (0.00) [45]	9.52 (0.00) [48]	9.52 (0.00) [46]	9.52 (0.00) [47]	9.52 (0.00) [45]	9.52 (0.00) [45]	34.95 (1.53) [48]	38.81 (1.60) [45]	46.73 (0.78) [46]	37.81 (2.05) [47]
ECOD	9.52 (0.00) [6]	9.52 (0.00) [46]	9.52 (0.00) [47]	9.52 (0.00) [46]	9.52 (0.00) [41]	9.52 (0.00) [45]	9.52 (0.00) [48]	9.52 (0.00) [46]	9.52 (0.00) [47]	9.52 (0.00) [45]	9.52 (0.00) [45]	34.95 (1.53) [48]	38.81 (1.60) [45]	46.73 (0.78) [46]	37.81 (2.05) [47]
FeatureBagging	9.18 (0.22) [36]	99.23 (0.25) [17]	70.00 (0.22) [6]	14.73 (0.52) [6]	35.41 (1.20) [7]	24.94 (1.22) [4]	45.97 (1.72) [4]	62.83 (0.66) [6]	98.67 (0.27) [7]	26.39 (1.03) [5]	59.38 (1.35) [9]	97.08 (0.81) [10]	66.38 (4.29) [15]	73.21 (2.63) [18]	71.90 (4.21) [18]
HBOS	9.25 (0.21) [26]	48.08 (1.33) [41]	22.90 (0.63) [40]	10.86 (0.25) [34]	9.77 (0.24) [40]	15.34 (0.84) [34]	16.75 (0.52) [39]	25.37 (0.98) [38]	65.69 (1.38) [36]	10.26 (0.24) [42]	19.32 (0.39) [40]	96.54 (1.15) [25]	62.20 (4.63) [25]	67.93 (1.63) [31]	70.60 (4.67) [27]
KNN	9.13 (0.21) [42]	99.51 (0.19) [12]	63.55 (1.87) [14]	13.46 (0.45) [14]	28.35 (1.01) [12]	21.57 (1.14) [14]	38.58 (1.84) [10]	53.34 (1.33) [13]	98.34 (0.32) [9]	19.29 (0.55) [17]	52.91 (1.72) [14]	96.96 (1.04) [13]	65.96 (4.34) [19]	73.51 (2.06) [15]	72.34 (4.19) [15]
LODA	9.03 (0.42) [46]	97.14 (2.97) [25]	41.80 (5.74) [30]	10.04 (0.95) [38]	15.20 (2.54) [32]	13.35 (1.62) [38]	20.38 (5.11) [35]	36.02 (7.34) [32]	89.02 (4.40) [29]	12.03 (0.85) [38]	26.76 (6.97) [34]	94.48 (0.62) [32]	56.06 (7.01) [33]	66.00 (4.14) [34]	62.38 (3.37) [34]
LOF	9.18 (0.22) [36]	99.17 (0.29) [19]	70.00 (1.80) [6]	14.72 (0.42) [7]	36.03 (1.46) [4]	24.70 (1.32) [5]	45.77 (1.77) [5]	61.77 (0.76) [7]	98.72 (0.14) [5]	26.03 (0.68) [8]	59.48 (1.30) [7]	96.95 (0.96) [14]	66.24 (4.14) [17]	73.40 (2.73) [16]	71.58 (4.02) [22]
MCD	9.58 (0.28) [4]	67.99 (0.08) [36]	29.42 (7.51) [38]	11.12 (0.62) [30]	17.38 (2.53) [28]	14.20 (0.96) [37]	18.31 (0.93) [36]	31.99 (5.04) [35]	77.49 (16.80) [33]	12.83 (0.30) [33]	23.82 (1.90) [37]	97.10 (1.86) [9]	71.46 (4.59) [12]	80.68 (1.65) [11]	72.49 (5.30) [14]
PCA	9.22 (0.22) [31]	99.51 (0.19) [12]	54.58 (1.83) [24]	11.45 (0.37) [28]	22.03 (0.81) [23]	18.50 (0.95) [26]	29.25 (1.77) [24]	44.51 (1.54) [22]	97.99 (0.36) [16]	14.30 (0.49) [30]	42.97 (1.78) [22]	96.37 (1.03) [26]	60.77 (4.42) [29]	60.64 (4.26) [25]	
DeepSVDD	9.41 (0.17) [14]	95.44 (2.10) [27]	43.80 (1.65) [28]	10.68 (0.69) [36]	16.22 (2.45) [30]	13.24 (0.92) [39]	17.74 (2.33) [37]	28.68 (4.32) [36]	85.96 (1.92) [31]	12.09 (1.17) [37]	21.73 (4.76) [39]	95.89 (2.42) [29]	77.61 (3.43) [10]	76.57 (6.47) [14]	83.63 (1.86) [8]
INNE	9.30 (0.23) [22]	88.82 (0.85) [32]	59.97 (1.34) [17]	12.14 (0.39) [20]	28.31 (1.82) [13]	21.37 (1.42) [16]	36.99 (2.49) [13]	58.70 (2.63) [9]	89.04 (0.47) [28]	17.94 (0.92) [20]	56.87 (2.00) [10]	96.81 (1.12) [19]	65.62 (4.01) [20]	71.44 (2.00) [22]	71.87 (4.00) [19]
KPCA	8.66 (0.13) [51]	95.71 (0.53) [26]	66.10 (1.60) [10]	13.72 (0.50) [12]	29.55 (0.93) [10]	22.25 (1.28) [11]	40.19 (1.81) [9]	56.25 (1.88) [11]	97.37 (0.49) [22]	20.63 (0.65) [15]	55.46 (1.66) [12]	99.06 (0.63) [2]	83.72 (3.35) [1]	91.10 (2.06) [2]	86.82 (1.75) [3]
KDE	8.70 (0.18) [49]	99.62 (0.18) [7]	58.57 (2.32) [18]	12.13 (0.35) [21]	20.15 (0.79) [26]	17.44 (0.49) [29]	29.35 (1.27) [23]	41.97 (1.28) [26]	97.15 (0.72) [23]	16.79 (0.59) [21]	39.09 (3.55) [27]	98.53 (0.62) [7]	79.89 (4.79) [8]	89.87 (1.71) [3]	86.33 (1.68) [4]
GMM	9.18 (0.13) [36]	99.45 (0.31) [16]	69.66 (1.71) [9]	14.54 (0.55) [9]	35.42 (1.02) [6]	24.28 (1.32) [7]	43.75 (1.81) [8]	64.94 (1.31) [4]	97.99 (0.79) [16]	26.29 (0.73) [6]	59.74 (1.79) [6]	91.30 (1.80) [1]	83.28 (3.91) [3]	92.61 (1.14) [45]	86.91 (1.77) [2]
CBLOF	9.22 (0.20) [31]	99.51 (0.19) [12]	57.64 (1.84) [19]	12.09 (0.38) [23]	26.35 (0.95) [18]	19.60 (0.99) [20]	32.51 (1.80) [19]	47.30 (1.49) [18]	98.10 (0.35) [13]	15.91 (0.43) [23]	46.12 (1.81) [18]	97.05 (1.07) [11]	65.04 (4.30) [22]	72.33 (2.33) [20]	71.95 (4.25) [16]
SOD	8.93 (0.19) [47]	79.17 (2.33) [34]	46.72 (2.26) [26]	12.72 (0.52) [17]	11.22 (0.54) [38]	18.93 (0.87) [24]	25.18 (1.26) [27]	43.34 (1.03) [25]	75.12 (2.06) [34]	21.14 (0.65) [14]	39.05 (2.12) [28]	91.99 (1.93) [40]	43.66 (2.97) [41]	58.17 (2.91) [40]	58.47 (2.93) [36]
LUNAR	9.48 (0.10) [11]	98.09 (1.11) [21]	80.60 (1.49) [1]	18.21 (0.57) [1]	44.36 (1.47) [2]	28.65 (1.96) [1]	61.18 (2.15) [1]	75.29 (2.06) [1]	98.28 (2.52) [10]	33.25 (0.53) [3]	73.53 (1.48) [1]	98.74 (0.60) [6]	77.87 (6.50) [9]	82.45 (3.01) [8]	78.69 (4.83) [10]
SOGAL	9.48 (0.62) [11]	58.62 (19.63) [38]	20.15 (5.88) [42]	9.63 (0.31) [45]	8.87 (1.68) [47]	9.06 (0.65) [50]	10.04 (1.56) [46]	7.96 (0.77) [49]	17.54 (9.96) [45]	8.45 (0.22) [50]	7.62 (0.57) [50]	78.03 (4.86) [37]	43.37 (2.98) [43]	56.35 (5.87) [43]	50.24 (9.73) [43]
ALAD	9.45 (0.13) [49]	23.32 (12.99) [44]	17.27 (0.64) [43]	9.29 (0.83) [50]	10.00 (0.87) [44]	11.25 (1.40) [44]	15.05 (4.05) [44]	15.05 (4.05) [44]	25.18 (13.16) [41]	9.73 (0.79) [43]	13.59 (2.83) [42]	63.76 (13.39) [43]	42.67 (1.93) [44]	52.61 (1.14) [45]	47.89 (2.36) [44]
AE	9.27 (0.22) [23]	99.52 (0.19) [10]	62.34 (1.81) [15]	13.03 (0.41) [16]	28.10 (0.94) [14]	21.49 (1.14) [15]	35.33 (1.89) [15]	52.63 (1.35) [15]	98.28 (0.32) [10]	18.54 (0.53) [18]	51.56 (1.72) [15]	97.02 (0.87) [12]	66.34 (4.45) [16]	71.76 (2.52) [21]	71.92 (2.60) [17]
CD	9.52 (0.00) [46]	9.52 (0.00) [46]	9.52 (0.00) [46]	9.52 (0.00) [46]	9.52 (0.00) [41]	9.52 (0.00) [45]	10.78 (2.52) [45]	18.36 (10.83) [41]	35.62 (14.34) [40]	9.52 (0.00) [45]	9.52 (0.00) [45]	34.95 (1.53) [48]	38.81 (1.60) [45]	45.08 (0.37) [49]	36.66 (1.87) [50]
MOGAL	9.55 (0.63) [5]	58.75 (25.00) [37]	22.90 (4.43) [40]	9.92 (0.44) [40]	8.13 (1.02) [49]	9.57 (0.17) [49]	9.53 (1.32) [47]	17.89 (12.75) [44]	8.60 (0.69) [49]	8.35 (0.86) [49]	8.08 (0.63) [49]	69.03 (6.13) [36]	43.52 (3.37) [42]	57.32 (3.37) [41]	52.91 (9.72) [42]
QMCD	20.91 (1.14) [1]	93.89 (0.92) [29]	5.27 (0.17) [51]	6.71 (0.13) [51]	5.50 (0.03) [51]	6.05 (0.12) [51]	5.17 (0.02) [51]	5.06 (0.01) [51]	22.87 (0.90) [51]	5.83 (0.04) [51]	5.09 (0.01) [51]	69.03 (1.45) [41]	23.64 (1.26) [51]	37.45 (0.77) [51]	34.63 (3.67) [51]
Sampling	9.41 (0.25) [14]	99.52 (0.19) [10]	57.27 (1.34) [20]	11.58 (0.25) [26]	23.10 (1.77) [22]	19.18 (0.68) [22]	31.47 (1.29) [20]	46.08 (1.43) [21]	98.09 (0.37) [14]	15.70 (0.78) [24]	45.50 (1.54) [19]	96.55 (0.98) [24]	61.99 (4.61) [27]	71.31 (1.46) [23]	72.59 (4.85) [13]
EIF	9.15 (0.17) [40]	94.27 (2.73) [28]	35.01 (3.08) [34]	10.90 (0.37) [33]	16.75 (2.68) [29]	16.84 (1.42) [30]	24.91 (2.06) [28]	40.87 (5.74) [28]	92.32 (1.02) [25]	12.39 (0.57) [35]	33.55 (3.51) [29]	96.84 (1.09) [17]	62.29 (4.84) [24]	69.13 (1.82) [26]	69.43 (4.84) [29]
Ensemble	9.18 (0.22) [36]	99.17 (0.29) [19]	70.00 (1.80) [6]	14.72 (0.42) [7]	36.03 (1.46) [4]	24.70 (1.32) [5]	45.77 (1.77) [5]	61.77 (0.76) [7]	98.72 (0.14) [5]	26.03 (0.68) [8]	59.48 (1.30) [7]	96.95 (0.96) [14]	66.24 (4.14) [17]	73.40 (2.73) [16]	71.58 (4.02) [22]
GENOUT	9.21 (0.19) [35]	97.98 (1.13) [23]	38.79 (6.36) [32]	11.01 (0.73) [31]	14.24 (2.61) [35]	16.81 (1.59) [31]	23.87 (1.93) [32]	41.79 (6.48) [27]	91.75 (5.22) [27]	12.41 (0.61) [34]	30.70 (5.93) [31]	96.84 (0.93) [17]	66.60 (6.21) [13]	70.78 (0.63) [25]	69.36 (5.29) [30]
DynamicHBOS	9.41 (0.09) [14]	42.41 (0.97) [42]	14.69 (0.40) [44]	9.74 (0.04) [42]	9.32 (0.02) [45]	11.48 (0.56) [43]	11.62 (0.37) [43]	16.36 (0.95) [42]	51.33 (0.96) [38]	9.55 (0.12) [44]	12.68 (0.26) [44]	76.52 (1.98) [39]	47.27 (3.39) [39]	55.21 (1.24) [44]	57.24 (2.68) [37]
COF	9.09 (0.11) [43]	12.33 (0.36) [45]	33.94 (1.69) [35]	13.69 (0.23) [13]	7.93 (0.15) [50]	22.01 (0.84) [12]	24.70 (1.25) [29]	36.28 (1.34) [31]	13.51 (0.77) [46]	22.21 (0.56) [12]	42.81 (2.03) [24]	57.92 (5.72) [44]	45.43 (5.80) [40]	59.52 (2.38) [38]	55.84 (3.09) [40]
ABOD	9.36 (0.11) [19]	99.76 (0.12) [5]	72.41 (1.60) [5]	14.91 (0.39) [5]	29.96 (1.06) [9]	23.64 (1.35) [9]	44.49 (1.84) [7]	64.59 (1.03) [5]	98.99 (0.26) [1]	26.14 (0.80) [7]	62.75 (1.91) [4]	37.00 (2.63) [47]	38.26 (2.20) [49]	44.80 (2.06) [50]	40.84 (4.24) [46]
LMDD	9.25 (0.12) [26]	73.32 (26.94) [35]	40.24 (2.65) [31]	10.01 (0.15) [39]	12.44 (1.83) [37]	15.28 (0.73) [35]	21.39 (3.23) [34]	34.38 (2.07) [34]	83.41 (21.42) [32]	11.25 (0.46) [33]	28.49 (5.46) [33]	71.13 (5.84) [40]	51.06 (6.72) [36]	58.80 (1.77) [39]	56.11 (3.11) [39]
DAGMM	9.52 (0.45) [6]	50.20 (25.32) [40]	29.79 (6.95) [37]	9.88 (0.38) [41]	17.98 (16.25) [27]	13.23 (0.59) [40]	17.05 (3.14) [38]	26.01 (6.72) [37]	61.14 (25.37) [37]	11.25 (0.27) [39]	21.92 (6.74) [38]	76.87 (8.15) [38]	48.11 (5.47) [38]	56.97 (5.13) [42]	57.05 (9.93) [38]
DBOCC	9.05 (0.42) [44]	82.06 (19.77) [33]	35.42 (5.94) [33]	12.13 (1.43) [21]	14.86 (6.30) [34]	14.92 (2.02) [36]	24.32 (6.67) [31]	24.60 (7.18) [39]	71.08 (4.92) [35]	14.75 (2.38) [27]	29.24 (11.22) [32]	89.33 (7.84) [35]	49.99 (5.33) [37]	60.24 (5.57) [36]	61.47 (11.03) [35]
GOAD	9.23 (0.22) [28]	99.53 (0.18) [9]	55.68 (1.85) [22]	11.55 (0.45) [27]	23.20 (1.09) [21]	18.91 (0.89) [25]	30.93 (1.52) [22]	46.21 (1.57) [20]	97.99 (0.42) [16]	14.80 (0.54) [26]	45.39 (2.36) [20]	96.29 (1.14) [28]	62.03 (4.42) [26]	68.40 (1.97) [28]	71.66 (2.40) [21]
ICL	8.90 (0.10) [48]	99.71 (0.13) [6]	74.54 (1.69) [4]	15.12 (0.71) [4]	30.61 (3.21) [8]	23.99 (0.89) [8]	38.03 (2.77) [12]	57.34 (1.17) [10]	98.91 (0.37) [12]	29.01 (1.17) [4]	60.49 (1.78) [5]	98.26 (0.74) [8]	82.72 (2.68) [6]	89.27 (2.56) [4]	87.93 (2.65) [1]
PlanerFlow	9.39 (0.15) [18]	98.70 (0.49) [22]	45.54 (1.46) [27]	10.12 (0.47) [37]	15.57 (3.03) [31]	16.33 (0.99) [33]	21.71 (2.38) [33]	35.42 (1.95) [33]	94.42 (2.16) [24]	10.80 (0.54) [41]	25.90 (1.67) [36]	95.47 (1.65) [30]	54.19 (4.40) [35]	66.18 (1.55) [33]	65.72 (4.69) [33]
VAE	9.22 (0.22) [31]	99.51 (0.19) [12]	54.58 (1.83) [24]	11.45 (0.37) [28]	22.03 (0.81) [23]	18.50 (0.95) [26]	29.25 (1.77) [24]	44.51 (1.54) [22]	97.99 (0.36) [16]	14.31 (0.49) [29]	42.97 (1.78) [22]	96.36 (1.04) [27]	60.71 (4.23) [30]	67.91 (2.16) [32]	70.62 (4.26) [26]
GANomaly	9.27 (0.25) [23]	99.18 (0.55) [18]	63.57 (3.48) [13]	11.66 (0.47) [24]	23.67 (1.80) [20]	19.35 (0.94) [21]	32.88 (3.12) [18]	47.31 (2.70) [17]	97.84 (0.41) [21]	15.97 (0.42) [22]	49.19 (2.10) [17]	96.83 (0.81) [21]	66.40 (4.88) [14]	72.93 (2.01) [19]	72.84 (3.42) [12]
SLAD	9.23 (0.13) [28]	99.87 (0.02) [1]	64.37 (1.76) [11]	12.64 (0.52) [18]	27.01 (0.95) [16]	21.81 (0.97) [13]	36.35 (1.53) [14]	54.59 (1.52) [12]	98.53 (0.36) [8]	21.68 (0.61) [13]	53.25 (1.85) [13]	99.03 (0.43) [3]	83.19 (2.28) [4]	88.63 (1.58) [7]	85.47 (2.32) [7]
DIF	9.71 (0.21) [3]	7.12 (0.17) [51]	11.69 (0.19) [46]	9.66 (0.37) [43]</											

[illegible]

Table 31: Mean, standard deviation and rank AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 7

