Representation Learning for Zero-Shot Anomaly Detection

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Abstract. The detection of anomalies in time series data is subject of current research in machine learning. Several methods are published in the past 3 years which try to detect anomalies in various ways. Mostly the patterns that represent time series are learned. This is particularly useful for a general knowledge about the data. The concepts used for this include CNNs, Contrastive Learning, Autoencoders and Transformers. This paper provides an overview of the recent developments in anomaly detection and presents methods that try to detect anomalies in time series data. The found methods are evaluated with regard to the adaptability on other tasks than they trained for and to multivariate input. Methods that are publicly available are investigated further using a completely new dataset with known anomalies provided by SMA. A proof of work on a Zero-Shot scenario without training the models is presented. None of the methods found the correct time point of an anomaly.

Keywords: Representation Learning · Zero Shot Learning · Anomaly Detection · Multivariate Time Series.

1 Introduction

Nowadays sensors can be found everywhere and they become more popular across multiple domains. Gyroscopes, cameras, compasses and accelerometers are integrated in smartphones. Physical machines are tracking their movement through vibration sensors, health care systems in hospitals visualize the heart beat of a patience and voltmeters measure the generated power in a solar plant. Everytime sensor values are collected, time series data (TSD) is produced.

In some scenarios the measurements of different sensors are combined. Physical machines sometimes track vibration and motor rotations, health care systems visualize the heart beat and solar plants measure voltage and current. Collections of different sensors measuring at a common time window produce Multivariate Time Series Data (MVTSD).

Applications that produce MVTSD may evaluate the data and further decisions tha lead to actions depend on a correct analysis. Normally the data is consistent and values change constantly in repetetive patterns. This is when the machine, the patience health or the solar plant is functioning like it is supposed to. But sometimes the values change unpredicted because of differing surroundings or other influences. This can lead to serious situations. Machine measurements detect a potential fault which may break the machine. When the patient's heart beat changes its pattern the health of the patient is seriously endangered. And a solar plant may detect a decline in the generated power which should further influence the power consumption for a better efficiency.

Recognising and reacting to these changes in MVTSD can therefore be very important. But these interruptions occur in different forms. They can be recognised as outliers or they are hidden and not obviously seen as anomalies. In some cases they form shapes which never occured before. This raises the demand for a tool to detect anomalies in time series data without any further knowledge of the anomaly.

A systematic literature research concerning the topic is conducted and the best choices are implemented on a test data set. In section 3 the basic methodology used in this paper is described and the main research questions are formulated. First basic necessary terms are explained in section 2. In section 4 the found papers and their methodologies are presented and explained. The methodologies are compared and evaluated for usability in the context of Zero-Shot Anomaly Detection in section 5. The implementation of suitable techniques is provided in section 6. Finally the results are discussed and concluded in section 7

2 Definitions and Conventions

The basic expressions used in this paper are explained in the following chapter. First Representation Learning is defined and the different approaches to find representations of data are explained. A description on how to evaluate the found representations is given. Afterwards Zero Shot Learning as well as Anomaly Detection is described and explained.

2.1 Representation Learning

Variations in data are not always visible for a human and even less possible to label them accordingly. Like [5] mentioned it is important for artificial intelligence to detect representations of data by machines. A machine should be able to extract information hidden in the low-level sensor measurings and continue working with the representations instead of the raw data. This is according to the paper the main requirement for a good representation, to be able using it as an input to a supervised predictor.

Representation Learning (RL) tries to detect meaningful interconnections in data relevant for further data analysis. These interconnections represent abstract information, so called background knowledge [27].

In neural networks representations are learned in every layer. The representations in hidden layers are incomprehensible to humans. They are produced by weights and biases and build so called neural representations. At a higher level of abstraction, these neural representations can be understood as spatial representations within a conceptual space, where concepts are represented as points or regions. When these spatial representations are transformed into language, they become symbolic representations, which are used to convey meaning in a human-understandable form. Together, neural, spatial, and symbolic representations build cognitive repesentations [18].

To extract representations a knowledge discovery process with different methods of machine learning and data mining methods are used. During the process representations are learned by the model. RL methods are divided into Propositionalization as symbolic representations and Embeddings as spatial representations [27, p. 4].

RL occurs in several machine learning areas. Depending on the underlying concept, different strategies to extract representations can be found. They work different in detecting patterns and store them in different ways [6].