		2781	2782	2783	2784	2785	2786	2787	2788	2789	2790	2791	2792	2793	2794	2795	2796	2797	2798	2799	2800	2801	2802	2803	2804	2805	2806	2807	2808	2809	2810	2811	2812	2813
		2813	2812	2811	2810	2809	2808	2807	2806	2805	2804	2803	2802	2801	2800	2799	2798	2797	2796	2795	2794	2793	2792	2791	2790	2789	2788	2787	2786	2785	2784	2783	2782	2781
Model	SVHN 5	SVHN 6	SVHN 7	SVHN 8	SVHN 9	agnews 0	agnews 1	agnews 2	agnews 3	amazon	imdb	yelp	20news 0	20news 1	20news 2	20news 3	20news 4	20news 5																
ffinet	14.39 (0.86) [31]	11.58 (0.89) [33]	17.50 (1.32) [11]	11.73 (0.85) [36]	10.71 (0.75) [36]	10.70 (0.27) [30]	11.41 (0.40) [29]	14.79 (0.34) [31]	11.58 (0.19) [32]	11.15 (0.81) [22]	8.90 (0.24) [35]	13.68 (0.82) [27]	12.97 (0.60) [30]	9.01 (0.45) [42]	8.93 (0.73) [44]	17.88 (3.65) [28]	12.49 (1.35) [21]	11.68 (1.60) [35]																
OCSVM	16.63 (0.70) [19]	12.98 (0.75) [22]	17.50 (1.03) [11]	14.50 (0.80) [25]	12.32 (1.07) [22]	11.18 (0.36) [28]	11.83 (0.33) [26]	16.31 (0.46) [25]	12.59 (0.26) [24]	11.20 (0.70) [20]	8.89 (0.15) [37]	13.98 (0.90) [19]	14.03 (0.44) [27]	9.11 (0.35) [39]	9.06 (0.60) [37]	19.52 (5.55) [22]	12.23 (1.34) [24]	11.82 (1.40) [32]																
COPOD	9.51 (0.00) [47]	9.53 (0.00) [47]	9.49 (0.00) [47]	9.50 (0.00) [44]	9.52 (0.00) [45]	10.05 (0.25) [37]	9.53 (0.17) [45]	14.09 (0.41) [35]	11.18 (0.32) [36]	11.35 (0.64) [16]	9.26 (0.10) [14]	13.87 (0.82) [23]	11.97 (0.54) [37]	9.03 (0.41) [41]	8.54 (0.62) [50]	18.43 (5.08) [26]	11.83 (1.32) [30]	11.22 (1.57) [39]																
ECOD	9.51 (0.00) [47]	9.53 (0.00) [47]	9.49 (0.00) [47]	9.50 (0.00) [44]	9.52 (0.00) [45]	9.57 (0.29) [45]	11.35 (0.44) [33]	12.71 (0.65) [33]	10.87 (0.29) [38]	10.46 (0.67) [36]	8.50 (0.15) [50]	12.48 (0.74) [35]	11.85 (0.75) [38]	8.67 (0.21) [48]	9.17 (0.71) [34]	17.03 (3.12) [33]	11.81 (0.92) [31]	12.28 (2.05) [24]																
FeatureBagging	18.49 (1.02) [5]	13.79 (0.61) [5]	17.42 (1.01) [14]	16.43 (0.76) [2]	13.50 (1.18) [7]	18.07 (0.73) [5]	31.58 (1.04) [2]	29.82 (1.66) [3]	24.48 (1.40) [3]	11.03 (0.49) [24]	9.09 (0.15) [22]	15.85 (1.03) [12]	26.93 (2.05) [5]	10.69 (1.01) [23]	10.10 (0.49) [12]	21.14 (4.84) [15]	12.86 (1.52) [16]	13.76 (1.81) [9]																
HBOS	10.85 (0.41) [45]	9.46 (0.34) [50]	16.40 (1.30) [28]	8.95 (0.52) [50]	9.04 (0.37) [50]	9.95 (0.26) [40]	10.46 (0.21) [37]	13.67 (0.45) [36]	11.08 (0.32) [37]	11.32 (0.78) [17]	8.94 (0.09) [31]	13.57 (0.85) [28]	11.69 (0.42) [39]	8.97 (0.45) [45]	8.58 (0.61) [49]	17.56 (4.40) [31]	12.89 (1.67) [15]	11.71 (1.49) [34]																
KNN	16.99 (0.78) [15]	13.28 (0.76) [15]	17.31 (1.01) [18]	15.15 (0.92) [14]	12.56 (1.08) [19]	13.52 (0.26) [16]	14.87 (0.39) [19]	21.86 (0.54) [17]	16.87 (0.63) [16]	11.90 (0.59) [46]	8.96 (0.16) [30]	16.27 (1.13) [7]	19.90 (0.87) [16]	11.15 (1.26) [16]	9.19 (0.29) [32]	23.51 (6.47) [11]	11.20 (1.51) [41]	11.99 (1.83) [26]																
LODA	14.05 (1.53) [33]	10.67 (1.39) [41]	15.76 (1.33) [31]	13.00 (2.22) [30]	11.00 (1.49) [34]	12.15 (0.94) [22]	10.11 (1.31) [39]	15.04 (1.48) [30]	11.57 (0.82) [33]	10.72 (0.94) [34]	8.65 (0.38) [47]	13.00 (2.46) [34]	10.57 (0.81) [41]	9.32 (1.06) [34]	9.08 (0.39) [36]	19.09 (5.41) [23]	13.07 (1.58) [10]	11.04 (2.27) [41]																
LOF	18.52 (1.07) [3]	13.78 (0.58) [6]	17.31 (0.96) [18]	16.19 (0.93) [3]	13.49 (1.14) [8]	18.12 (0.69) [3]	31.50 (1.07) [3]	29.75 (1.72) [4]	24.48 (1.37) [3]	11.01 (0.50) [25]	9.10 (0.13) [19]	15.91 (0.98) [10]	27.16 (1.88) [3]	10.79 (0.95) [19]	10.14 (0.52) [10]	20.96 (4.91) [17]	12.83 (1.53) [17]	13.72 (1.87) [10]																
MCD	12.37 (0.84) [39]	11.40 (0.51) [35]	12.29 (0.59) [38]	13.05 (1.43) [29]	12.45 (1.85) [20]	12.71 (0.17) [19]	13.92 (0.23) [21]	18.71 (0.29) [20]	13.25 (0.37) [23]	11.84 (0.68) [8]	9.48 (0.28) [10]	14.25 (0.56) [17]	16.40 (0.47) [20]	10.75 (0.70) [21]	9.85 (0.52) [17]	20.50 (6.72) [19]	13.78 (1.84) [6]	19.44 (2.68) [4]																
PCA	16.30 (0.67) [23]	12.80 (0.80) [23]	17.58 (1.03) [8]	14.35 (0.90) [26]	12.08 (1.05) [27]	10.03 (0.34) [38]	11.39 (0.27) [30]	14.26 (0.46) [33]	11.40 (0.29) [34]	10.87 (0.68) [29]	8.72 (0.15) [44]	13.34 (0.85) [30]	12.63 (0.77) [33]	8.96 (0.33) [44]	8.96 (0.62) [38]	17.62 (4.46) [29]	11.72 (1.33) [32]	11.06 (1.54) [27]																
DeepSVDD	14.51 (0.75) [29]	11.84 (1.28) [30]	11.87 (0.46) [40]	12.47 (0.54) [31]	11.24 (1.00) [31]	10.22 (1.51) [34]	9.38 (0.93) [48]	13.61 (1.23) [42]	9.7 (1.15) [48]	10.23 (1.19) [41]	8.64 (0.50) [48]	10.13 (0.50) [46]	12.39 (1.66) [35]	9.06 (0.88) [40]	10.59 (1.47) [7]	22.98 (3.13) [12]	12.85 (1.20) [26]	12.35 (1.28) [22]																
INNE	16.94 (0.96) [17]	13.71 (0.98) [9]	17.74 (0.94) [6]	14.92 (1.11) [19]	12.92 (1.20) [12]	12.41 (0.50) [21]	15.61 (0.55) [17]	18.64 (0.65) [21]	13.62 (0.26) [22]	11.24 (0.73) [18]	8.92 (0.16) [33]	10.83 (0.79) [22]	16.82 (0.57) [19]	9.40 (0.36) [33]	9.22 (0.73) [30]	19.90 (4.93) [19]	12.61 (1.73) [39]	12.66 (1.73) [19]																
KPCA	17.19 (0.70) [13]	13.60 (0.77) [11]	17.45 (1.13) [13]	15.10 (0.86) [16]	12.97 (1.15) [11]	14.25 (0.27) [9]	17.11 (0.44) [12]	23.44 (0.49) [11]	20.50 (0.84) [8]	12.05 (0.68) [4]	9.08 (0.15) [23]	16.68 (1.14) [5]	22.41 (0.88) [11]	12.03 (1.43) [9]	9.88 (0.43) [15]	39.87 (10.43) [3]	13.00 (1.57) [12]	13.33 (1.78) [14]																
KDE	14.91 (0.83) [28]	13.08 (0.81) [20]	16.70 (1.08) [25]	14.95 (0.72) [18]	12.06 (0.96) [13]	11.25 (0.56) [27]	14.72 (0.61) [20]	17.72 (0.55) [25]	14.32 (0.68) [21]	10.76 (0.35) [52]	8.80 (0.22) [42]	13.04 (0.48) [33]	15.26 (1.30) [24]	11.59 (1.37) [12]	10.81 (0.72) [6]	32.62 (8.38) [5]	11.52 (1.42) [36]	13.06 (1.14) [15]																
GMM	18.56 (1.16) [2]	14.39 (0.75) [2]	17.81 (1.18) [5]	15.14 (0.97) [15]	13.63 (1.20) [5]	17.16 (0.40) [6]	23.32 (0.28) [6]	28.60 (0.37) [6]	23.31 (0.99) [6]	12.00 (0.66) [5]	8.94 (0.19) [31]	16.74 (1.02) [3]	23.30 (0.68) [8]	12.66 (1.17) [5]	11.17 (0.70) [5]	41.21 (9.73) [1]	15.78 (1.60) [3]	16.05 (2.80) [4]																
CBLof	16.56 (0.66) [21]	12.89 (0.76) [25]	17.40 (1.03) [16]	14.91 (0.99) [20]	12.44 (1.10) [21]	12.46 (0.36) [20]	12.80 (0.30) [22]	17.87 (0.61) [22]	12.58 (0.36) [25]	11.66 (0.54) [9]	9.03 (0.20) [24]	14.08 (0.76) [18]	16.07 (1.30) [21]	10.84 (1.01) [18]	8.95 (0.64) [42]	22.41 (5.90) [13]	11.47 (1.67) [38]	11.53 (1.41) [36]																
SOD	16.00 (0.69) [27]	12.72 (0.88) [27]	15.34 (1.10) [34]	15.03 (0.83) [17]	12.32 (1.04) [22]	12.41 (0.43) [23]	20.48 (0.40) [19]	14.65 (0.46) [19]	12.33 (0.26) [16]	15.03 (0.90) [14]	9.23 (0.61) [15]	9.23 (0.61) [15]	18.69 (0.91) [17]	11.51 (1.08) [14]	9.34 (0.36) [28]	12.66 (2.53) [41]	12.58 (1.31) [23]	12.55 (2.04) [20]																
LINAR	17.24 (0.82) [12]	14.11 (0.73) [4]	18.70 (0.80) [2]	16.02 (1.23) [8]	13.96 (1.36) [2]	14.14 (0.41) [10]	17.08 (0.39) [13]	24.28 (0.58) [8]	18.67 (0.86) [10]	11.59 (0.58) [11]	8.97 (0.23) [28]	16.73 (0.96) [4]	23.24 (1.27) [10]	12.50 (1.49) [6]	9.48 (0.28) [25]	29.39 (5.96) [7]	11.61 (1.55) [35]	12.80 (1.74) [17]																
SOGAIL	12.19 (1.76) [41]	10.58 (1.36) [42]	10.95 (1.70) [43]	11.42 (1.52) [37]	10.43 (1.42) [40]	9.06 (0.30) [49]	9.86 (0.21) [41]	10.56 (0.27) [46]	9.97 (0.27) [44]	9.67 (0.26) [48]	8.81 (0.12) [41]	10.94 (0.56) [41]	9.93 (0.35) [45]	8.61 (0.39) [49]	8.97 (0.51) [40]	15.27 (2.47) [37]	10.20 (0.72) [47]	10.23 (1.33) [45]																
ALAD	9.50 (0.54) [50]	11.76 (0.58) [31]	9.04 (1.52) [46]	10.08 (0.55) [38]	8.83 (0.15) [50]	10.77 (0.41) [41]	8.83 (0.15) [50]	10.02 (0.89) [49]	9.33 (0.49) [50]	8.92 (0.60) [48]	8.61 (0.61) [48]	9.71 (0.96) [49]	8.47 (0.63) [50]	11.87 (1.88) [10]	10.36 (0.87) [8]	12.55 (2.75) [42]	9.55 (1.18) [50]	10.80 (1.29) [43]																
AE	17.16 (0.76) [14]	13.36 (0.74) [14]	17.56 (1.09) [10]	15.37 (0.96) [12]	12.64 (1.14) [18]	13.32 (0.25) [18]	16.33 (0.51) [14]	23.53 (0.63) [10]	17.15 (0.45) [13]	11.49 (0.63) [13]	9.19 (0.17) [18]	15.66 (0.83) [13]	23.89 (1.53) [9]	12.13 (1.21) [8]	8.96 (0.27) [41]	21.09 (4.48) [16]	12.98 (1.41) [13]	13.00 (1.52) [16]																
CD	12.32 (3.87) [40]	10.14 (0.77) [44]	9.98 (0.97) [45]	9.50 (0.00) [44]	9.98 (0.91) [43]	15.56 (0.14) [16]	24.26 (0.35) [9]	9.71 (1.08) [14]	8.39 (0.15) [28]	8.39 (0.15) [28]	9.30 (0.39) [25]	14.15 (2.46) [26]	9.47 (0.00) [32]	9.41 (0.00) [26]	9.40 (0.00) [51]	8.43 (0.00) [51]	9.52 (0.00) [50]	9.52 (0.00) [50]																
MOGAIL	11.91 (1.25) [43]	10.89 (1.47) [40]	10.62 (1.53) [44]	10.55 (1.06) [42]	10.24 (1.32) [42]	9.11 (0.44) [48]	9.85 (0.45) [45]	10.85 (0.20) [44]	10.06 (0.22) [42]	9.76 (0.45) [45]	8.74 (0.11) [43]	11.30 (0.43) [40]	9.73 (0.46) [47]	8.46 (0.37) [51]	8.84 (0.53) [46]	15.90 (2.32) [34]	10.83 (0.74) [44]	10.31 (1.38) [44]																
QMCD	9.74 (0.26) [51]	9.20 (0.10) [51]	7.23 (0.17) [50]	9.21 (0.33) [49]	9.51 (0.46) [48]	7.81 (0.08) [51]	6.91 (0.13) [51]	6.03 (0.05) [51]	6.94 (0.20) [51]	7.17 (0.14) [51]	8.82 (0.12) [51]	6.34 (0.12) [51]	6.89 (0.04) [51]	8.50 (0.75) [50]	9.90 (0.20) [51]	10.03 (0.32) [51]	10.78 (1.16) [45]	10.04 (0.97) [48]																
Sampling	16.60 (0.70) [20]	13.11 (0.59) [18]	17.22 (1.08) [22]	14.69 (0.99) [22]	12.28 (0.99) [24]	11.45 (0.65) [26]	11.29 (0.42) [34]	17.33 (0.39) [24]	12.52 (0.77) [26]	11.24 (0.72) [18]	8.92 (0.55) [33]	13.90 (0.94) [21]	14.47 (0.82) [25]	9.70 (0.66) [27]	9.31 (0.37) [29]	17.33 (4.02) [32]	11.19 (1.82) [42]	11.49 (1.26) [37]																
EIF	14.50 (0.61) [30]	11.52 (0.55) [34]	16.73 (1.28) [24]	11.77 (0.90) [35]	11.20 (1.05) [32]	10.74 (0.18) [29]	11.62 (0.49) [27]	15.40 (0.36) [28]	11.90 (0.34) [30]	11.16 (0.63) [21]	9.02 (0.20) [25]	13.69 (0.82) [26]	13.91 (0.71) [28]	9.23 (0.61) [36]	8.78 (0.52) [47]	21.30 (9.14) [14]	12.49 (1.52) [21]	11.84 (1.66) [31]																
Ensemble	18.52 (1.07) [3]	13.78 (0.58) [6]	17.31 (0.96) [18]	16.19 (0.93) [3]	13.49 (1.14) [8]	18.12 (0.69) [3]	31.50 (1.07) [3]	29.75 (1.72) [4]	24.48 (1.37) [3]	11.01 (0.50) [25]	9.10 (0.13) [19]	15.91 (0.98) [10]	27.16 (1.88) [3]	10.79 (0.95) [19]	10.14 (0.52) [10]	20.96 (4.91) [17]	12.83 (1.53) [17]	1																

		alor	abalone	amethyst	arthritis	buckaroo	browse	campaign	Cardiostography	cardio	celery	ceruus	cover	donors	ecoli	faah	frail	glass	Hepatitis
Model																			
Overall	-1.42 (0.30) [39]	57.59 (5.85) [14]	47.07 (2.44) [15]	46.64 (11.66) [17]	-0.42 (2.59) [42]	92.80 (1.48) [4]	29.41 (1.89) [31]	30.56 (2.74) [10]	63.84 (4.42) [15]	14.21 (1.35)	-0.88 (1.28) [19]	9.58 (1.41) [35]	35.73 (3.41) [26]	61.05 (7.18) [32]	1.90 (3.31) [44]	32.38 (6.53) [45]	9.52 (6.47) [39]	33.89 (7.74) [31]	
HCsvm	-1.66 (0.55) [13]	61.03 (5.62) [10]	49.69 (1.51) [19]	45.67 (0.71) [33]	0.01 (0.35) [19]	92.87 (1.67) [3]	34.01 (0.36) [12]	34.47 (1.19) [7]	59.05 (2.46) [12]	23.50 (2.09) [21]	31.82 (0.96) [29]	78.76 (6.40)	44.14 (0.02) [25]	1.36 (3.31) [25]	44.14 (0.02) [25]	11.55 (9.52) [36]	52.39 (2.84) [20]		
ECOD	-1.63 (0.20) [41]	50.70 (3.78) [27]	21.97 (1.44) [45]	-20.12 (10.27) [48]	-5.08 (0.00) [47]	91.18 (1.29) [15]	36.67 (0.65) [10]	27.65 (1.64) [11]	64.99 (3.64) [10]	20.02 (1.01) [38]	-13.20 (0.00) [49]	17.78 (0.77) [24]	35.34 (3.30) [27]	27.15 (10.14)	-4.20 (0.99) [47]	48.02 (4.28) [21]	14.30 (11.58) [28]	36.62 (0.67) [30]	
ECCOD	-1.72 (0.39) [42]	57.59 (5.85) [14]	29.59 (1.97) [47]	-20.12 (10.27) [48]	-5.08 (0.00) [47]	90.81 (1.93) [20]	35.75 (0.54) [15]	19.26 (1.64) [11]	69.34 (3.19) [3]	-10.12 (0.00) [49]	-13.20 (0.00) [49]	23.68 (1.27) [24]	39.12 (10.20)	31.81 (9.06) [39]	-1.24 (0.67) [41]	41.23 (2.83) [49]	12.63 (6.89) [34]	19.23 (4.97) [38]	
FeatureSubset	2.81 (1.10) [6]	69.05 (4.59) [4]	41.99 (7.91) [23]	45.05 (8.81) [22]	58.88 (8.73) [14]	22.58 (24.06) [42]	17.80 (6.66) [40]	40.26 (1.17) [18]	54.92 (4.13) [21]	-2.33 (0.57) [43]	-0.12 (0.50) [48]	77.51 (8.96) [4]	49.35 (13.10) [15]	75.59 (10.09) [24]	-4.20 (0.59) [47]	70.15 (4.83) [3]	22.82 (10.11) [18]	16.52 (16.46) [42]	
HNN	1.26 (0.65) [14]	60.06 (2.81) [48]	26.18 (1.90) [41]	48.02 (3.91) [14]	2.59 (0.48) [36]	91.75 (1.98) [12]	34.38 (0.71) [22]	6.40 (2.02) [41]	48.06 (3.04) [24]	19.54 (1.20) [11]	-0.96 (0.92) [40]	8.50 (1.13) [36]	13.64 (3.64) [41]	66.76 (2.73) [41]	4.27 (1.73) [38]	45.53 (0.69) [25]	22.45 (14.79) [39]	40.07 (4.99) [28]	
KBOs	-0.12 (0.51) [30]	66.76 (6.69) [7]	55.69 (1.51) [7]	45.97 (0.90) [18]	49.91 (2.16) [16]	91.88 (1.01) [16]	37.52 (0.35) [7]	53.78 (3.28) [26]	13.44 (1.06) [19]	14.46 (1.70) [15]	12.32 (0.76) [15]	94.18 (0.98) [5]	74.60 (5.19) [25]	68.59 (3.41) [26]	75.42 (0.93) [26]	48.33 (4.92) [19]	26.90 (16.42) [16]		
LOF	0.46 (1.22) [23]	22.05 (17.23) [42]	36.77 (6.79) [33]	34.54 (12.80) [36]	-0.42 (2.49) [43]	90.61 (1.40) [20]	12.58 (6.67) [44]	30.78 (12.08) [9]	57.44 (2.58) [18]	9.00 (7.63) [29]	5.20 (0.93) [29]	20.33 (10.71) [23]	15.10 (25.55) [40]	68.00 (6.66) [31]	0.80 (2.85) [42]	49.17 (0.05) [42]	53.8 (9.67) [47]	22.61 (18.1) [37]	
LDA	0.08 (0.79) [8]	70.19 (2.29) [12]	41.84 (1.73) [24]	36.78 (6.84) [23]	70.51 (1.95) [12]	72.59 (6.21) [15]	27.47 (0.41) [35]	12.42 (3.40) [23]	54.24 (2.04) [23]	-2.64 (2.27) [43]	14.1 (0.90) [37]	82.11 (0.95) [1]	72.01 (1.64) [9]	78.76 (6.40) [3]	-2.67 (1.18) [44]	63.05 (6.53) [5]	21.52 (10.62) [17]	10.87 (1.26) [40]	
MCD	-2.33 (0.36) [46]	24.34 (12.34) [38]	41.84 (1.46) [24]	55.13 (7.87) [9]	16.05 (26.39) [21]	90.20 (2.48) [24]	33.40 (2.50) [24]	0.92 (1.41) [45]	51.95 (3.96) [29]	20.48 (5.12) [7]	20.44 (3.45) [1]	1.68 (0.81) [44]	25.55 (13.76) [33]	67.90 (8.59) [30]	10.09 (1.69) [18]	59.44 (5.54) [10]	15.89 (9.28) [26]	27.74 (4.12) [34]	
PCA	1.85 (0.51) [11]	57.59 (5.85) [14]	47.10 (1.48) [28]	41.93 (6.85) [30]	3.77 (1.03) [31]	90.67 (0.92) [18]	35.50 (0.35) [16]	40.06 (1.29) [12]	60.80 (2.0) [1]	23.66 (1.04) [12]	10.28 (0.77) [14]	14.91 (1.80) [24]	29.88 (1.20) [39]	78.76 (6.40) [3]	7.85 (2.00) [27]	36.18 (4.47) [32]	11.55 (9.52) [36]	44.64 (11.73) [22]	
DeepSVDD	-0.64 (0.32) [13]	5																	

Table 33: Mean, standard deviation and rank ADJ F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 1

Model	hvs anomalies opt	hvs anomalies sat	hnp	inter-lcd	lensophore	landsat	lenter	lymphography	magic maps	mammography	mif	mtv	mnist	mnistres	mnisk	mniskp	PageRank
Forest	12.54 (0.92) [13]	9.05 (1.30) [33]	28.35 (1.39) [32]	8.12 (4.55) [50]	68.41 (3.21) [30]	12.04 (2.47) [22]	-4.05 (2.50) [22]	79.70 (8.12) [31]	36.83 (2.14) [22]	35.13 (2.74) [22]	19.29 (3.79) [31]	23.14 (4.74) [21]	43.58 (4.56) [30]	99.34 (0.15) [28]	42.32 (0.67) [41]	10.36 (2.64) [22]	7.74 (3.21) [48]
OC5V6	8.23 (0.55) [26]	15.59 (0.79) [17]	99.44 (0.46) [5]	21.09 (2.42) [23]	5.99 (1.59) [29]	84.99 (3.32) [11]	-12.58 (0.93) [19]	100.00 (0.00) [1]	34.22 (0.51) [27]	38.08 (1.82) [14]	57.90 (0.83) [19]	20.36 (0.67) [28]	47.30 (0.56) [28]	99.34 (0.15) [28]	5.69 (0.47) [48]	20.66 (0.87) [22]	10.21 (2.61) [48]
ECOD	12.21 (0.60) [15]	11.98 (0.57) [20]	6.21 (5.05) [39]	20.69 (5.67) [25]	39.91 (4.29) [45]	4.50 (1.36) [33]	-9.55 (2.67) [28]	80.63 (6.50) [22]	23.17 (0.90) [38]	49.23 (1.51) [1]	-18.69 (0.00) [49]	-16.79 (0.00) [48]	-20.28 (0.00) [49]	62.88 (0.49) [39]	85.67 (4.85) [31]	4.73 (2.03) [34]	-5.92 (0.00) [45]
CFOP	19.11 (0.00) [12]	16.82 (0.41) [2]	1.96 (1.24) [42]	20.69 (5.67) [25]	27.54 (5.58) [47]	-4.07 (0.92) [47]	-6.53 (3.58) [47]	85.42 (1.16) [28]	17.25 (0.70) [44]	49.23 (1.51) [1]	-18.69 (0.00) [49]	-16.79 (0.00) [48]	-20.28 (0.00) [49]	75.11 (0.68) [36]	-5.88 (1.22) [48]	-5.92 (0.00) [45]	38.45 (0.91) [31]
Feature-Bagging	10.36 (1.24) [29]	12.22 (1.71) [19]	47.35 (0.00) [46]	35.36 (0.00) [46]	73.41 (0.03) [26]	29.35 (1.05) [1]	-13.24 (2.56) [12]	93.55 (24.58) [39]	51.29 (1.71) [31]	35.84 (2.53) [21]	8.40 (3.56) [29]	26.54 (0.61) [15]	64.20 (1.32) [13]	100.00 (0.00) [1]	11.05 (0.18) [38]	42.56 (5.23) [17]	57.41 (0.98) [31]
HROS	7.75 (1.19) [38]	1.76 (0.47) [38]	1.96 (1.24) [42]	-5.61 (3.61) [47]	34.89 (1.89) [46]	26.84 (1.12) [5]	-4.91 (2.56) [19]	88.76 (6.53) [24]	31.97 (0.30) [30]	13.24 (2.67) [43]	14.73 (0.91) [15]	16.25 (0.04) [31]	8.41 (1.30) [44]	94.66 (1.50) [24]	100.00 (0.00) [1]	38.31 (2.10) [49]	-5.71 (0.00) [31]
KNN	12.33 (1.01) [14]	14.35 (0.35) [11]	100.00 (0.00) [1]	28.23 (1.42) [18]	81.50 (4.49) [15]	25.29 (1.25) [18]	-12.58 (0.93) [19]	93.76 (5.54) [15]	50.49 (0.25) [12]	36.74 (2.67) [17]	10.16 (0.48) [24]	26.68 (0.82) [14]	66.95 (0.82) [4]	100.00 (0.00) [1]	100.00 (0.00) [1]	15.86 (1.44) [14]	15.50 (6.33) [14]
LDA	3.74 (6.59) [47]	2.96 (4.34) [46]	0.65 (1.04) [45]	16.86 (4.65) [32]	56.62 (0.53) [24]	2.52 (6.13) [35]	-11.44 (1.19) [35]	22.75 (20.71) [43]	28.10 (2.08) [34]	46.14 (5.34) [33]	23.62 (11.42) [1]	-1.04 (9.86) [47]	20.27 (8.92) [42]	99.88 (0.19) [23]	91.18 (5.85) [30]	4.51 (1.73) [23]	33.32 (2.99) [37]
LOF	9.49 (0.53) [29]	10.94 (0.94) [27]	96.32 (2.44) [10]	74.19 (4.81) [24]	33.91 (2.21) [32]	74.59 (1.84) [24]	28.55 (1.21) [32]	-1.62 (2.20) [18]	50.08 (0.32) [13]	35.53 (2.72) [20]	17.27 (0.74) [19]	66.15 (1.49) [6]	24.73 (0.45) [14]	99.34 (0.15) [28]	47.34 (1.20) [41]	58.36 (0.85) [4]	10.21 (2.61) [48]
MCD	5.13 (3.25) [44]	10.89 (0.80) [29]	93.17 (0.13) [13]	4.01 (2.42) [42]	70.06 (1.06) [18]	19.61 (14.67) [14]	-10.69 (1.93) [29]	82.06 (4.57) [29]	33.35 (0.57) [28]	-2.07 (0.85) [49]	12.84 (1.92) [14]	29.15 (1.16) [10]	44.72 (2.82) [19]	100.00 (0.00) [1]	51.87 (16.65) [39]	8.48 (2.46) [47]	-48.32 (0.21) [34]
PCA	8.30 (0.48) [33]	11.13 (0.54) [25]	92.80 (0.98) [14]	20.16 (2.42) [27]	57.66 (6.51) [40]	-1.09 (0.81) [43]	-12.58 (0.93) [19]	93.00 (1.38) [24]	27.53 (0.90) [44]	17.58 (0.55) [12]	2.72 (0.69) [44]	5.79 (1.26) [20]	2.22 (0.69) [44]	100.00 (0.00) [1]	2.84 (0.39) [37]	-5.69 (0.47) [48]	35.37 (1.47) [35]
DeepSVDD	-0.48 (0.53) [51]	-2.11 (4.10) [51]	28.50 (29.99) [31]	33.65 (6.51) [39]	87.56 (1.44) [46]	13.14 (2.49) [19]	-8.42 (2.56) [23]	87.78 (10.10) [25]	16.72 (1.77) [45]	22.90 (11.49) [35]	4.17 (8.91) [39]	3.48 (17.03) [41]	33.96 (10.64) [33]	100.00 (0.00) [1]	4.36 (0.		

Table 34: Mean, standard deviation and rank ADJ F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 2

[illegible]

Table 35: Mean, standard deviation and rank ADJ F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 3

Model	WBC	wbc2	WBIC	WIR	wire	WBIC	yearst	yearst0	CPIAR10	CPIAR11	CPIAR12	CPIAR13	CPIAR14	CPIAR15	CPIAR16	CPIAR17	CPIAR18	CPIAR19
Bestest	91.19 (2.67) [4]	62.86 (4.16) [22]	83.82 (4.42) [20]	-8.37 (1.62) [33]	66.80 (7.41) [26]	0.26 (8.34) [37]	-12.49 (0.34) [43]	3.16 (4.00) [11]	18.44 (2.33) [26]	-0.17 (1.74) [40]	6.87 (1.49) [34]	2.77 (1.25) [33]	26.83 (1.44) [27]	-0.87 (1.12) [42]	10.04 (2.53) [33]	12.84 (2.01) [31]	10.33 (1.36) [32]	12.70 (1.90) [33]
OC5VM	89.62 (1.25) [10]	63.51 (3.16) [20]	86.83 (6.49) [16]	-8.92 (0.46) [41]	74.97 (8.54) [21]	0.67 (5.54) [34]	-0.67 (5.54) [34]	1.16 (3.73) [17]	15.94 (6.61) [16]	11.44 (2.82) [19]	4.27 (2.84) [33]	7.95 (2.64) [33]	28.23 (2.01) [17]	5.29 (1.44) [27]	15.64 (1.22) [19]	12.84 (0.71) [24]	12.84 (0.71) [24]	12.84 (0.71) [24]
ECOD	84.03 (7.07) [17]	70.69 (7.19) [11]	88.88 (3.89) [13]	-9.10 (0.65) [33]	54.69 (3.96) [33]	1.38 (10.00) [35]	-16.77 (2.14) [51]	20.13 (3.16) [1]	17.18 (1.61) [32]	-1.57 (1.74) [43]	2.77 (0.89) [41]	0.52 (2.05) [41]	-10.52 (0.00) [49]	-5.48 (2.63) [48]	8.64 (0.95) [39]	-1.01 (1.16) [48]	-10.52 (0.00) [49]	-10.52 (0.00) [49]
ECOP	84.03 (7.07) [17]	70.67 (7.80) [33]	-5.92 (1.68) [25]	93.2 (1.28) [31]	0.83 (3.82) [36]	-9.28 (1.68) [25]	-9.28 (1.68) [25]	18.16 (4.47) [29]	-0.87 (1.95) [49]	3.19 (0.99) [40]	-4.64 (0.02) [47]	-10.52 (0.00) [49]	-4.64 (0.02) [47]	4.99 (1.05) [40]	-0.87 (1.82) [47]	-10.52 (0.00) [49]	-10.52 (0.00) [49]	-10.52 (0.00) [49]
FeatureBagging	-2.25 (16.41) [47]	69.25 (2.99) [33]	80.63 (6.71) [8]	9.54 (12.38) [17]	14.63 (10.15) [42]	4.92 (8.39) [29]	-7.26 (2.65) [24]	-3.83 (2.00) [38]	25.01 (7.74) [1]	21.65 (2.00) [38]	9.76 (2.69) [43]	19.10 (2.06) [33]	20.97 (2.92) [10]	12.28 (1.56) [1]	22.22 (2.31) [1]	21.20 (2.36) [1]	21.10 (2.05) [12]	25.15 (2.90) [1]
HROS	83.23 (5.76) [19]	76.16 (8.23) [25]	76.26 (8.82) [29]	72.29 (1.73) [19]	75.46 (8.77) [26]	15.96 (10.71) [17]	-13.56 (2.87) [45]	-1.16 (3.73) [17]	16.90 (1.74) [37]	-4.36 (1.12) [47]	0.59 (1.77) [44]	-0.59 (1.77) [44]	21.38 (1.80) [36]	6.13 (0.82) [42]	11.58 (2.19) [34]	5.57 (1.16) [34]	12.90 (1.12) [36]	12.90 (1.12) [36]
KNN	85.14 (4.55) [16]	65.53 (3.16) [20]	84.91 (4.98) [17]	-8.52 (0.75) [19]	84.85 (3.17) [14]	0.24 (2.75) [15]	-9.41 (1.50) [29]	1.16 (3.73) [17]	21.80 (1.89) [19]	10.05 (2.75) [22]	6.55 (2.37) [20]	7.81 (2.32) [18]	26.08 (1.79) [20]	4.59 (1.95) [25]	17.18 (1.14) [14]	16.90 (2.23) [20]	14.52 (2.08) [19]	20.12 (1.95) [12]
LDF	71.02 (15.66) [25]	63.35 (5.90) [30]	63.81 (2.15) [34]	-10.40 (0.84) [46]	49.00 (12.86) [35]	1.75 (7.10) [33]	-7.12 (4.93) [23]	0.16 (4.40) [20]	16.62 (3.20) [35]	6.41 (2.88) [30]	5.29 (2.44) [29]	2.29 (1.15) [36]	24.88 (3.56) [32]	4.15 (1.74) [28]	12.84 (3.58) [26]	17.88 (2.92) [10]	14.60 (4.60) [31]	16.34 (1.81) [28]
LOF	11.78 (8.99) [42]	68.59 (3.72) [14]	90.63 (6.71) [8]	9.63 (1.79) [19]	8.69 (6.23) [23]	-6.32 (1.62) [20]	-6.32 (1.62) [20]	24.88 (1.91) [23]	22.36 (2.54) [1]	11.73 (2.27) [1]	10.88 (1.91) [1]	28.23 (2.56) [17]	11.16 (1.82) [17]	20.26 (3.04) [13]	21.20 (2.80) [13]	20.96 (0.77) [33]	25.15 (2.97) [1]	25.15 (2.97) [1]
MCD	73.09 (14.65) [23]	55.09 (5.76) [33]	66.53 (4.76) [32]	-3.47 (1.06) [21]	26.16 (18.10) [27]	8.56 (7.76) [26]	-9.67 (1.01) [34]	-4.83 (0.00) [40]	16.62 (2.23) [35]	5.29 (3.90) [31]	4.73 (2.30) [36]	2.63 (1.95) [35]	26.09 (1.56) [28]	3.33 (2.14) [33]	5.71 (1.56) [43]	11.44 (2.06) [35]	4.87 (2.30) [39]	17.75 (5.38) [17]
PCA	88.94 (1.82) [12]	61.4 (3.52) [27]	83.5 (6.12) [22]	-9.24 (0.71) [40]	-4.05 (6.26) [42]	-16.1 (0.66) [49]	-8.84 (3.73) [23]	22.07 (1.91) [14]	9.90 (2.95) [23]	6.27 (2.70) [33]	7.95 (2.53) [23]	28.51 (1.74) [15]	5.01 (1.68) [19]	15.52 (1.12) [19]	12.84 (0.71) [24]	12.84 (0.71) [24]	12.84 (0.71) [24]	12.84 (0.71) [24]
DeepSVDD	48.61 (16.38) [36]	77.31 (8.23) [6]	83.71 (9.50) [21]	-10.69 (0.54) [47]	71.58 (12.04) [23]													

Table 36: Mean, standard deviation and rank ADJ F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 4

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Table 37: Mean, standard deviation and rank ADJ F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 5