In the book of [15, p. 525] a general detailed description of representation learning is given. They summarize that representations should make the subsequent learning tasks easier. This implies that to find the best fitting representation and the underlying representation learning technique, we need to know the task it should perform afterwards.

Concepts The most straight-forward approach to detect representations are Multi Layer Perceptrons (MLP). An input vector is processed by interconnected artificial neurons. The neurons build layers starting with an input layer, followed by hidden layers with a final output layer. The produced output layer typically classifies the input and predicts the label. The difference between predicted and labeled output indicates the performance of the network. Adjusting the interconnections using weights and biases of each neuron enables a learning process. [39]

Convolutional Neural Networks (CNN) are a variation of the MLP building subsets of the input vector. This is mainly used in image processing.

Recurrent neural networks (RNN) are another variation of the traditional feed-forward MLP. Every neuron has an additional input containing the previous state. This is especially useful for time series data.

Traditional neural networks like MLP, RNN, and CNN have limitations in learning robust, generalizable, and semantically meaningful representations, especially with limited labeled data [53].

Learning representations in time series data is done in several different ways. One solution according to [72] is contrastive learning (CL). Pairs of data points are labeled as similar and dissimilar. These data points are put into a feature space where the distance between the two represents their similarity. Similar data points are grouped together and dissimilar data points are distant from each other. With a contrastive loss function and a label of similarity between two points, the model is trained by putting the similar data points together and separating dissimilar points. Using this method groups of similar data points are formed [53].

Autoencoders are another important method in representation learning. An autoencoder is a framework implemented by neural networks. It is used to learn efficient codings of input data in an unsupervised manner. It consists of an encoder that compresses the input into a latent-space representation and a decoder that reconstructs the input from this representation. The goal is to minimize the difference between the real and the reconstructed input.

Transformers, initially developed for natural language processing tasks, have become a powerful tool in representation learning. They use self-attention mechanisms to weigh the significance of each part of the input data differently, enabling the model to capture long-range dependencies. The dependencies represent abstract and valuable infromation [61].

Based on the transformer architecture, Large Language Models (LLM) are developed and used increasingly in different applications. Known as chatbots they can help in language specific tasks. Beside that they can be used in anomaly detection and forecasting. [56] examine a literature review on how LLMs perform on anomaly detection tasks concerning time series data. LLMs in anomaly detection are specifically useful when the time series data is in the form of words. This can be the case in log analysis. Logs are generated over time and hold a lot of information which can detect errors and system failures. They conclude that LLMs have potential in detecting anomalies but challenges remain. The occurrence of hallucinations and the need for computational efficiency to name a few.

In summary, representation learning can be achieved using different techniques, each suitable for different types of data and tasks. From neural networks and autoencoders to transformers, these methods provide the tools necessary to transform raw data into meaningful representations that facilitate further analysis and learning.

2.2 Anomalies in Time Series

Several definitions of anomalies in data can be found in literature. In this paper the definition of [17, p. 54] is used. It seperates anomaly and novelty detection as different tasks. Anomalies can be understood as outliers from the regular class. But these anomalies can vary in their cause. If there is a specific cause and the anomalies occur in its own cluster, they form a novelty. If instead the outliers randomly occur with no specific root cause, they are called noise. The cause for noise then is of a different kind and cannot be classified. Figure Figure 1 visualizes the different

Instead of dividing anomalies by their cause the shape of anomalies can vary in several ways. In real measurement data of any shape is possible and it is totally unpredictable [52]. For training purposes anomaly injection is crucial. Then the anomalies are simulated as point anomalies or subsequence anomalies. Point anomalies occur once and can be global or contextual. Subsequence anomalies on the other hand change the values in a given time window or on long term. They can be divided in seasonal, shapelet and trend anomalies (see Figure 2).

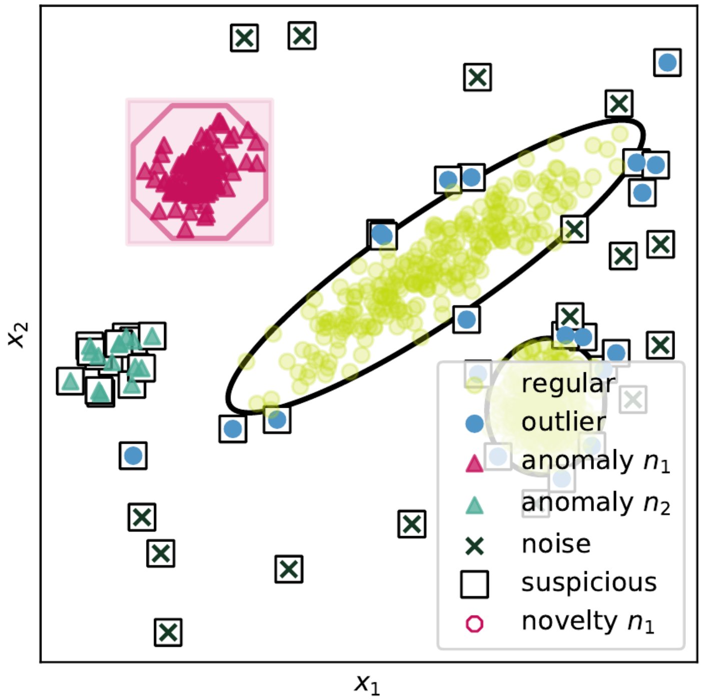
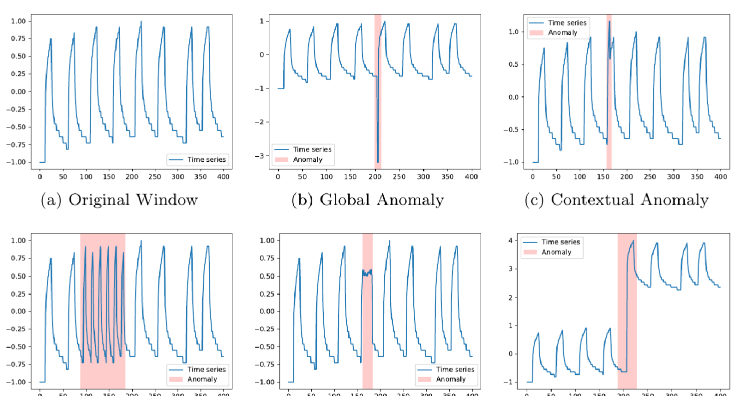


Fig. 1. Classification of outliers [17, p. 54]

Seasonal and shapelet anomalies change the values in a limited time window, trend anomalies are changing all following values [9, p. 9].



(a) Original Window (b) Global Anomaly (c) Contextual Anomaly

(d) Seasonal Anomaly (e) Shapelet Anomaly (f) Trend Anomaly

Fig. 2. Classification of time series anomaly types [9]

In this paper we want to focus on single time events, which are in any case anomalies because they cannot form its own cluster. This defines our goal as an Anomaly Detection (AD) task.

2.3 Zero Shot Learning

In this paper the definition made by [41] is used. They seperate Single Task Learning, where every model is trained seperately for each task, from Multi Task Learning (MTL) where one model is trained and evaluated on several tasks. For Zero Shot Learning (ZSL) in comparison the model is trained on several tasks like in MTL but tested on completely new ones.

Zero Shot Learning is therefore an extreme form of transfer learning. While transfer learning is the concept of transferring the knowledge and weights gained at one task using them at solving another task, Zero-Shot Learning means there are no samples for the other task. The transformation of knowledge can help solving tasks where there are few or no samples available. The gained knowledge is normally stored as representations of data. Representations which are abstract enough to not see a specific item but information about items. This also means that ZSL is only possible because additional information has been discovered during training [15, p. 536].

[43] were the first to implement a successful Zero-Shot Anomaly Detection followed by [55] who used semantic word vector representations to classify words in groups with a fully unsupervised model.

Zero-shot learning involves training a model on certain classes and then testing its ability to recognize new, unseen classes without any retraining. In the context of anomaly detection, this means the model should be able to detect types of anomalies it has not encountered during the training phase.

3 Systematic Literature Review

A literature review to contribute in the development of an anomaly detection tool is presented in this paper. It provides an overview on the latest trends in representation learning and extracts the possible solutions addressing the problem described in section 1. The review conforms to the methodology presented by [25]. First the research questions are formulated. Finally Inclusion and Exclusion Criteria are formulated in order to filter the found literature for the application. The search process and the websites used are listed.

Further analysis with a systematic quality assessment and data collection like in [25] are excluded.