	2979	2980	2981	2982	2983	2984	2985	2986	2987	2988	2989	2990	2991	2992	2993	2994	2995	2996	2997	2998	2999	3000	3001	3002	3003	3004	3005	3006	3007	3008	3009	3010	3011
Model	MNIST-C identity	MNIST-C impulse noise	MNIST-C motion blur	MNIST-C rotate	MNIST-C scale	MNIST-C shear	MNIST-C shot noise	MNIST-C quarter	MNIST-C stripe	MNIST-C translate	MNIST-C zigzag	MVTeC-AD bottle	MVTeC-AD cable	MVTeC-AD capsule	MVTeC-AD carpet																		
FlareNet	-1.98 (0.82) [42]	88.51 (3.26) [30]	30.96 (2.51) [33]	2.22 (0.89) [31]	7.01 (3.21) [35]	11.65 (1.69) [32]	17.47 (2.18) [33]	36.19 (3.56) [28]	82.02 (1.44) [30]	5.24 (0.26) [34]	29.12 (1.13) [30]	84.99 (2.31) [26]	31.03 (5.54) [32]	21.45 (5.07) [32]	33.81 (3.76) [31]																		
OC SVM	-0.95 (1.19) [24]	97.57 (0.44) [11]	45.62 (1.59) [22]	3.62 (0.68) [21]	21.82 (1.26) [19]	14.60 (1.22) [25]	26.54 (2.17) [21]	42.45 (1.17) [19]	92.71 (0.49) [16]	10.77 (1.13) [24]	42.45 (1.57) [19]	85.74 (0.77) [25]	29.86 (4.85) [33]	19.36 (4.71) [36]	32.54 (6.52) [33]																		
COPROD	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [47]	-10.53 (0.00) [48]	-10.53 (0.00) [49]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	35.45 (9.16) [41]	53.90 (8.59) [11]	87.61 (3.35) [1]	49.15 (10.81) [10]																		
ECOD	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [47]	-10.53 (0.00) [48]	-10.53 (0.00) [49]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	35.45 (9.16) [41]	53.90 (8.59) [11]	87.61 (3.35) [1]	49.15 (10.81) [10]																		
FeatureBagging	-1.10 (0.92) [31]	97.35 (0.36) [12]	60.80 (1.33) [8]	5.90 (0.55) [11]	34.57 (1.72) [7]	21.45 (1.24) [9]	42.38 (0.89) [4]	59.70 (1.88) [5]	94.69 (0.38) [8]	24.92 (2.07) [7]	57.63 (0.93) [7]	87.91 (0.85) [11]	34.75 (5.22) [25]	28.90 (6.07) [25]	37.55 (4.34) [19]																		
HBOS	-2.05 (0.52) [43]	48.57 (1.66) [39]	18.43 (1.06) [39]	2.08 (0.54) [33]	-3.67 (1.18) [43]	10.84 (2.12) [34]	11.43 (1.20) [38]	21.53 (1.56) [36]	62.72 (1.43) [36]	-0.06 (1.35) [42]	13.71 (0.91) [40]	83.11 (2.77) [30]	35.01 (4.93) [24]	19.15 (3.21) [37]	38.44 (6.55) [18]																		
KNN	-0.58 (0.66) [19]	96.98 (0.25) [18]	51.96 (1.20) [16]	4.80 (0.64) [18]	26.24 (1.62) [15]	18.43 (1.25) [15]	33.83 (2.60) [12]	48.84 (1.43) [14]	93.74 (0.47) [13]	14.53 (1.36) [19]	49.08 (1.42) [14]	86.98 (0.87) [16]	34.36 (5.46) [27]	30.42 (3.00) [22]	36.14 (3.96) [25]																		
LODA	-1.54 (1.03) [39]	95.28 (3.70) [26]	35.89 (5.79) [30]	1.56 (1.70) [38]	7.53 (5.19) [33]	7.89 (3.23) [38]	17.03 (7.16) [34]	31.47 (6.86) [33]	82.34 (5.18) [29]	4.65 (2.74) [37]	24.25 (8.07) [34]	81.30 (4.30) [33]	22.93 (5.04) [39]	18.83 (6.23) [38]	26.51 (7.62) [37]																		
LOF	-1.02 (0.85) [27]	96.91 (0.38) [22]	61.39 (1.22) [6]	6.27 (0.98) [9]	34.64 (1.79) [5]	21.60 (1.70) [6]	41.35 (1.69) [5]	59.18 (1.84) [6]	94.99 (0.18) [4]	24.99 (1.47) [5]	57.78 (1.33) [5]	87.20 (0.90) [14]	33.41 (5.50) [28]	29.12 (6.29) [23]	36.30 (4.88) [23]																		
MCD	-0.36 (1.00) [16]	66.11 (9.51) [36]	22.70 (0.60) [37]	1.70 (1.57) [36]	8.19 (6.03) [32]	7.01 (2.09) [41]	9.88 (2.22) [39]	23.80 (3.04) [33]	69.27 (14.17) [34]	2.29 (1.48) [41]	16.95 (3.98) [38]	86.48 (1.02) [19]	43.52 (6.38) [16]	46.67 (4.35) [14]	37.39 (7.11) [20]																		
PCA	-1.17 (1.72) [32]	96.98 (0.28) [18]	44.81 (2.01) [24]	2.66 (0.82) [29]	19.61 (1.08) [24]	14.60 (1.26) [25]	24.55 (1.87) [24]	40.98 (1.67) [23]	92.34 (0.43) [21]	9.89 (1.11) [28]	40.76 (1.62) [23]	83.37 (2.23) [28]	26.25 (4.38) [37]	17.52 (4.82) [39]	32.53 (2.20) [34]																		
DeepSVD	0.01 (0.68) [8]	91.45 (4.69) [27]	38.69 (2.20) [27]	3.23 (1.94) [25]	15.92 (4.07) [27]	8.41 (2.68) [37]	15.12 (2.19) [36]	28.08 (5.92) [34]	79.88 (1.75) [31]	6.20 (3.32) [31]	20.57 (7.19) [36]	86.48 (2.54) [19]	54.12 (6.69) [10]	34.22 (8.93) [20]	57.06 (2.11) [8]																		
INNE	-0.58 (1.38) [19]	87.47 (1.30) [32]	57.63 (1.82) [10]	5.02 (0.82) [17]	29.27 (1.56) [11]	18.21 (2.20) [16]	36.26 (2.94) [10]	45.35 (2.37) [10]	87.55 (3.20) [26]	14.89 (1.48) [16]	55.50 (3.35) [10]	88.18 (1.74) [8]	34.39 (3.20) [26]	22.86 (3.40) [21]	35.79 (6.01) [26]																		
KPCA	-1.02 (0.82) [27]	95.51 (0.43) [24]	54.17 (0.98) [12]	5.32 (0.77) [13]	28.68 (1.73) [12]	19.39 (1.15) [12]	36.56 (2.10) [19]	50.93 (1.42) [12]	94.92 (0.83) [6]	16.22 (1.69) [15]	51.81 (1.13) [12]	90.87 (2.51) [4]	67.78 (5.61) [1]	69.00 (4.76) [6]	61.50 (2.48) [2]																		
KDE	-1.09 (0.38) [30]	98.01 (0.30) [5]	53.58 (1.26) [14]	5.17 (0.95) [15]	23.08 (1.42) [22]	15.26 (1.16) [22]	29.93 (1.46) [16]	40.24 (1.13) [25]	93.96 (0.95) [10]	14.75 (1.68) [18]	39.65 (1.34) [26]	88.66 (3.26) [7]	57.70 (6.02) [8]	67.74 (3.88) [7]	59.52 (5.24) [5]																		
GMM	-0.09 (0.97) [5]	97.71 (0.36) [9]	58.96 (1.18) [9]	7.97 (0.64) [7]	35.05 (1.35) [4]	22.63 (0.87) [5]	40.68 (2.06) [7]	57.78 (1.50) [8]	94.11 (0.64) [9]	23.59 (1.69) [10]	57.63 (1.46) [7]	91.16 (2.21) [1]	64.38 (3.63) [5]	69.42 (3.16) [3]	60.56 (1.86) [3]																		
CBLOF	-0.65 (1.35) [21]	97.05 (0.23) [14]	46.80 (1.64) [19]	3.32 (0.50) [24]	24.62 (1.33) [17]	16.74 (1.26) [19]	28.08 (2.50) [18]	42.82 (1.64) [18]	92.71 (0.49) [16]	10.62 (1.45) [25]	43.34 (1.46) [18]	85.85 (2.23) [22]	38.22 (5.95) [18]	27.55 (3.19) [26]	36.47 (6.98) [22]																		
SOD	-2.50 (0.75) [46]	73.03 (1.46) [34]	41.12 (1.77) [26]	3.40 (1.19) [23]	1.78 (2.04) [39]	14.90 (1.21) [24]	21.89 (1.94) [27]	39.65 (2.50) [26]	70.23 (2.00) [33]	18.14 (0.82) [13]	38.77 (2.47) [27]	76.47 (3.63) [34]	0.38 (3.87) [49]	2.17 (6.90) [50]	22.01 (6.07) [42]																		
LUNAR	0.01 (0.83) [8]	99.26 (0.33) [1]	73.47 (0.87) [1]	13.50 (1.10) [1]	43.34 (1.17) [1]	28.38 (2.15) [1]	57.19 (2.89) [1]	68.17 (1.29) [1]	98.23 (0.88) [1]	30.81 (0.75) [3]	67.06 (1.06) [1]	90.64 (2.70) [5]	54.94 (7.44) [9]	45.68 (6.78) [16]	48.53 (6.56) [13]																		
SOGAAL	-0.29 (2.25) [15]	63.82 (23.18) [37]	17.99 (7.33) [40]	1.41 (1.06) [40]	-1.76 (3.82) [41]	1.12 (1.84) [44]	0.67 (3.08) [45]	-1.54 (1.84) [46]	15.63 (12.11) [41]	-0.28 (2.05) [44]	-1.61 (1.39) [46]	53.74 (8.86) [37]	2.85 (5.91) [47]	4.22 (7.34) [49]	8.64 (14.79) [49]																		
ALAD	0.60 (0.43) [3]	18.28 (15.80) [42]	9.81 (8.82) [43]	-0.65 (2.08) [46]	-1.93 (4.34) [38]	0.60 (2.11) [45]	2.29 (3.15) [43]	8.19 (8.18) [43]	16.95 (14.15) [40]	-0.06 (1.45) [42]	7.31 (5.30) [43]	33.12 (18.83) [45]	0.85 (0.13) [48]	5.71 (9.94) [45]	8.87 (0.01) [48]																		
AE	-0.06 (1.08) [10]	97.05 (0.23) [14]	50.48 (1.69) [17]	4.80 (0.64) [18]	26.91 (1.59) [14]	18.51 (1.22) [14]	31.40 (2.65) [15]	48.86 (1.87) [15]	93.15 (0.30) [14]	14.82 (1.13) [17]	48.94 (1.37) [15]	87.93 (0.99) [10]	33.70 (2.61) [22]	26.69 (4.61) [28]	34.45 (4.94) [28]																		
CD	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	35.45 (9.16) [41]	53.90 (8.59) [11]	63.73 (4.73) [11]	19.29 (34.71) [44]																		
MOGAIL	-0.06 (2.61) [40]	54.61 (28.17) [38]	17.11 (5.54) [41]	1.49 (1.69) [39]	-2.42 (2.81) [42]	-0.45 (0.68) [46]	-0.80 (2.54) [46]	-3.82 (1.17) [47]	9.00 (13.75) [45]	-0.73 (0.89) [45]	-1.46 (0.83) [45]	52.98 (8.55) [38]	2.93 (1.49) [46]	4.65 (4.75) [48]	11.06 (17.10) [47]																		
QMCD	9.15 (0.69) [1]	87.70 (1.47) [31]	-0.72 (0.36) [47]	-7.58 (0.23) [47]	-10.53 (0.00) [47]	-8.39 (0.63) [47]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [48]	-10.53 (0.00) [47]	-10.53 (0.00) [47]	31.50 (2.85) [47]	-66.49 (7.09) [51]	-39.75 (5.76) [51]																			
Sampling	-0.65 (1.26) [21]	97.05 (0.23) [14]	46.13 (1.22) [20]	3.11 (0.47) [28]	21.30 (2.29) [20]	15.41 (0.98) [21]	26.76 (1.86) [20]	42.45 (0.94) [19]	92.70 (0.36) [18]	11.14 (0.82) [21]	42.30 (1.01) [21]	85.96 (0.90) [21]	31.22 (3.91) [31]	30.48 (3.68) [21]	35.30 (9.02) [27]																		
EIP	-2.20 (0.69) [45]	91.16 (2.54) [28]	32.28 (2.71) [32]	1.63 (1.70) [37]	10.10 (4.72) [29]	12.91 (1.89) [30]</																											

	3012	3013	3014	3015	3016	3017	3018	3019	3020	3021	3022	3023	3024	3025	3026	3027	3028	3029	3030	3031	3032	3033	3034	3035	3036	3037	3038	3039	3040	3041	3042	3043	3044
Model	MVTrc-AD grid	MVTrc-AD baselin	MVTrc-AD loether	MVTrc-AD metal nut	MVTrc-AD pill	MVTrc-AD screw	MVTrc-AD tile	MVTrc-AD toothbrush	MVTrc-AD transistor	MVTrc-AD wood	MVTrc-AD zipper	SVHN 0	SVHN 1	SVHN 2	SVHN 3	SVHN 4																	
Worst	30.51 (5.21) [28]	37.45 (2.93) [20]	92.77 (2.73) [13]	28.94 (3.94) [34]	26.33 (4.98) [36]	10.43 (9.23) [41]	56.11 (3.92) [26]	61.92 (7.92) [31]	32.45 (7.59) [22]	42.26 (3.36) [27]	49.31 (6.59) [32]	6.07 (1.46) [27]	9.74 (1.42) [16]	11.14 (2.08) [30]	3.99 (0.55) [41]	11.59 (1.43) [6]																	
OCSVM	32.08 (3.92) [26]	36.19 (2.73) [26]	91.64 (3.96) [21]	30.21 (4.36) [30]	27.26 (6.22) [33]	16.43 (5.51) [31]	56.28 (4.58) [25]	57.98 (4.23) [32]	31.09 (5.97) [28]	41.46 (6.36) [29]	50.28 (5.81) [30]	6.63 (1.70) [25]	10.03 (1.08) [13]	12.91 (2.37) [22]	9.52 (1.80) [23]	10.84 (0.23) [17]																	
COPOD	2.57 (5.99) [44]	-26.41 (10.75) [48]	63.82 (6.71) [39]	76.54 (2.81) [1]	93.74 (5.05) [1]	53.10 (10.32) [7]	52.50 (6.24) [32]	75.62 (3.29) [15]	-28.22 (0.61) [48]	18.02 (10.38) [43]	89.35 (5.52) [1]	-10.51 (0.00) [49]	-10.53 (0.00) [49]	-10.53 (0.00) [48]	-10.52 (0.00) [49]	-10.51 (0.00) [49]																	
ECOD	2.57 (5.99) [44]	-26.41 (10.75) [48]	63.82 (6.71) [39]	76.54 (2.81) [1]	93.74 (5.05) [1]	53.10 (10.32) [7]	52.50 (6.24) [32]	75.62 (3.29) [15]	-28.22 (0.61) [48]	18.02 (10.38) [43]	89.35 (5.52) [1]	-10.51 (0.00) [49]	-10.53 (0.00) [49]	-10.53 (0.00) [48]	-10.52 (0.00) [49]	-10.51 (0.00) [49]																	
FeatureBagging	34.03 (2.00) [21]	38.38 (2.22) [19]	90.79 (3.60) [27]	32.74 (3.56) [22]	31.78 (7.05) [23]	22.66 (8.28) [20]	57.67 (3.60) [19]	71.50 (8.15) [29]	29.60 (6.73) [32]	50.23 (3.34) [16]	60.41 (8.58) [20]	9.61 (1.59) [11]	5.98 (1.91) [33]	14.23 (1.72) [5]	12.74 (1.06) [6]	10.27 (1.38) [25]																	
HBOS	11.21 (3.71) [39]	39.33 (4.68) [14]	88.53 (5.12) [32]	14.77 (3.01) [43]	27.85 (5.76) [32]	11.75 (8.87) [34]	55.93 (3.32) [28]	65.05 (8.78) [27]	31.46 (8.09) [27]	31.93 (3.00) [36]	46.59 (7.17) [35]	1.82 (2.40) [39]	9.00 (0.93) [21]	7.16 (1.42) [36]	-1.03 (0.45) [46]	12.16 (1.00) [4]																	
KNN	34.58 (1.60) [18]	37.34 (4.07) [22]	92.30 (3.69) [17]	31.10 (4.12) [28]	32.54 (3.83) [20]	20.25 (7.62) [24]	58.58 (2.71) [14]	80.77 (7.71) [13]	31.06 (6.55) [29]	42.95 (3.85) [25]	57.60 (7.28) [25]	7.48 (2.03) [20]	9.44 (1.35) [17]	12.91 (2.35) [22]	10.76 (2.05) [18]	11.59 (0.52) [6]																	
LODA	20.89 (6.31) [35]	33.49 (4.36) [32]	88.54 (2.72) [31]	23.09 (7.38) [39]	25.54 (2.64) [37]	9.80 (8.62) [43]	48.61 (7.52) [37]	36.27 (9.46) [40]	29.04 (5.93) [34]	37.95 (2.27) [34]	45.06 (7.27) [38]	4.93 (1.51) [33]	8.26 (3.09) [25]	6.49 (2.98) [38]	4.66 (3.15) [37]	6.98 (2.31) [36]																	
LOF	33.78 (1.73) [23]	38.96 (2.07) [15]	90.35 (3.65) [28]	31.50 (3.42) [25]	31.79 (6.82) [21]	21.60 (7.26) [22]	57.66 (3.72) [20]	70.46 (9.26) [20]	29.92 (6.94) [30]	51.68 (2.86) [14]	60.18 (7.06) [21]	9.33 (1.00) [13]	5.83 (1.11) [34]	13.79 (1.88) [8]	12.99 (1.04) [3]	10.09 (1.44) [26]																	
MCD	46.34 (5.86) [11]	41.26 (1.41) [11]	88.20 (3.84) [33]	47.27 (5.43) [17]	42.24 (5.38) [13]	32.01 (10.14) [17]	61.83 (4.65) [12]	76.97 (4.97) [14]	49.95 (6.91) [11]	58.14 (3.82) [11]	72.36 (6.49) [15]	4.37 (1.55) [35]	5.46 (3.81) [36]	9.22 (2.47) [13]	4.66 (3.00) [37]	7.64 (1.94) [34]																	
PCA	30.48 (2.25) [29]	33.72 (3.94) [30]	91.62 (4.53) [22]	27.05 (4.19) [36]	27.91 (3.78) [30]	11.17 (4.34) [36]	56.29 (4.32) [23]	47.00 (4.84) [35]	32.14 (4.94) [25]	39.84 (5.74) [31]	47.93 (5.31) [33]	5.64 (0.69) [28]	10.10 (1.12) [11]	13.35 (1.91) [12]	8.61 (1.66) [26]	10.46 (0.23) [21]																	
DeepSVDD	54.54 (5.02) [9]	48.45 (6.51) [10]	93.36 (2.41) [10]	53.04 (6.26) [14]	38.50 (6.01) [17]	41.28 (4.92) [14]	70.85 (3.68) [8]	83.64 (6.68) [12]	54.58 (0.68) [10]	67.71 (3.00) [9]	71.62 (4.46) [28]	5.64 (1.64) [28]	7.82 (3.46) [28]	8.93 (1.43) [34]	5.97 (1.81) [34]	5.37 (1.38) [40]																	
INNE	33.21 (2.10) [25]	38.69 (2.43) [17]	94.96 (1.16) [5]	30.01 (3.97) [31]	29.70 (5.53) [27]	16.62 (6.81) [28]	58.55 (4.02) [15]	66.63 (6.93) [24]	35.10 (7.38) [15]	49.44 (5.46) [17]	61.48 (6.97) [19]	11.02 (1.15) [5]	8.78 (2.67) [12]	12.76 (2.62) [22]	10.31 (1.14) [24]	10.37 (1.14) [24]																	
KPCA	63.47 (4.13) [6]	55.50 (5.18) [7]	94.72 (1.84) [7]	69.41 (3.50) [8]	60.52 (4.87) [8]	56.96 (4.61) [4]	75.69 (2.66) [2]	98.94 (1.35) [2]	69.67 (4.97) [1]	74.59 (4.00) [4]	83.62 (4.14) [7]	7.91 (2.06) [19]	10.33 (1.41) [7]	13.27 (2.36) [17]	11.09 (1.70) [15]	11.59 (0.59) [6]																	
KDE	63.78 (4.49) [5]	56.53 (3.41) [3]	92.95 (3.00) [12]	67.54 (4.14) [9]	58.16 (6.02) [9]	58.40 (3.07) [2]	69.12 (3.21) [10]	98.94 (1.35) [2]	68.18 (4.89) [4]	74.04 (3.42) [5]	81.32 (7.04) [9]	9.75 (1.82) [10]	5.02 (1.67) [37]	11.43 (1.33) [28]	9.44 (1.44) [25]	7.26 (1.50) [35]																	
GM	64.78 (5.72) [4]	53.29 (5.57) [8]	95.13 (3.23) [3]	71.54 (5.12) [3]	65.17 (4.12) [5]	73.25 (5.30) [6]	98.94 (1.35) [2]	65.69 (2.86) [6]	75.10 (4.94) [1]	80.30 (5.52) [8]	10.74 (1.61) [7]	10.55 (1.62) [6]	14.82 (2.28) [3]	12.90 (1.09) [5]	11.21 (0.55) [15]																		
CBLOF	34.54 (3.66) [14]	38.62 (3.97) [18]	92.31 (3.49) [16]	31.08 (5.99) [29]	29.59 (5.83) [28]	19.25 (5.26) [26]	56.70 (4.72) [22]	65.12 (6.09) [26]	32.48 (6.61) [21]	46.49 (3.50) [18]	55.95 (3.64) [26]	8.05 (1.04) [17]	9.15 (1.06) [20]	12.61 (2.37) [25]	10.26 (1.89) [19]	10.46 (0.48) [21]																	
SOD	19.80 (3.87) [36]	30.48 (5.77) [35]	90.48 (3.56) [35]	11.26 (8.07) [44]	84.45 (3.66) [35]	11.26 (8.07) [44]	21.2 (6.14) [38]	38.31 (8.34) [41]	22.44 (8.31) [39]	45.02 (4.09) [21]	28.14 (4.36) [42]	9.89 (2.07) [9]	4.80 (1.58) [38]	12.98 (1.73) [20]	10.18 (1.70) [20]	9.80 (1.00) [30]																	
LUNAR	51.76 (8.01) [10]	49.79 (4.46) [9]	95.18 (0.85) [1]	50.74 (9.54) [15]	36.74 (13.12) [18]	41.37 (6.43) [13]	69.61 (5.69) [9]	97.89 (1.97) [6]	59.40 (8.16) [9]	63.08 (2.19) [16]	73.64 (7.97) [13]	13.29 (1.83) [2]	15.78 (1.08) [1]	14.89 (1.42) [2]	10.84 (1.46) [17]	13.38 (1.96) [2]																	
SOGAAL	2.25 (11.50) [48]	-10.26 (10.53) [46]	14.43 (33.31) [50]	1.67 (3.23) [49]	5.34 (6.49) [46]	0.50 (5.72) [48]	19.96 (10.47) [48]	3.17 (10.01) [48]	11.20 (5.03) [43]	7.76 (16.41) [49]	-0.83 (8.69) [50]	0.83 (3.20) [43]	1.78 (1.13) [42]	2.15 (2.29) [42]	4.90 (1.66) [36]	-0.82 (2.09) [45]																	
ALAD	4.25 (7.09) [43]	-1.84 (14.88) [44]	37.25 (12.24) [45]	-2.99 (10.81) [50]	0.46 (5.56) [50]	-2.11 (7.10) [50]	18.96 (10.22) [46]	-21.89 (15.32) [46]	3.92 (2.34) [45]	4.76 (14.88) [50]	6.03 (13.85) [48]	2.38 (1.97) [38]	1.78 (2.52) [44]	1.78 (2.52) [44]	1.78 (2.52) [44]	1.15 (0.91) [43]																	
AE	34.29 (2.28) [19]	37.31 (2.56) [23]	92.74 (3.30) [14]	32.73 (4.47) [23]	30.16 (3.97) [26]	20.16 (5.72) [25]	58.31 (4.47) [16]	65.14 (6.38) [25]	29.57 (2.63) [33]	45.00 (2.65) [22]	57.63 (6.04) [24]	6.92 (2.04) [23]	8.78 (1.25) [22]	13.79 (2.12) [8]	11.00 (1.55) [14]	11.31 (0.38) [14]																	
CD	2.57 (5.99) [44]	-26.41 (10.75) [48]	63.82 (6.71) [39]	76.54 (2.81) [1]	20.10 (6.41) [39]	53.10 (10.32) [7]	52.50 (6.24) [32]	49.50 (5.174) [33]	-28.22 (0.61) [48]	18.02 (10.38) [43]	45.85 (54.03) [36]	4.70 (7.20) [47]	6.64 (5.13) [30]	-0.53 (0.00) [48]	9.69 (1.45) [22]	-3.08 (0.11) [46]																	
MOGAL	7.49 (8.41) [41]	-4.29 (10.96) [45]	18.72 (34.81) [49]	2.71 (4.60) [48]	4.60 (3.06) [47]	-0.26 (5.23) [49]	19.74 (10.04) [49]	-1.32 (9.60) [49]	11.57 (5.34) [42]	13.72 (18.05) [47]	-0.55 (8.89) [49]	0.54 (2.38) [45]	0.60 (0.71) [46]	2.07 (2.64) [43]	7.05 (3.89) [31]	-0.63 (1.58) [44]																	
QMCD	-34.57 (3.13) [51]	-37.47 (3.13) [47]	-74.89 (3.22) [51]	-59.77 (9.74) [37]	-34.25 (9.40) [51]	-42.54 (1.23) [51]	-34.25 (9.59) [51]	-36.78 (6.73) [51]	-13.41 (4.31) [47]	-9.96 (6.82) [51]	-74.77 (9.27) [51]	-3.00 (1.71) [46]	-7.87 (0.28) [48]	-4.63 (1.12) [47]	-3.92 (0.26) [47]	-4.49 (0.35) [47]																	
Sampling	34.27 (3.28) [20]	35.55 (5.33) [28]	91.87 (3.60) [19]	29.17 (2.73) [33]	31.34 (5.49) [24]	11.93 (3.62) [33]	57.71 (2.94) [18]	63.77 (5.14) [28]	33.14 (6.46) [20]	43.49 (4.48) [24]	52.97 (7.66) [27]	6.92 (2.08) [23]	9.96 (1.62) [15]	12.09 (1.66) [27]	9.52 (2.10) [23]	10.74 (0.55) [18]																	
EIF	28.08 (4.47) [32]	37.36 (5.62) [21]	91.41 (4.75) [26]	31.23 (3.18) [27]	26.74 (5.19) [35]	10.68 (10.15) [40]	55.97 (3.27) [27]	73.37 (10.67) [18]	33.78 (10.92) [16]	42.65 (3.01) [26]	51.51 (6.16) [29]	4.37 (1.61) [35]	9.22 (2.00) [19]	10.77 (2.38) [31]	5.65 (1.15) [35]	11.40 (1.35) [11]																	
Ensemble	33.78 (1.73) [23]	38.96 (2.07) [15]	90.35 (3.65) [28]	31.50 (3.42) [25]	31.79 (6.82) [21]	21.60 (7.26) [22]	57.66 (3.72) [20]	70.46 (9.26) [20]	29.92 (6.94) [30]	51.68 (2.86) [14]	60.18 (7.06) [21]	9.33 (1.00) [13]	5.83 (1.11) [34]	13.79 (1.88) [8]	12.99 (1.04) [3]	10.09 (1.44) [26]																	
GENZOUT	34.75 (6.05) [17]	40.64 (4.25) [12]	91.45 (3.47) [25]	34.48 (7.43) [20]	28.68 (4.44) [29]	11.49 (10.25) [35]	55.92 (7.06) [29]	70.16 (8.86) [32]	33.44 (7.76) [18]	45.10 (3.34) [20]	52.05 (4.60) [28]	5.22 (1.64) [32]	10.11 (2.56) [9]	11.36 (2.49) [29]	3.99 (1.74) [41]	12.25 (1.85) [3]																	
DynamicHBOS	-2.58 (4.24) [50]	32.82 (6.05) [33]	80.75 (9.60) [36]	65.75 (5.31) [10]	75.75 (4.48) [48]	38.89 (12.83) [15]	46.94 (4.90) [38]	66.95 (4.76) [23]	28.79 (7.20) [35]	11.08 (4.90) [48]	73.85 (5.99) [12]	1.68 (2.30) [40]	7.90 (1.85) [27]	5.47 (2.25) [39]	-0.95 (0.95) [45]	11.59 (0.67) [6]																	
COF	11.05 (3.41) [40]	28.33 (10.18) [36]	29.91 (13.50) [47]	3.41 (3.60) [46]	1.92 (6.94) [49]	7.21 (4.95) [46]	30.62 (11.40) [44]	10.78 (12.21) [46]	18.27 (10.64) [41]	29.16 (4.09) [37]	18.21 (8.06) [46]	8.48 (1.04) [16]	1.85 (1.52) [41]	13.57 (2.34) [11]	12.33 (1.46) [8]	6.13 (1.70) [38]																	

		3077	3076	3075	3074	3073	3072	3071	3070	3069	3068	3067	3066	3065	3064	3063	3062	3061	3060	3059	3058	3057	3056	3055	3054	3053	3052	3051	3050	3049	3048	3047	3046	3045	
Model	SVHN 5	SVHN 6	SVHN 7	SVHN 8	SVHN 9	agnex0	agnex1	agnex2	agnex3	amazon	imdb	jeop	2news0	2news1	2news2	2news3	2news4	2news5																	
Iforce	7.31 (0.72) [14]	5.36 (2.22) [32]	14.73 (2.24) [13]	3.95 (1.48) [26]	2.71 (2.36) [36]	0.23 (2.00) [35]	1.48 (1.20) [30]	8.26 (0.57) [34]	2.44 (0.89) [38]	1.85 (2.34) [17]	-3.67 (0.83) [26]	7.52 (0.99) [22]	2.00 (1.80) [37]	-0.69 (-2.20) [46]	-1.20 (2.19) [30]	11.10 (5.98) [27]	4.91 (3.61) [12]	-2.28 (3.90) [17]																	
OC5VM	11.38 (1.55) [23]	8.66 (1.84) [19]	5.64 (2.21) [5]	7.70 (1.72) [26]	6.31 (2.67) [23]	2.00 (2.00) [36]	1.79 (0.43) [28]	1.01 (0.45) [28]	4.58 (0.96) [24]	3.81 (1.78) [3]	-3.89 (0.62) [33]	5.36 (1.92) [26]	3.81 (1.91) [27]	5.76 (1.92) [26]	-0.26 (2.02) [24]	15.16 (7.73) [18]	4.46 (2.30) [15]	-1.92 (3.75) [46]																	
COFOD	-10.52 (0.00) [49]	-10.51 (0.00) [49]	-10.51 (0.00) [49]	-10.51 (0.00) [49]	-10.52 (0.00) [49]	-1.61 (1.66) [37]	-3.38 (0.38) [47]	8.80 (0.97) [31]	3.62 (0.76) [29]	2.22 (1.43) [20]	-3.68 (0.86) [29]	8.71 (1.83) [16]	-0.16 (2.90) [41]	-3.39 (0.99) [42]	-0.99 (2.42) [27]	15.16 (7.73) [18]	2.65 (3.23) [31]	-3.24 (2.63) [44]																	
ECOD	-10.52 (0.00) [49]	-10.51 (0.00) [49]	-10.51 (0.00) [49]	-10.51 (0.00) [49]	-10.52 (0.00) [49]	-0.88 (-2.12) [45]	-0.31 (1.38) [25]	5.24 (1.18) [40]	0.67 (1.33) [44]	0.51 (1.62) [34]	-4.48 (-1.14) [30]	5.83 (2.47) [34]	2.00 (1.22) [37]	-1.63 (1.62) [42]	-6.99 (1.74) [43]	15.16 (7.73) [18]	2.20 (1.81) [37]	-1.32 (2.80) [47]																	
FeatureBagging	14.54 (0.67) [7]	10.49 (1.57) [7]	13.21 (0.80) [24]	12.15 (1.94) [5]	9.80 (3.46) [4]	12.54 (0.89) [3]	29.56 (1.83) [3]	26.17 (1.59) [5]	23.59 (1.24) [6]	-0.06 (1.37) [60]	-2.86 (0.85) [3]	10.99 (1.83) [7]	27.22 (1.89) [5]	0.14 (2.53) [22]	-0.30 (1.12) [18]	16.63 (1.19) [14]	5.36 (2.41) [11]	4.45 (2.80) [17]																	
HBOS	1.60 (1.49) [43]	0.42 (1.26) [43]	12.85 (1.52) [4]	-1.47 (1.52) [44]	-2.55 (0.90) [44]	0.82 (1.57) [33]	3.89 (0.36) [45]	7.31 (1.23) [37]	3.30 (0.95) [28]	1.93 (1.35) [16]	-3.45 (0.86) [22]	8.34 (1.87) [19]	-2.80 (2.47) [47]	-6.04 (1.61) [28]	-2.39 (2.05) [44]	14.70 (0.86) [20]	3.56 (2.63) [22]	-4.20 (1.17) [49]																	
KNN	11.86 (1.63) [17]	9.03 (1.81) [16]	14.86 (2.62) [11]	8.68 (1.43) [22]	7.23 (2.80) [16]	8.04 (1.41) [12]	-7.89 (0.90) [24]	18.73 (0.88) [14]	12.76 (0.63) [15]	2.29 (1.33) [9]	-5.00 (0.62) [44]	10.33 (1.90) [12]	6.80 (1.96) [16]	10.11 (1.72) [22]	-1.20 (1.36) [20]	20.24 (0.38) [10]	2.66 (4.00) [29]	3.00 (1.71) [24]																	
LOF	7.7 (2.17) [31]	2.80 (3.33) [40]	11.85 (2.50) [32]	5.48 (1.45) [32]	3.32 (3.26) [34]	4.06 (2.45) [25]	-1.24 (2.42) [42]	9.96 (1.96) [26]	3.62 (1.75) [24]	2.00 (1.14) [14]	-2.86 (1.13) [24]	5.98 (2.83) [33]	-1.60 (1.63) [43]	-2.51 (2.21) [32]	-1.49 (1.89) [34]	11.83 (1.70) [25]	4.91 (2.21) [32]	-3.72 (2.80) [46]																	
LDA	14.74 (1.34) [12]	10.10 (1.26) [11]	13.10 (1.52) [25]	8.28 (1.32) [9]	4.39 (0.75) [14]	12.99 (0.75) [14]	8.28 (1.32) [9]	12.29 (0.71) [4]	14.26 (1.35) [4]	-0.14 (1.72) [42]	-3.38 (0.86) [20]	11.36 (1.97) [44]	27.94 (0.32) [14]	0.73 (2.39) [16]	0.30 (1.71) [14]	16.63 (1.19) [14]	5.88 (2.53) [10]	5.88 (2.53) [10]		</															

Table 40: Mean, standard deviation and rank ADJ F1-Score performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 8

Model	AL01	abalone	amblyoph	anrhythmia	backdoor	bcaste	campaign	Cardiologegraphy	cardio	celebs	cenus	cover	donors	ecoli	fault	fraud	glass	Hepatitis
Forest	0.11 (0.17) [41]	43.12 (5.78) [27]	52.46 (6.39) [20]	49.63 (4.19) [30]	5.42 (0.80) [31]	98.58 (0.32) [2]	31.54 (2.24) [28]	39.45 (2.98) [9]	73.77 (6.11) [12]	8.49 (2.08) [19]	3.02 (0.64) [33]	7.20 (1.31) [24]	33.13 (4.73) [24]	51.30 (13.32) [33]	13.37 (3.00) [31]	21.89 (8.77) [27]	17.50 (5.99) [35]	40.05 (7.71) [29]
OSVM	0.62 (0.18) [13]	60.41 (12.08) [12]	53.01 (8.12) [17]	54.44 (11.32) [12]	3.31 (0.17) [37]	97.96 (0.70) [9]	36.26 (2.55) [8]	46.02 (1.97) [6]	79.88 (2.09) [4]	16.96 (1.47) [3]	9.50 (0.55) [12]	21.09 (1.91) [21]	35.71 (2.22) [23]	80.49 (6.35) [9]	19.93 (3.58) [18]	32.76 (6.16) [29]	25.49 (8.70) [26]	49.01 (4.92) [18]
COPD	0.25 (0.07) [47]	36.17 (6.42) [30]	20.62 (0.64) [44]	0.03 (1.98) [48]	0.00 (0.10) [47]	98.25 (0.66) [5]	38.93 (0.64) [1]	36.67 (1.93) [14]	73.26 (3.26) [19]	13.33 (1.43) [10]	0.00 (0.22) [44]	11.59 (0.63) [30]	27.57 (1.43) [31]	33.17 (0.96) [39]	2.14 (1.30) [42]	42.04 (4.80) [28]	14.75 (7.02) [40]	43.52 (6.62) [28]
ECOD	0.05 (0.13) [33]	59.32 (5.14) [13]	33.18 (1.34) [33]	33.62 (1.54) [33]	0.03 (1.98) [48]	98.23 (0.58) [47]	31.49 (0.58) [4]	51.61 (1.74) [3]	76.85 (2.89) [6]	13.79 (1.43) [10]	0.00 (0.22) [44]	13.79 (1.43) [10]	36.62 (1.67) [41]	40.77 (1.74) [46]	35.31 (4.73) [34]	23.72 (7.34) [21]	33.51 (4.73) [34]	31.51 (4.73) [34]
FeatureBagging	0.89 (0.37) [7]	64.73 (8.54) [30]	40.97 (8.35) [30]	49.69 (8.15) [29]	46.03 (9.70) [14]	3.90 (0.61) [45]	12.84 (0.65) [42]	7.26 (3.35) [17]	62.83 (3.84) [23]	0.63 (0.24) [46]	0.21 (0.48) [42]	76.96 (1.35) [24]	95.82 (9.52) [33]	64.80 (16.14) [28]	-3.13 (2.72) [49]	49.67 (4.66) [3]	37.70 (12.22) [17]	26.21 (0.10) [29]
HBOS	0.47 (0.19) [21]	18.13 (3.54) [41]	29.40 (1.98) [52]	52.51 (0.59) [18]	4.62 (0.34) [34]	97.97 (1.22) [15]	38.26 (3.70) [7]	66.28 (3.77) [34]	5.68 (0.34) [17]	2.62 (0.29) [35]	3.47 (0.45) [24]	27.42 (1.43) [40]	5.55 (1.30) [44]	34.89 (6.26) [28]	2.47 (0.48) [40]	49.91 (9.56) [26]	40.91 (9.56) [26]	40.91 (9.56) [26]
KNN	0.09 (0.15) [36]	65.15 (11.38) [3]	62.23 (1.44) [5]	52.52 (0.82) [17]	4.31 (1.80) [15]	97.27 (0.56) [16]	35.61 (0.48) [9]	31.90 (1.86) [21]	72.14 (2.26) [15]	7.97 (0.76) [29]	10.99 (0.90) [4]	55.62 (4.44) [12]	87.89 (1.54) [7]	80.08 (6.38) [11]	21.17 (2.45) [16]	42.88 (6.59) [19]	41.35 (10.74) [11]	87.60 (4.40) [12]
KNN	0.03 (0.43) [36]	16.80 (10.34) [44]	38.31 (6.75) [31]	45.76 (1.14) [33]	1.26 (3.69) [42]	61.81 (2.99) [29]	11.41 (0.43) [29]	31.97 (0.27) [13]	67.27 (4.12) [22]	5.50 (0.67) [28]	4.30 (5.56) [28]	18.16 (6.69) [12]	19.76 (20.24) [39]	6.10 (5.06) [39]	39.79 (15.47) [22]	10.71 (4.86) [47]	27.64 (13.31) [38]	27.64 (13.31) [38]
LOF	0.59 (0.21) [15]	61.49 (6.09) [9]	46.39 (1.63) [26]	50.22 (1.89) [27]	50.93 (2.00) [12]	63.04 (13.92) [38]	25.14 (0.22) [33]	32.02 (1.98) [19]	64.28 (2.32) [26]	4.07 (0.89) [48]	2.20 (0.55) [37]	83.33 (3.43) [1]	59.22 (1.41) [11]	71.55 (9.72) [23]	-3.46 (2.47) [50]	60.92 (5.44) [7]	39.11 (11.58) [14]	24.85 (12.89) [48]
MCD	0.32 (0.19) [48]	24.51 (5.00) [35]	52.53 (1.59) [29]	62.15 (0.68) [10]	18.65 (13.18) [20]	96.03 (0.30) [21]	37.54 (2.55) [19]	34.28 (2.52) [32]	60.39 (3.30) [31]	15.05 (3.40) [26]	20.99 (2.67) [1]	1.64 (0.44) [42]	22.37 (13.99) [33]	59.31 (5.99) [31]	24.48 (10.14) [7]	62.11 (3.37) [1]	15.93 (6.65) [38]	39.25 (10.36) [30]
PCA	0.64 (0.19) [11]	54.92 (10.46) [16]	48.80 (1.80) [24]	51.99 (0.73) [21]	3.38 (0.22) [35]	97.78 (0.34) [11]	35.48 (0.23) [11]	51.64 (1.75) [1]	82.91 (2.36) [1]	17.96 (1.61) [1]	9.23 (0.44) [12]	69.04 (12.58) [25]	18.36 (1.67) [25]	27.39 (1.31) [31]	18.33 (6.68) [42]	56.02 (6.72) [28]	56.02 (6.72) [28]	56.02 (6.72) [28]
DeepSVDD	0.45 (0.36) [22]	24.90 (7.92) [34]	13.71 (3.79) [46]	59.70 (12.62) [11]	69.49 (16.27) [8]													

Table 41: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 1

	Model	hva anomalies vpt	hva anomalies mid	hnp	IntersectAd	iosphere	landuse	letter	Lymphography	magic-gamma	mammography	mlf	miv	mlst	mlcores	mlusk	mlsu	mydlight	PageBlocks
	IFcore	13.19 (0.49) [20]	7.52 (1.14) [40]	56.16 (9.76) [29]	-3.91 (1.64) [28]	84.56 (4.37) [30]	20.00 (4.90) [14]	-3.87 (0.27) [42]	92.65 (3.34) [28]	58.72 (2.08) [22]	34.33 (3.53) [20]	22.83 (2.62) [2]	25.18 (1.86) [11]	44.83 (7.53) [29]	98.96 (0.54) [27]	47.08 (2.49) [41]	10.12 (2.99) [23]	10.18 (3.39) [19]	32.86 (1.53) [40]
	OC5VM	9.75 (0.67) [29]	13.52 (0.87) [21]	59.09 (0.38) [6]	14.14 (1.56) [21]	3.88 (0.56) [32]	-3.92 (0.12) [51]	3.03 (0.54) [32]	56.69 (0.59) [17]	74.22 (0.44) [13]	22.80 (0.80) [12]	60.23 (2.17) [19]	77.24 (0.78) [12]	57.21 (0.46) [34]	98.96 (0.54) [27]	47.08 (2.49) [41]	10.12 (2.99) [23]	10.18 (3.39) [19]	32.86 (1.53) [40]
	ECOD	15.14 (0.52) [17]	15.28 (0.75) [16]	47.56 (6.01) [34]	18.36 (22.42) [13]	58.96 (6.92) [41]	0.52 (0.81) [39]	-3.51 (0.46) [38]	95.22 (3.37) [23]	42.91 (7.17) [37]	52.45 (1.42) [12]	0.00 (0.00) [47]	-0.01 (0.00) [48]	66.52 (0.51) [38]	94.33 (2.52) [30]	4.08 (0.54) [37]	-0.00 (0.00) [37]	29.57 (1.40) [31]	55.41 (0.96) [32]
	FIPOD	21.22 (0.43) [18]	21.21 (0.60) [8]	28.65 (1.45) [40]	18.43 (2.51) [32]	53.50 (4.76) [44]	-3.74 (0.60) [46]	-1.95 (0.79) [44]	94.12 (3.85) [25]	34.88 (7.00) [34]	52.94 (1.86) [29]	0.00 (0.00) [47]	-0.01 (0.00) [48]	72.55 (0.77) [37]	99.12 (0.38) [28]	49.17 (0.25) [50]	-0.00 (0.00) [37]	50.59 (1.72) [29]	50.59 (1.72) [29]
	FeatureBagging	17.16 (5.75) [11]	22.51 (3.16) [6]	74.78 (0.81) [44]	28.92 (7.04) [24]	89.78 (2.53) [24]	41.98 (1.15) [1]	0.19 (1.27) [14]	65.07 (22.00) [38]	72.45 (0.58) [8]	26.61 (0.30) [27]	22.16 (0.40) [27]	20.10 (0.74) [21]	64.09 (1.56) [16]	100.00 (0.00) [1]	11.02 (1.10) [19]	37.27 (1.47) [6]	64.73 (0.67) [46]	64.73 (0.67) [46]
	HROS	7.56 (0.63) [39]	8.45 (0.50) [35]	36.62 (6.63) [38]	-0.47 (2.20) [46]	25.61 (4.51) [26]	39.58 (1.02) [44]	-3.38 (0.55) [33]	96.48 (0.29) [21]	52.55 (4.99) [27]	12.57 (1.75) [34]	12.56 (0.24) [5]	22.12 (0.42) [19]	97.29 (1.07) [30]	100.00 (0.00) [1]	1.57 (0.57) [49]	46.67 (1.76) [4]	6.30 (1.12) [48]	6.30 (1.12) [48]
	KNN	12.82 (0.65) [22]	17.66 (0.48) [13]	100.00 (0.00) [1]	25.62 (1.91) [20]	95.88 (1.15) [12]	31.43 (1.56) [38]	-3.38 (0.15) [33]	98.86 (1.01) [13]	70.73 (0.36) [12]	37.46 (3.24) [12]	7.07 (0.57) [33]	28.11 (0.81) [6]	67.68 (1.70) [8]	100.00 (0.00) [1]	100.00 (0.00) [1]	16.95 (0.74) [12]	24.93 (2.01) [13]	61.23 (1.37) [11]
	LOF	6.63 (4.21) [44]	5.88 (4.49) [46]	7.12 (8.83) [45]	14.23 (3.36) [38]	68.63 (4.61) [37]	2.28 (8.23) [38]	-4.18 (1.07) [49]	22.84 (16.22) [45]	49.89 (1.83) [31]	41.18 (5.95) [6]	22.46 (8.53) [6]	2.32 (6.55) [45]	21.09 (9.32) [41]	99.76 (0.29) [26]	91.46 (1.10) [62]	9.19 (4.61) [26]	-1.40 (0.68) [46]	36.20 (2.78) [35]
	LDA	16.82 (0.94) [12]	22.06 (0.77) [44]	97.16 (5.52) [10]	27.10 (1.57) [16]	89.01 (2.62) [26]	41.07 (1.08) [12]	0.18 (1.48) [35]	85.64 (4.03) [33]	71.74 (0.36) [9]	13.12 (0.36) [24]	18.81 (0.26) [24]	65.35 (1.15) [49]	68.86 (0.88) [6]	94.33 (2.52) [30]	4.08 (0.54) [37]	-0.00 (0.00) [37]	29.57 (1.40) [31]	55.41 (0.96) [32]
	MCD	7.41 (1.51) [40]	9.75 (2.32) [32]	95.91 (1.58) [14]	6.12 (2.50) [37]	94.24 (1.37) [19]	8.47 (0.73) [27]	-3.89 (0.45) [44]	86.99 (0.36) [12]	52.78 (4.60) [26]	3.54 (0.42) [49]	49.72 (8.72) [30]	17.82 (1.28) [20]	44.72 (8.72) [30]	100.00 (0.00) [1]	63.17 (1.28) [36]	1.77 (0.49) [42]	1.75 (0.40) [42]	55.41 (0.96) [32]
	PCA	8.39 (0.65) [33]	10.37 (1.03) [30]	91.36 (1.25) [51]	22.60 (1.84) [27]	22.60 (1.84) [27]	-2.89 (0.58) [44]	-4.20 (0.13) [30]	96.81 (0.47) [15]	48.46 (8.59) [35]	38.26 (1.89) [11]	22.79 (0.35) [31]	15.37 (0.33) [30]	58.76 (2.00) [48]	100.00 (0.00) [1]	100.00 (0.00) [1]	0.48 (0.05) [35]	51.35 (1.37) [27]	51.35 (1.37) [27]
	DeepSVDD	7.71 (3.16) [38]	3.81 (3.40) [47]																

Table 42: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 2

Model	Pathloss	prop_sgnl	prop_global	prop_local	Pmax	satellite	satimage-2	satimage-bumps	shuttle	skin	smp	Spunbase	speech	Stumps	thyroid	ventral	vowels	Worsetem
Birest	78.33 (3.64) [24]	55.18 (5.71) [16]	75.32 (4.38) [23]	0.86 (0.29) [13]	49.57 (3.05) [13]	65.22 (2.16) [24]	95.13 (0.55) [16]	5.16 (1.87) [20]	98.31 (0.42) [14]	45.53 (1.91) [21]	1.11 (0.10) [45]	70.16 (2.18) [3]	0.49 (0.118) [11]	56.44 (7.56) [21]	79.59 (5.60) [13]	-2.64 (2.65) [38]	6.65 (2.66) [34]	5.77 (1.80) [24]
CCSYM	81.89 (2.74) [21]	48.96 (3.64) [20]	89.30 (0.98) [17]	0.22 (0.08) [38]	44.78 (5.52) [14]	69.95 (0.64) [4]	96.35 (0.64) [4]	5.33 (1.29) [32]	97.47 (0.32) [20]	40.85 (0.55) [17]	70.64 (1.43) [3]	78.55 (0.96) [19]	-0.08 (0.49) [33]	63.66 (4.45) [13]	79.09 (2.24) [17]	-0.81 (2.42) [29]	25.57 (6.31) [21]	6.36 (1.08) [22]
CCOPO	25.56 (10.10) [29]	28.62 (3.14) [20]	28.10 (3.79) [44]	0.08 (0.03) [43]	4.62 (2.57) [19]	51.31 (0.65) [39]	87.80 (1.11) [29]	0.00 (0.00) [47]	98.23 (0.18) [15]	6.20 (3.80) [44]	1.09 (0.15) [46]	43.74 (1.82) [33]	-0.33 (0.40) [46]	52.84 (2.83) [23]	32.27 (1.53) [45]	-8.41 (2.45) [50]	-0.09 (0.45) [47]	2.60 (0.79) [26]
ECOD	-18.16 (0.03) [21]	29.74 (3.65) [23]	28.17 (4.06) [43]	0.10 (0.04) [43]	33.58 (3.27) [31]	5.15 (0.61) [31]	0.00 (0.00) [47]	95.74 (0.23) [49]	95.74 (0.23) [49]	79.13 (1.85) [35]	0.21 (0.04) [26]	45.96 (5.70) [33]	0.20 (0.04) [26]	45.96 (5.70) [33]	7.26 (5.12) [28]	-2.69 (1.59) [20]	1.49 (0.18) [20]	5.49 (0.73) [26]
FeatureBagging	79.43 (4.68) [23]	82.84 (2.00) [9]	93.31 (0.03) [15]	41.96 (7.49) [2]	36.04 (5.90) [25]	72.61 (0.74) [24]	91.58 (1.65) [22]	14.94 (1.37) [31]	37.27 (2.79) [39]	22.82 (1.94) [31]	0.20 (0.05) [49]	24.34 (3.34) [41]	0.23 (0.52) [22]	64.24 (3.31) [12]	34.27 (18.74) [44]	10.12 (1.00) [12]	32.74 (5.50) [14]	26.74 (4.60) [4]
HROS	92.58 (1.68) [13]	29.04 (4.53) [23]	33.36 (0.50) [37]	0.51 (0.12) [37]	53.95 (3.60) [8]	73.58 (0.72) [3]	93.85 (0.07) [27]	13.32 (2.57) [21]	97.02 (0.08) [21]	28.32 (0.67) [28]	1.32 (0.20) [34]	46.88 (0.97) [31]	0.59 (0.96) [30]	46.25 (5.34) [31]	77.09 (2.38) [30]	-0.50 (0.66) [29]	4.50 (0.66) [29]	
KNN	90.02 (2.96) [15]	96.31 (0.67) [5]	99.61 (0.67) [39]	0.09 (0.58) [17]	52.85 (3.65) [11]	72.89 (1.02) [4]	97.08 (0.71) [3]	6.99 (1.01) [26]	97.74 (0.46) [19]	97.48 (0.55) [2]	57.92 (0.64) [9]	61.25 (0.98) [13]	-0.07 (0.48) [32]	70.43 (10.02) [18]	81.89 (1.93) [21]	3.75 (3.79) [19]	26.45 (2.76) [19]	21.73 (2.75) [7]
LOF	64.36 (10.34) [14]	77.57 (10.22) [24]	42.31 (1.67) [39]	2.10 (0.07) [39]	22.52 (16.79) [37]	60.45 (1.89) [30]	94.05 (0.95) [18]	-3.19 (2.83) [50]	36.93 (0.84) [40]	26.89 (10.56) [29]	9.53 (7.71) [34]	61.56 (8.04) [12]	0.22 (1.15) [23]	50.77 (0.67) [21]	66.04 (6.32) [29]	-7.12 (2.18) [47]	5.95 (4.25) [37]	3.10 (1.23) [35]
LDA	77.29 (4.20) [26]	35.29 (2.34) [10]	93.51 (1.99) [13]	31.29 (0.01) [4]	40.47 (5.36) [28]	72.70 (0.79) [13]	89.38 (0.14) [24]	3.37 (0.02) [29]	98.78 (0.13) [4]	57.43 (0.78) [26]	71.32 (1.43) [37]	64.04 (0.78) [13]	63.03 (0.58) [17]	60.01 (3.26) [13]	11.49 (2.64) [9]	33.36 (0.60) [12]	25.67 (2.30) [12]	
MCA	73.61 (6.46) [30]	9.84 (1.09) [41]	42.13 (5.77) [34]	0.21 (0.09) [39]	36.64 (5.13) [24]	61.08 (8.35) [24]	98.16 (0.43) [1]	28.30 (0.63) [15]	90.02 (0.35) [4]	42.58 (0.64) [12]	11.9 (0.20) [44]	57.80 (1.15) [26]	-0.10 (0.40) [19]	32.06 (0.93) [40]	80.86 (0.47) [20]	-2.26 (3.86) [37]	-2.43 (1.00) [48]	2.83 (0.84) [30]
PCA	73.73 (6.31) [26]	35.30 (3.11) [26]	45.63 (6.13) [34]	0.03 (0.04) [45]	44.38 (5.02) [45]	75.10 (0.15) [36]	92.06 (0.69) [21]	-1.04 (0.06) [51]	98.86 (0.43) [27]	7.28 (0.34) [42]	57.07 (1.26) [39]	81.84 (2.31) [4]	0.44 (2.16) [43]	5.97 (3.09) [36]		3.83 (0.87) [33]		
DeepSVD	98.62 (0.38) [13]	3.85 (3.76) [46]	76.79 (0.65) [42]	11.25 (1.29) [19]	17.76 (5.15) [41]	63.98 (2.74) [24]	78.65 (3.72) [33]	58.67 (5.26) [3]	97.84 (0.29) [18]	12.31 (1.36) [35]	44.31 (24.12) [25]							

Table 43: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 3

Model	WBC	wbc2	WDBC	Wit	wine	WPBC	year0	year06	CFIAR10.0	CFIAR10.1	CFIAR10.2	CFIAR10.3	CFIAR10.4	CFIAR10.5	CFIAR10.6	CFIAR10.7	CFIAR10.8	CFIAR10.9
fforest	95.96 (2.71) [9]	70.76 (9.80) [27]	89.45 (2.24) [25]	-1.44 (0.68) [15]	63.27 (1.17) [30]	8.06 (6.96) [31]	8.59 (1.49) [45]	5.53 (1.29) [9]	13.97 (1.78) [26]	0.71 (0.44) [39]	3.54 (0.40) [29]	2.22 (0.78) [49]	20.62 (1.44) [29]	0.94 (0.23) [40]	8.85 (1.24) [39]	10.71 (1.09) [29]	8.94 (0.72) [30]	10.95 (1.10) [32]
OCVM	95.96 (2.71) [9]	77.87 (3.88) [17]	94.73 (4.26) [12]	-3.31 (0.55) [48]	86.10 (5.68) [18]	8.63 (5.55) [30]	8.63 (5.55) [30]	5.25 (1.24) [44]	16.46 (1.23) [16]	5.73 (1.27) [22]	4.90 (0.55) [31]	5.42 (1.54) [15]	24.62 (2.31) [19]	13.27 (1.18) [13]	11.22 (0.92) [13]	13.72 (1.18) [13]	12.00 (0.58) [13]	15.91 (0.97) [15]
COPD	96.58 (2.39) [12]	83.85 (2.51) [8]	94.70 (3.41) [13]	-3.56 (0.08) [50]	52.26 (7.77) [35]	5.29 (6.15) [36]	8.45 (1.22) [43]	12.06 (3.42) [1]	13.06 (0.94) [31]	-0.71 (0.46) [49]	2.68 (0.33) [37]	0.70 (0.94) [43]	0.01 (0.00) [48]	-0.54 (0.38) [49]	6.25 (0.45) [37]	3.71 (4.54) [43]	0.01 (0.00) [46]	0.01 (0.00) [47]
ECOD	95.62 (2.01) [11]	64.30 (5.14) [31]	75.31 (2.74) [12]	-2.47 (0.18) [41]	27.01 (7.54) [41]	8.83 (4.59) [42]	-3.13 (1.16) [46]	3.57 (1.03) [46]	13.81 (0.94) [28]	0.19 (0.54) [43]	3.14 (0.32) [31]	1.56 (1.16) [40]	0.01 (0.00) [48]	0.28 (0.34) [44]	7.11 (0.47) [35]	4.30 (2.55) [40]	0.01 (0.00) [46]	0.01 (0.00) [46]
FeatureBagging	6.56 (8.53) [46]	79.69 (4.93) [13]	97.46 (1.73) [17]	0.89 (1.31) [29]	87.91 (5.94) [17]	8.29 (3.81) [30]	-2.65 (1.82) [14]	3.58 (1.06) [29]	18.06 (1.36) [46]	0.38 (2.17) [13]	6.28 (0.82) [31]	6.67 (4.62) [1]	25.39 (2.33) [8]	7.26 (0.88) [31]	15.64 (1.44) [33]	15.75 (1.58) [13]	0.65 (0.72) [2]	19.07 (1.92) [1]
HNB	91.88 (3.75) [17]	76.35 (6.68) [19]	89.30 (4.64) [26]	-2.57 (0.19) [44]	74.46 (13.95) [25]	11.27 (6.22) [32]	-2.39 (1.31) [31]	5.30 (1.46) [11]	12.53 (1.07) [32]	-1.94 (0.30) [51]	2.11 (0.31) [41]	0.06 (0.61) [48]	17.72 (1.73) [35]	-1.59 (0.12) [51]	4.55 (0.36) [41]	6.54 (0.66) [37]	8.53 (0.64) [36]	6.28 (0.97) [36]
KNN	89.72 (5.98) [19]	76.51 (4.58) [21]	91.52 (4.12) [19]	2.17 (0.36) [19]	94.61 (0.00) [12]	16.35 (4.93) [17]	4.58 (1.03) [28]	4.58 (0.88) [19]	5.90 (1.23) [11]	5.86 (1.30) [11]	4.70 (0.63) [21]	3.59 (1.43) [22]	25.70 (2.09) [6]	17.50 (2.09) [22]	12.36 (1.09) [15]	13.73 (0.91) [17]	12.37 (0.80) [17]	15.93 (0.97) [17]
LOF	75.03 (17.92) [28]	75.03 (17.92) [28]	75.03 (17.92) [28]	-2.55 (0.80) [43]	53.65 (4.86) [34]	4.47 (6.23) [38]	-4.93 (5.62) [34]	2.45 (1.53) [34]	17.21 (0.27) [34]	3.74 (2.07) [32]	3.44 (0.60) [30]	17.41 (0.99) [37]	17.84 (2.15) [34]	2.97 (1.96) [28]	17.12 (0.27) [33]	14.22 (1.96) [23]	8.54 (0.68) [33]	12.51 (2.62) [33]
LDA	18.62 (8.99) [42]	69.23 (4.66) [15]	97.08 (1.87) [51]	8.81 (0.86) [13]	89.46 (4.40) [15]	8.64 (3.78) [26]	-4.52 (1.69) [19]	5.86 (1.25) [25]	17.88 (1.03) [8]	14.19 (3.17) [1]	6.35 (0.85) [1]	3.94 (0.57) [21]	27.84 (2.15) [16]	23.14 (0.91) [14]	15.25 (1.50) [44]	15.77 (1.30) [1]	15.88 (0.66) [31]	19.03 (1.44) [31]
MCD	87.51 (8.37) [22]	56.61 (9.88) [34]	68.08 (4.83) [14]	12.42 (0.61) [7]	76.36 (10.54) [24]	15.05 (5.62) [18]	-9.57 (1.20) [48]	1.90 (0.68) [37]	12.38 (0.84) [33]	5.18 (2.42) [24]	3.21 (0.31) [32]	2.31 (0.41) [33]	17.42 (1.15) [36]	2.31 (0.56) [44]	6.55 (0.88) [36]	8.00 (1.34) [35]	5.38 (0.63) [38]	9.05 (2.08) [35]
PCA	94.31 (1.72) [15]	73.78 (6.30) [25]	90.19 (4.17) [24]	-4.05 (0.17) [51]	64.54 (9.90) [27]	65.96 (6.00) [33]	8.44 (1.49) [42]	5.46 (1.10) [40]	16.30 (1.17) [18]	4.97 (1.18) [27]	4.36 (0.51) [22]	4.11 (0.11) [49]	24.84 (2.05) [14]	3.88 (0.43) [39]	11.00 (0.97) [22]	12.89 (1.20) [18]	12.15 (0.97) [19]	15.13 (0.93) [19]
DeepSVD	57.14 (10.75) [19]	83.42 (5.88) [10]	90.70 (5.50) [21]	4.44 (0.04) [19]	81.22 (3.94) [22]	5.88 (5.46												

Table 44: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 4

[illegible]

Table 45: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 5

Model	MINST-C identity	MINST-C impulse noise	MINST-C motion blur	MINST-C rotate	MINST-C scale	MINST-C shear	MINST-C shot noise	MINST-C spatter	MINST-C stripe	MINST-C translate	MINST-C rigging	MYTeAc dBottle	MYTeAc dCable	MYTeAc dCapsule	MYTeAc dCarpet
IForest	-0.42 (0.10) [41]	89.26 (4.17) [31]	25.09 (2.41) [23]	1.30 (0.39) [35]	6.27 (1.99) [32]	7.59 (0.79) [32]	16.70 (1.72) [30]	32.16 (4.33) [30]	96.09 (1.80) [30]	2.09 (0.63) [25]	24.01 (1.25) [30]	94.82 (1.62) [32]	36.48 (7.15) [28]	39.99 (5.01) [28]	49.56 (0.31) [24]
OCvnet	-0.33 (0.25) [30]	91.95 (2.21) [21]	51.95 (2.21) [21]	2.36 (0.43) [24]	15.84 (0.94) [19]	10.55 (0.17) [23]	41.46 (1.78) [19]	87.77 (0.55) [20]	90.77 (0.55) [20]	6.05 (0.62) [25]	39.49 (0.88) [21]	94.72 (1.22) [22]	38.64 (7.70) [23]	45.06 (3.88) [27]	50.31 (6.79) [24]
COPPOD	-0.00 (0.00) [6]	-0.00 (0.00) [46]	-0.00 (0.00) [47]	-0.00 (0.00) [47]	-0.00 (0.00) [41]	-0.00 (0.00) [45]	-0.00 (0.00) [48]	-0.00 (0.00) [46]	-0.00 (0.00) [47]	-0.00 (0.00) [45]	-0.00 (0.00) [45]	-0.01 (2.35) [48]	0.00 (2.62) [45]	-0.03 (1.47) [46]	-0.10 (0.31) [47]
ECOD	-0.00 (0.00) [6]	-0.00 (0.00) [46]	-0.00 (0.00) [47]	-0.00 (0.00) [46]	-0.00 (0.00) [41]	-0.00 (0.00) [45]	-0.00 (0.00) [48]	-0.00 (0.00) [46]	-0.00 (0.00) [47]	-0.00 (0.00) [45]	-0.00 (0.00) [45]	-0.01 (2.35) [48]	0.00 (2.62) [45]	-0.03 (1.47) [46]	-0.10 (0.31) [47]
FeatureBagging	-0.38 (0.24) [36]	89.19 (2.25) [17]	66.84 (2.53) [18]	5.75 (0.58) [6]	28.61 (1.32) [17]	17.03 (1.35) [4]	40.29 (1.91) [4]	58.92 (0.30) [6]	98.53 (0.30) [6]	18.64 (1.14) [5]	55.11 (1.49) [9]	95.50 (1.24) [10]	45.96 (7.01) [15]	49.70 (4.94) [18]	54.77 (6.77) [18]
HNNS	-0.00 (0.23) [26]	92.62 (4.47) [41]	14.79 (0.79) [40]	1.48 (0.28) [34]	0.27 (0.27) [40]	6.43 (0.93) [34]	7.98 (0.58) [39]	17.51 (0.58) [38]	62.08 (1.53) [36]	81.01 (2.06) [42]	10.83 (0.43) [40]	94.68 (1.77) [25]	38.21 (7.50) [25]	39.79 (0.05) [31]	52.67 (7.51) [27]
KBOs	-0.43 (0.23) [42]	99.72 (2.07) [14]	99.72 (2.07) [14]	13.31 (2.12) [12]	20.81 (1.12) [12]	33.12 (2.03) [10]	48.43 (1.46) [13]	98.46 (0.61) [17]	47.96 (0.90) [14]	95.42 (0.61) [17]	47.96 (0.90) [14]	95.42 (0.61) [17]	44.46 (7.09) [19]	50.26 (8.33) [15]	55.47 (6.74) [15]
LODA	-0.54 (0.46) [46]	96.84 (3.28) [25]	94.63 (3.55) [26]	0.57 (0.15) [38]	6.28 (2.81) [32]	4.22 (1.79) [38]	12.00 (0.55) [35]	29.28 (8.11) [32]	87.86 (4.87) [29]	27.0 (94.94) [38]	35.05 (7.71) [34]	91.51 (0.96) [32]	28.19 (1.14) [32]	36.15 (1.78) [34]	39.45 (4.53) [34]
LRF	-0.38 (0.24) [36]	90.08 (0.32) [19]	68.55 (1.99) [6]	5.74 (0.46) [7]	29.30 (1.62) [4]	16.78 (1.45) [5]	40.07 (1.95) [5]	18.24 (0.76) [8]	98.58 (0.15) [14]	22.4 (76.38) [38]	19.21 (1.44) [10]	94.43 (0.67) [17]	57.75 (0.56) [12]	54.25 (6.46) [22]	54.25 (6.46) [22]
MCD	0.06 (0.31) [4]	64.62 (10.03) [36]	21.99 (8.29) [38]	1.76 (0.69) [30]	8.69 (2.80) [28]	5.18 (1.06) [37]	9.72 (1.03) [36]	24.83 (5.57) [35]	75.12 (18.56) [33]	3.66 (0.34) [33]	15.80 (2.10) [37]	95.54 (2.86) [19]	53.36 (7.50) [12]	63.73 (3.11) [11]	55.71 (8.54) [14]
PCA	-0.34 (0.24) [31]	99.46 (0.21) [12]	49.80 (2.03) [24]	2.13 (0.41) [28]	13.82 (0.90) [23]	9.42 (1.05) [26]	21.80 (1.95) [24]	38.67 (1.70) [22]	97.78 (0.39) [17]	5.29 (0.54) [22]	36.97 (1.56) [22]	94.41 (1.58) [26]	35.89 (7.00) [29]	38.90 (0.99) [36]	52.75 (8.65) [29]
DeepSVDD	-0.13 (0.19) [36]	94.96 (2.32) [17]	17.77 (0.38) [28]	1.28 (0.36) [26]	7.41 (2.71) [30]	4.10 (1.02) [30]	9.08 (2.58) [39]	14.84 (1.22) [36]	84.48 (1.22) [39]	2.84 (3.00) [37]	13.89 (0.73) [29]	93.88 (0.73) [29]	56.01 (8.77) [14]	71.65 (2.99) [8]	71.65 (2.99) [8]
KPNC	-0.25 (0.25) [22]	87.64 (0.93) [22]	55.76 (1.48) [17]	2.89 (0.43) [20]	20.77 (2.01) [13]	13.09 (1.56) [16]	30.36 (2.75) [13]	54.35 (2.90) [9]	87.88 (2.73) [28]	9.00 (1.01) [20]	54.54 (2.31) [10]	95.90 (1.72) [19]	43.82 (6.56) [20]	46.38 (9.31) [22]	54.72 (6.49) [22]
INFA	-0.86 (0.15) [51]	95.25 (0.59) [26]	62.52 (1.77) [10]	4.64 (0.55) [12]	22.14 (1.03) [10]	14.07 (1.41) [11]	33.89 (2.00) [29]	51.64 (2.00) [22]	97.09 (0.54) [22]	12.58 (0.72) [15]	50.77 (1.83) [12]	95.85 (0.97) [21]	78.78 (2.81) [21]	83.30 (3.87) [21]	78.78 (2.81) [21]
KDE	-0.90 (0.20) [38]	99.58 (0.20) [8]	54.21 (4.27) [18]	2.88 (0.39) [21]	11.74 (0.87) [26]	8.75 (0.54) [29]	21.92 (1.40) [23]	35.86 (1.42) [26]	96.85 (0.80) [23]	8.04 (0.66) [21]	32.87 (1.70) [27]	97.74 (0.86) [7]	67.14 (7.83) [8]	80.99 (3.21) [3]	78.00 (2.70) [4]
GBM	-0.38 (0.19) [36]	99.39 (0.34) [16]	66.46 (1.89) [9]	5.54 (0.61) [9]	28.62 (1.12) [6]	16.31 (1.47) [7]	37.83 (2.00) [8]	61.25 (1.45) [4]	97.79 (0.87) [15]	18.53 (0.80) [6]	55.50 (1.98) [6]	98.72 (0.41) [1]	72.67 (0.39) [1]	53.67 (3.38) [1]	78.93 (2.85) [2]
CMBF	-0.33 (0.22) [30]	91.99 (0.24) [19]	2.83 (0.42) [25]	1.68 (0.18) [38]	11.14 (1.09) [20]	25.40 (1.99) [10]	41.75 (1.65) [19]	7.06 (0.48) [30]	40.40 (0.21) [18]	95.47 (1.64) [11]	42.86 (7.02) [42]	48.05 (4.83) [26]	54.45 (6.83) [16]	54.45 (6.83) [16]	54.45 (6.83) [16]
SD	-0.66 (0.21) [47]	76.98 (2.58) [34]	41.41 (2.50) [26]	3.54 (0.57) [17]	1.87 (0.60) [38]	10.39 (0.96) [24]	17.31 (1.40) [25]	37.38 (1.14) [25]	72.26 (2.26) [34]	12.84 (0.72) [14]	32.62 (2.34) [28]	87.69 (0.20) [34]	7.93 (4.84) [21]	21.44 (4.77) [40]	33.16 (4.72) [36]
SUNAR	-0.04 (0.18) [11]	99.10 (1.23) [21]	78.50 (1.65) [1]	9.60 (0.61) [1]	38.51 (1.62) [1]	21.14 (2.16) [1]	27.93 (2.37) [1]	98.10 (2.78) [10]	96.22 (0.58) [3]	76.74 (1.44) [1]	98.06 (0.02) [6]	63.83 (0.62) [9]	67.04 (5.56) [9]	67.04 (5.56) [9]	67.04 (5.56) [9]
SOGAAL	-0.05 (0.69) [12]	54.27 (21.69) [38]	11.74 (6.49) [42]	0.12 (0.30) [45]	-0.73 (1.86) [47]	-0.51 (0.71) [50]	0.57 (1.73) [46]	-1.73 (0.86) [49]	8.86 (1.00) [45]	-1.18 (2.34) [50]	-2.11 (0.65) [50]	66.22 (4.74) [37]	7.45 (4.83) [47]	18.09 (11.02) [43]	19.90 (15.66) [43]
ALAD	-0.09 (0.59) [14]	15.25 (14.35) [44]	8.57 (8.68) [43]	-0.26 (0.91) [50]	1.32 (2.95) [49]	0.52 (0.96) [44]	1.91 (5.44) [44]	6.10 (4.86) [44]	17.30 (14.55) [41]	0.22 (0.87) [43]	4.49 (3.15) [42]	44.29 (20.89) [43]	6.31 (3.15) [44]	11.01 (7.77) [45]	11.63 (5.25) [44]
AE	-0.28 (0.25) [23]	91.45 (4.41) [9]	58.37 (2.00) [15]	3.48 (0.43) [16]	20.54 (1.03) [14]	13.23 (2.16) [15]	28.52 (0.90) [15]	47.61 (0.30) [15]	98.10 (0.15) [15]	9.97 (0.59) [18]	46.87 (1.13) [15]	95.41 (1.33) [12]	44.99 (7.28) [16]	46.97 (4.73) [21]	54.81 (5.79) [17]
CD	-0.00 (0.00) [6]	-0.00 (0.00) [46]	-0.00 (0.00) [46]	-0.00 (0.00) [46]	-0.00 (0.00) [41]	-0.00 (0.00) [45]	-0.00 (0.00) [45]	-0.00 (0.00) [45]	-0.00 (0.00) [45]	-0.00 (0.00) [45]	-0.01 (2.35) [48]	0.00 (2.62) [45]	-0.03 (1.47) [46]	-0.10 (0.31) [47]	-0.10 (0.31) [47]
MOC	0.03 (0.72) [5]	54.41 (27.63) [37]	14.78 (4.90) [4]	0.43 (0.48) [40]	-1.54 (1.13) [49]	-0.28 (0.18) [49]	0.01 (1.46) [47]	21.31 (0.40) [50]	92.85 (1.58) [40]	-1.01 (0.76) [49]	-1.29 (0.95) [49]	69.29 (0.43) [50]	7.69 (5.51) [42]	19.86 (1.67) [42]	22.14 (15.65) [42]
QMCD	12.59 (1.26) [1]	93.25 (1.01) [29]	-4.70 (0.19) [51]	-3.11 (0.15) [51]	-4.45 (0.03) [51]	-3.84 (0.13) [51]	-4.81 (0.02) [51]	-4.93 (0.01) [51]	14.74 (0.76) [42]	-4.08 (0.05) [51]	-4.00 (0.01) [51]	52.39 (2.22) [41]	-24.80 (2.06) [51]	-17.44 (1.44) [51]	-5.21 (0.81) [51]
Sampling	-0.12 (0.27) [15]	99.47 (0.21) [11]	52.77 (1.48) [20]	2.27 (0.28) [26]	15.01 (1.96) [22]	10.67 (0.75) [22]	24.25 (1.43) [20]	40.40 (1.59) [21]	97.89 (0.41) [14]	6.83 (0.86) [24]	39.77 (1.70) [19]	94.69 (1.51) [24]	37.89 (5.74) [22]	46.12 (2.71) [23]	55.88 (7.81) [13]
EIF	-0.41 (0.19) [40]	93.66 (0.31) [28]	28.17 (3.40) [34]	1.52 (0.41) [33]	7.98 (2.96) [29]	8.09 (1.57) [28]	17.06 (2.28) [28]	34.64 (6.34) [28]	91.52 (1.13) [25]	3.17 (0.62) [35]	26.56 (3.88) [29]	95.31 (1.67) [17]	38.07 (7.91) [24]	42.04 (4.31) [26]	50.80 (7.79) [29]
Ensemble	-0.38 (0.24) [36]	99.08 (0.32) [19]	66.85 (1.99) [6]	5.74 (0.46) [7]	29.30 (1.62) [4]	16.78 (1.45) [5]	40.07 (1.95) [5]	57.75 (0.84) [7]	98.58 (0.15) [14]	18.24 (0.76) [8]	55.21 (1.47) [9]	95.50 (1.24) [10]	44.83 (6.77) [17]	50.06 (5.12) [16]	54.25 (6.46) [22]
GENOUT	-0.34 (0.22) [33]	97.76 (1.25) [23]	32.25 (0.77) [23]	1.64 (0.81) [31]	5.22 (0.80) [33]	8.06 (1.76) [33]	15.85 (1.32) [32]	35.66 (1.27) [33]	92.89 (0.57) [27]	13.24 (0.65) [31]	95.14 (1.43) [17]	45.82 (1.03) [19]	45.83 (1.19) [25]	46.08 (8.82) [30]	46.08 (8.82) [30]
DynamiHBOS	-0.13 (0.03) [46]	36.35 (1.07) [42]	5.71 (0.44) [44]	0.24 (0.05) [42]	-0.22 (0.02) [45]	2.16 (0.62) [43]	2.32 (0.41) [43]	7.56 (1.06) [42]	46.20 (1.16) [38]	0.02 (0.13) [44]	3.49 (0.29) [44]	63.89 (0.05) [39]	13.82 (5.53) [39]	15.90 (2.33) [44]	31.17 (4.31) [43]
COB	-0.48 (0.13) [43]	3.10 (4.00) [45]	26.99 (1.87) [35]	4.60 (0.25) [43]	-1.76 (0.16) [50]	13.80 (0.93) [42]	16.78 (1.39) [29]	29.57 (1.53) [31]	41 (4.85) [46]	14.03 (0.62) [12]	36.79 (2.25) [24]	35.30 (8.80) [44]	10.81 (8.90) [40]	23.98 (4.46) [38]	28.93 (4.88) [40]
AIFD	-0.18 (0.12) [20]	99.73 (0.13) [5]	99.51 (1.77) [5]	0.59 (0.43) [5]	22.58 (1.17) [19]	9.58 (0.14) [19]	39.20 (0.23) [17]	60.87 (1.14) [5]	99.89 (0.28) [1]	18.36 (0.88) [7]	58.83 (2.11) [4]	31.5 (4.03) [47]	0.91 (3.59) [49]	-3.66 (0.38) [50]	47.7 (6.82) [46]
LMDD	-0.00 (0.13) [26]	70.51 (29.77) [35]	3.34 (2.93) [31]	0.54 (0.16) [31]	3.21 (2.02) [37]	6.36 (0.80) [35]	13.11 (3.57) [34]	27.48 (2.22) [34]	81.67 (23.67) [32]	1.91 (0.53) [39]	29.07 (0.64) [33]	55.62 (0.97) [40]	20.01 (10.99) [36]	22.65 (3.32) [39]	29.36 (5.01) [39]
DMMGM	-0.41 (0.50) [10]	44.98 (27.86) [40]	22.40 (7.67) [37]	0.39 (0.42) [41]	9.35 (1.74) [38]	8.31 (4.74) [38]	4.22 (1.37) [37]	55.75 (28.04) [37]	91.51 (0.53) [29]	13.71 (7.48) [38]	64.63 (1.25) [38]	15.9 (8.58) [38]	19.20 (6.03) [42]	30.56 (1.03) [40]	30.56 (1.03) [40]
DRACO	-0.53 (0.46) [33]	90.07 (2.84) [33]	28.83 (6.50) [33]	2.88 (1.51) [24]	5.90 (6.60) [34]	5.97 (2.23) [36]	16.35 (3.37) [31]	16.03 (7.94) [20]	68.03 (5.44) [35]	5.78 (2.64) [27]	21.79 (23.39) [32]	83.40 (12.05) [35]	18.27 (8.30) [37]	25.34 (10.04) [36]	37.99 (17.76) [35]
GDD	-0.33 (0.25) [30]	99.48 (0.20) [29]	51.01 (2.04) [22]	2.24 (0.50) [27]	15.12 (1.20) [21]	10.38 (0.99) [25]	23.66 (1.68) [22]	40.55 (1.74) [20]	97.78 (0.47) [17]	57.8 (2.59) [22]	39.64 (3.75) [28]	94.30 (1.75) [28]	37.94 (2.73) [26]	40.66 (3.76) [28]	54.38 (6.76) [21]
ICL	-0.69 (0.11) [48]	99.68 (0.14) [6]	71.86 (1.87) [4]	6.18 (0.79) [4]	23.30 (3.55) [8]	15.99 (0.99) [8]	31.51 (3.06) [12]	52.85 (1.29) [10]	98.80 (0.37) [2]	21.54 (1.30) [4]	56.33 (1.96) [5]	97.32 (1.14) [8]	71.75 (4.38) [6]	79.85 (4.80) [5]	88.57 (4.26) [1]
PlaneFlow	-0.15 (0.17) [19]	98.56 (5.44) [22]	39.81 (1.62) [27]	0.66 (0.52) [37]	6.68 (3.33) [31]	7.52 (1.10) [33]	13.47 (2.63) [33]	28.62 (2.31) [33]	93.83 (2.39) [24]	1.41 (0.59) [41]	18.10 (1.84) [36]	93.04 (2.53) [30]	25.12 (7.19) [35]	36.50 (2.88) [33]	44.83 (7.55) [33]
VIA	-0.34 (0.24) [33]	92.62 (4.47) [41]	49.80 (2.03) [24]	2.13 (0.41) [28]	13.82 (0.90) [23]	9.42 (1.05) [26]	21.80 (1.95) [24]	38.67 (1.70) [22]	97.78 (0.39) [17]	5.29 (0.54) [22]	36.97 (1.56) [22]	94.40 (1.59) [27]	38.71 (6.86) [26]	52.71 (6.86) [26]	52.71 (6.86) [26]
Ganomaly	-0.28 (0.27) [24]	99.09 (0.61) [18]	94.78 (3.85) [13]	2.36 (0.54) [23]	15.64 (1.99) [20]	6.86 (1.04) [21]	25.81 (3.45) [18]	41.76 (2.98) [17]	97.61 (0.45) [21]	17.2 (0.46) [22]	43.85 (2.32) [17]	94.83 (1.25) [21]	49.09 (7.99) [14]	49.17 (7.96) [19]	56.28 (5.50) [12]
SLAD	-0.32 (0.14) [28]	99.86 (0.02) [1]	60.62 (1.95) [11]	3.45 (0.58) [18]	19.33 (1.05) [16]	13.58 (1.07) [13]	29.63 (1.54) [14]	49.81 (1.68) [12]	98.38 (0.40) [18]	13.44 (0.60) [13]	48.32 (2.04) [13]	96.51 (0.65) [13]	72.53 (3.73) [14]	78.65 (2.97) [17]	78.65 (2.97) [17]
DIF	0.21 (0.23) [3]	-2.65 (0.19) [51]	2.39 (0.21) [46]	0.15 (0.40) [43]	-0.42 (0.47) [46]	2.33 (0.42) [42]	4.16 (0.89) [41]	3.40 (0.44) [45]	11.01 (0.68) [43]	4.01 (0.98) [31]	3.79 (0.43) [43]	25.68 (6.47) [45]	32.97 (5.12) [31]	56.14 (4.23) [13]	25.05 (13.07) [41]
DDPM	-0.22 (0.30) [21]	99.59 (0.14) [													

Table 46: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 6

		3276	3277	3278	3279	3280	3281	3282	3283	3284	3285	3286	3287	3288	3289	3290	3291	3292	3293	3294	3295	3296	3297	3298	3299	3300	3301	3302	3303	3304	3305	3306	3307	3308	
Model	MVTeC-AD grid	MVTeC-AD baselin	MVTeC-AD knn	MVTeC-AD metal net	MVTeC-AD pill	MVTeC-AD screw	MVTeC-AD tile	MVTeC-AD toothbrush	MVTeC-AD transmitter	MVTeC-AD wood	MVTeC-AD zipper	SVHN 0	SVHN 1	SVHN 2	SVHN 3	SVHN 4																			
iforest	28.56 (5.52) [33]	50.35 (4.25) [22]	97.35 (1.69) [29]	32.62 (6.33) [33]	35.59 (5.26) [32]	15.31 (3.19) [36]	71.85 (2.79) [18]	70.77 (9.37) [29]	38.56 (7.93) [32]	50.53 (3.81) [33]	55.08 (8.89) [29]	4.42 (1.05) [30]	7.42 (0.86) [16]	8.23 (1.31) [27]	3.38 (0.55) [36]	7.62 (0.82) [7]																			
OCVM	38.25 (3.65) [27]	48.81 (4.07) [26]	97.73 (1.17) [23]	46.25 (5.26) [25]	37.09 (4.48) [28]	26.45 (1.79) [23]	69.51 (2.47) [29]	78.46 (3.23) [25]	44.77 (7.16) [24]	61.69 (2.80) [24]	62.38 (7.14) [24]	5.60 (1.07) [24]	7.74 (0.93) [12]	8.90 (1.34) [17]	5.93 (0.76) [21]	6.11 (0.34) [19]																			
COPOD	-0.02 (1.02) [47]	-0.03 (2.59) [48]	-0.05 (2.28) [48]	0.05 (1.16) [46]	0.00 (3.30) [47]	-0.04 (3.30) [47]	0.00 (2.00) [48]	0.01 (1.31) [46]	-0.07 (2.33) [48]	-0.11 (2.05) [48]	-0.07 (3.67) [47]	0.00 (0.00) [47]	-0.00 (0.00) [48]	-0.00 (0.00) [47]	-0.01 (0.00) [47]	-0.00 (0.00) [46]																			
ECOD	-0.02 (1.02) [47]	-0.03 (2.59) [48]	-0.05 (2.28) [48]	0.05 (1.16) [46]	0.00 (3.30) [47]	-0.04 (3.30) [47]	0.00 (2.00) [48]	0.01 (1.31) [46]	-0.07 (2.33) [48]	-0.11 (2.05) [48]	-0.07 (3.67) [47]	0.00 (0.00) [47]	-0.00 (0.00) [48]	-0.00 (0.00) [47]	-0.01 (0.00) [47]	-0.00 (0.00) [46]																			
FeatureBagging	42.52 (3.19) [22]	51.30 (4.65) [14]	97.64 (0.72) [24]	51.80 (5.30) [15]	44.71 (6.40) [15]	31.49 (2.84) [14]	70.67 (2.39) [23]	86.89 (3.76) [18]	47.80 (6.00) [18]	66.14 (4.03) [14]	74.81 (6.44) [13]	8.93 (1.34) [2]	6.14 (0.84) [24]	9.62 (1.05) [6]	8.84 (1.06) [1]	5.80 (0.46) [24]																			
HBOS	10.18 (1.12) [42]	50.74 (4.61) [18]	95.38 (2.76) [32]	21.92 (3.31) [37]	36.21 (4.39) [29]	14.28 (5.46) [39]	70.73 (2.69) [22]	77.37 (8.55) [26]	32.45 (8.76) [35]	34.32 (3.69) [39]	49.38 (7.68) [32]	1.22 (0.68) [41]	5.42 (0.27) [29]	6.01 (1.22) [36]	0.90 (0.19) [45]	8.60 (0.62) [2]																			
KNN	45.17 (3.23) [15]	50.87 (4.02) [17]	98.35 (0.73) [12]	49.75 (4.42) [20]	42.93 (4.66) [19]	31.44 (1.45) [15]	71.55 (2.00) [19]	91.75 (3.69) [13]	47.77 (7.14) [19]	64.27 (3.01) [18]	70.30 (6.84) [19]	6.62 (1.23) [17]	7.72 (0.97) [13]	9.34 (1.36) [11]	6.62 (0.88) [15]	6.49 (0.33) [13]																			
LDA	27.72 (5.36) [34]	41.96 (9.64) [32]	92.64 (3.26) [35]	27.27 (10.47) [34]	34.38 (5.60) [33]	13.87 (5.44) [30]	64.53 (4.74) [32]	37.36 (7.74) [39]	32.90 (4.74) [34]	49.31 (4.45) [34]	53.29 (1.33) [30]	2.47 (1.44) [36]	4.84 (2.23) [31]	3.98 (1.99) [38]	2.88 (1.75) [39]	3.83 (2.34) [37]																			
LOF	42.94 (3.83) [20]	50.94 (4.54) [15]	97.42 (0.56) [25]	51.57 (5.40) [16]	44.36 (6.11) [16]	31.39 (2.87) [16]	69.86 (2.32) [26]	87.17 (3.71) [16]	47.87 (6.59) [15]	66.35 (3.79) [12]	74.50 (6.30) [14]	8.87 (1.38) [3]	5.79 (0.73) [26]	9.49 (1.12) [8]	8.74 (1.17) [2]	5.85 (0.66) [22]																			
MCD	60.64 (2.11) [19]	56.87 (2.25) [11]	97.38 (1.31) [28]	60.64 (7.65) [12]	54.95 (8.41) [10]	39.68 (3.08) [12]	76.75 (4.12) [11]	89.65 (4.65) [14]	60.36 (6.44) [11]	75.13 (4.73) [11]	83.51 (4.26) [11]	5.17 (0.81) [28]	4.07 (1.21) [37]	6.08 (1.61) [35]	3.54 (1.10) [35]	4.50 (1.06) [34]																			
PCA	38.07 (2.66) [28]	47.71 (4.32) [28]	98.11 (0.72) [16]	43.24 (5.14) [27]	35.78 (3.90) [30]	25.46 (1.19) [26]	70.14 (1.81) [24]	68.98 (1.83) [31]	43.89 (7.16) [26]	61.29 (2.44) [25]	59.54 (6.97) [26]	5.41 (1.04) [26]	7.88 (0.94) [10]	8.62 (1.37) [19]	5.70 (0.79) [25]	6.13 (0.30) [17]																			
DeepSVDD	60.05 (5.96) [10]	59.54 (7.01) [10]	98.47 (0.69) [11]	69.62 (7.80) [19]	56.47 (8.15) [19]	49.8 (4.00) [8]	84.34 (4.55) [8]	95.28 (3.67) [12]	62.63 (13.43) [10]	80.18 (5.19) [8]	86.26 (2.35) [9]	2.79 (0.58) [35]	4.73 (2.94) [32]	4.41 (1.76) [37]	2.72 (1.33) [40]	2.24 (0.89) [42]																			
DNNE	44.01 (4.24) [16]	47.91 (5.58) [27]	96.04 (2.15) [30]	50.19 (5.25) [19]	43.68 (6.25) [18]	27.88 (3.79) [32]	73.09 (3.24) [12]	86.29 (3.21) [19]	45.61 (4.78) [32]	66.07 (5.15) [26]	76.71 (5.27) [12]	7.92 (1.21) [10]	6.75 (0.79) [21]	7.74 (1.17) [31]	6.63 (0.82) [14]	5.71 (0.41) [25]																			
KPCA	71.96 (5.74) [3]	70.98 (4.00) [2]	98.75 (0.80) [8]	81.54 (4.41) [5]	74.85 (8.82) [2]	63.65 (2.66) [3]	86.15 (5.73) [5]	99.82 (0.28) [4]	75.69 (7.39) [1]	86.32 (5.48) [5]	89.89 (3.65) [5]	6.77 (1.16) [16]	7.91 (0.97) [8]	9.60 (1.41) [7]	6.42 (0.74) [19]	6.92 (0.39) [11]																			
KDE	72.67 (5.64) [2]	70.09 (3.73) [7]	98.82 (0.52) [7]	79.98 (3.47) [6]	71.50 (7.33) [7]	64.99 (2.26) [2]	84.45 (3.73) [7]	99.77 (0.35) [6]	75.51 (8.06) [2]	87.18 (5.05) [1]	86.88 (5.17) [8]	3.97 (1.00) [31]	4.45 (0.93) [34]	7.79 (1.21) [30]	4.97 (0.97) [27]	4.04 (0.69) [35]																			
GMM	70.19 (6.16) [5]	70.31 (2.73) [6]	99.03 (0.58) [5]	82.50 (4.92) [1]	76.82 (8.14) [1]	61.61 (3.80) [4]	87.68 (2.43) [4]	99.80 (0.25) [2]	70.92 (8.08) [7]	86.84 (3.95) [2]	88.60 (2.12) [6]	8.33 (1.32) [7]	8.87 (1.12) [2]	10.31 (1.36) [4]	7.63 (1.06) [7]	7.00 (0.46) [9]																			
CBLOF	43.47 (2.96) [18]	52.40 (4.32) [12]	98.04 (0.77) [20]	48.80 (5.60) [23]	40.57 (4.21) [25]	29.14 (3.73) [19]	72.01 (2.23) [17]	82.80 (3.07) [22]	46.85 (7.30) [21]	64.38 (5.16) [17]	67.01 (4.06) [21]	6.37 (1.17) [19]	7.39 (0.98) [17]	8.65 (1.34) [18]	6.13 (0.85) [20]	6.05 (0.35) [21]																			
SOD	22.50 (6.63) [36]	36.74 (5.09) [35]	93.66 (1.32) [34]	13.74 (6.70) [42]	15.76 (12.85) [42]	13.74 (2.65) [41]	49.72 (5.86) [34]	40.37 (6.96) [37]	25.47 (0.88) [39]	52.05 (3.89) [32]	40.52 (9.09) [37]	6.33 (1.15) [20]	4.42 (0.55) [35]	9.26 (1.31) [12]	6.74 (1.00) [12]	4.97 (0.49) [30]																			
LUNAR	62.57 (6.81) [8]	64.85 (5.08) [9]	99.15 (0.31) [1]	68.50 (5.62) [10]	52.82 (7.85) [12]	48.77 (6.89) [9]	79.73 (3.78) [10]	99.67 (0.47) [8]	69.91 (8.56) [8]	77.89 (5.56) [10]	84.91 (3.65) [10]	9.38 (1.52) [1]	10.22 (0.93) [1]	12.35 (1.48) [1]	7.18 (1.00) [11]	9.54 (0.68) [1]																			
SOGAAL	12.32 (1.43) [41]	2.79 (7.79) [46]	71.67 (32.19) [44]	18.26 (6.15) [38]	17.58 (4.40) [40]	10.12 (10.34) [43]	31.02 (10.32) [43]	18.06 (10.16) [44]	16.70 (10.35) [42]	21.38 (18.19) [43]	15.84 (9.30) [44]	0.59 (1.75) [43]	1.62 (1.70) [44]	1.34 (0.47) [42]	2.51 (1.11) [41]	-0.73 (0.81) [49]																			
ALAD	9.82 (4.34) [41]	4.19 (9.07) [43]	52.81 (16.12) [39]	4.0 (12.62) [45]	1.91 (8.87) [45]	33.01 (8.83) [42]	-14.52 (7.53) [45]	8.46 (4.42) [50]	10.62 (13.51) [46]	14.94 (9.85) [45]	1.52 (1.17) [39]	0.82 (1.63) [46]	1.98 (1.39) [41]	0.12 (1.56) [44]	0.55 (0.99) [45]																				
AE	43.18 (2.67) [19]	51.30 (4.64) [13]	98.12 (0.71) [15]	48.00 (5.36) [22]	42.31 (4.19) [20]	28.29 (1.94) [21]	72.22 (2.20) [15]	81.50 (3.13) [23]	47.83 (6.48) [17]	64.06 (2.93) [20]	69.78 (6.57) [20]	6.55 (1.18) [18]	7.52 (1.04) [15]	9.18 (1.33) [15]	6.61 (0.90) [16]	6.35 (0.39) [14]																			
CI	-0.02 (1.02) [47]	-0.03 (2.59) [48]	-0.05 (2.28) [48]	0.05 (1.16) [46]	-0.05 (3.90) [50]	-0.04 (3.30) [47]	0.00 (2.00) [48]	-4.97 (0.89) [49]	-0.07 (2.33) [48]	-0.11 (2.05) [48]	-1.19 (4.44) [50]	-0.07 (3.67) [47]	0.00 (0.00) [47]	5.77 (2.89) [24]	1.68 (2.08) [44]																				
MOGAAL	17.18 (0.79) [39]	3.67 (9.47) [45]	42.85 (34.44) [42]	16.87 (5.00) [39]	18.38 (2.73) [39]	11.42 (10.56) [42]	33.76 (12.27) [44]	19.33 (8.83) [43]	16.33 (10.97) [44]	27.80 (18.86) [41]	13.23 (8.93) [46]	0.57 (1.57) [44]	0.52 (0.83) [47]	1.05 (0.80) [44]	3.86 (2.35) [33]	-0.80 (1.02) [50]																			
QMCD	-10.57 (2.81) [51]	0.63 (3.20) [47]	79.73 (3.30) [36]	-29.47 (6.90) [51]	-29.50 (6.02) [51]	-23.32 (2.01) [51]	0.77 (8.36) [47]	1.88 (48.50) [45]	0.82 (4.22) [46]	14.40 (5.94) [44]	-28.76 (5.73) [51]	-1.65 (0.42) [50]	-3.08 (0.10) [51]	-2.21 (0.18) [51]	-1.70 (0.14) [51]	-2.46 (0.20) [51]																			
Sampling	42.22 (4.81) [23]	49.51 (4.99) [24]	98.18 (0.74) [14]	46.39 (3.60) [24]	41.04 (5.35) [22]	25.73 (2.01) [24]	71.14 (1.63) [21]	80.58 (3.68) [24]	46.31 (7.98) [22]	63.87 (2.20) [21]	65.54 (7.36) [22]	5.52 (1.30) [25]	7.90 (1.34) [9]	8.32 (1.28) [24]	5.79 (0.77) [23]	6.34 (0.34) [15]																			
EIF	30.66 (2.09) [31]	50.25 (4.66) [23]	98.05 (1.31) [21]	36.87 (5.54) [31]	37.72 (3.72) [25]	16.02 (6.56) [35]	72.18 (2.33) [16]	87.40 (6.69) [15]	41.72 (1.00) [30]	56.03 (5.27) [31]	57.28 (6.29) [28]	3.66 (0.45) [32]	7.28 (0.89) [18]	8.33 (1.28) [23]	5.15 (0.99) [49]	7.15 (0.78) [8]																			
Ensemble	42.94 (3.83) [20]	50.94 (4.54) [15]	97.42 (0.56) [25]	51.57 (5.40) [16]	44.36 (6.11) [16]	31.39 (2.87) [16]	69.86 (2.32) [26]	87.17 (3.71) [16]	47.87 (6.59) [15]	66.35 (3.79) [12]	74.50 (6.30) [14]	8.87 (1.38) [3]	5.79 (0.73) [26]	9.49 (1.12) [8]	8.74 (1.17) [2]	5.85 (0.66) [22]																			
GENOUT	34.83 (5.71) [30]	50.38 (4.60) [20]	97.88 (1.58) [22]	38.00 (7.75) [30]	40.09 (5.15) [24]	16.09 (5.32) [34]	71.20 (4.66) [20]	76.62 (6.52) [22]	42.22 (7.12) [29]	58.90 (5.46) [28]	62.79 (5.81) [23]	2.92 (1.05) [33]	8.52 (2.18) [5]	7.97 (1.32) [29]	3.06 (0.58) [38]	7.97 (1.36) [4]																			
DynamicHBOS	2.83 (0.01) [45]	24.52 (5.13) [40]	76.64 (6.42) [37]	5.24 (1.44) [44]	14.13 (2.86) [43]	3.81 (3.86) [44]	42.97 (4.41) [37]	54.00 (8.06) [35]	17.95 (8.86) [42]	12.98 (6.63) [45]	25.19 (6.12) [42]	0.28 (0.24) [45]	1.76 (0.27) [43]	1.10 (0.31) [43]	-0.04 (0.05) [50]	2.47 (0.30) [40]																			
COF	19.37 (2.37) [38]	36.90 (7.08) [34]	41.71 (13.61) [43]	15.99 (6.65) [40]	10.23 (6.77) [44]	16.79 (2.82) [33]	41.22 (12.04) [38]	28.89 (7.64) [41]	29.04 (6.08) [37]	43.51 (6.63) [36]	31.92 (9.77) [40]	7.40 (1.00) [12]	2.65 (0.53) [39]	9.20 (1.66) [14]	7.41 (0.93) [9]	3.87 (0.29) [36]																			

Table 48: Mean, standard deviation and rank ADJ AUC-PR performance comparison of all methods in the benchmark for each dataset. The best performance is highlighted in **bold** (For a fair comparison against the baselines, NCSBAD and NCSBADVAL are counted individually). Part 8