3.1 Research question

The covered topic includes different areas of machine learning, all being further developed in recent years. In order to break it down into separate concerns the following research questions are formulated:

- RQ1: How can representations be learned using artificial intelligence?
- RQ2: Which representation learning (RL) types can be used for multivariate time series?
- RQ3: How to use RL for anomaly detection?
- RQ4: Are the methods useful for Zero Shot Learning Scenarios?

These question form a path for further chapters. RQ1 and RQ2 are explained in section 2. Answering RQ3 involves a literature review in section 4 which presents useful methods. RQ4 is answered in section 5. The research questions build a basis for the formulation of the following Criteria.

3.2 Inclusion and Exclusion Criteria

This paper focuses on published methods for anomaly detection in Zero Shot Scenarios on MVTSD. In order to structure the search for and selection of relevant articles, the necessary guidelines are formulated below. Articles that are considered in more detail must meet the following inclusion criteria:

- IC1: Methods using a representation learning concept
- IC2: Methods handling time series data
- IC3: Methods used for Anomaly Detection
- IC4: Published in recent years ($<$ 6 years)

The chosen articles are examined in more detail. They are described and explained in section 4. Using the gained knowledge all described articles are filtered by the following exclusion criteria in section 5.

- EC1: Methods not tested on Zero-Shot Learning
- EC2: Methods designed for univariate data
- EC3: Multiple publications reporting the same methodologies
- EC4: Methods with restricted availability

Using these exclusion criteria ensures to find methodologies that meet the desired use case described in the research questions.

EC1 excludes methods that are not tested in a Zero-Shot Learning scenario. The second exclusion criteria filter for methods handling multiple input variables only. EC3 avoids duplicated papers and EC4 ensures that the method is publicly available and does contain a description on how to implement and reproduce the outcomes.

3.3 Search process

A manual search of specific conference proceedings and journal papers was made. Considering the pace on which new developments emerge in the area of machine learning the help of research tools was needed. Specifically in the field of anomaly detection the publications are made in recent years. This makes it difficult to assure finding every relevant paper.

The main tool used to find papers was Consensus, which is an academic search engine. They use large language models (LLMs) and purpose-built search technology. The chatbot is based on ChatGPT 4.0 and should answer questions based on papers including their reference. For reassuring the existence of the papers conventional bibliographies are used.

4 Representation Learning Methods

In this chapter any found paper proposing a RL strategy used for time series data with adaptability on anomaly detection tasks is presented. For the literature research the inclusion criteria as described in subsection 3.2 are applied.

The different RL strategies are explained focusing on compliance of the exclusion criteria. The strategies are organized by their underlying concept. We begin with straight-forward methods which are based on one concept and increase the complexity throughout the chapter. In the end combinations of different concepts are presented.

MLP Using a simple MLP is a straight-forward way to learn representations and to detect anomalies in time series data [39]. The input variable for the MLP are time points and the output variable represents the value at these time points. The model is trained to learn this mapping. With the trained model, the values in a live scenario are predicted and the difference to the actual values is measured. If the difference exceeds a certain threshold, an anomaly is found. A method called INRAD, Implicit Neural Representation of Time-Series Data is using this concept. The method takes multiple variables as input and the model is trained with data including anomalies. It is not suitable for Zero-Shot Learning [21].

RNN [57] propose a method called OmniAnomaly for anomaly detection in multivariate time series data using a Stochastic Recurrent Neural Network to model the temporal dependencies in multivariate time series data. The key advantage of this method is its robustness to noisy and high-dimensional data according to the authors. The model learns to represent normal patterns in time series and identifies deviations from these patterns as anomalies. Since OmniAnomaly depends on having access to representative normal data to learn patterns, it is not suitable for zero-shot scenarios.

CNN Methods based on CNNs are normally used for classification of images but in recent papers they are used to detect anomalies in images. [3] develop a Texture Anomaly Detection and achieve a high performance in ZSL. They compare Zero-Shot against Many-Shot Learning in their work. Several image anomaly detection tools can be found ([51], [3]). But CNNs perform on time series data as well.

The main idea of using CNNs is to predict a value based on the input frame. If the distance between the predicted and the actual value exceeds a predefined threshold, the anomaly can be detected.

This idea is used to detect cyberattacks in industrial control systems. The study by [26] uses a dataset from a Secure Water Treatment testbed to identify cyber anomalies by measuring the statistical deviation between predicted and observed values. They explore different deep learning architectures, including CNNs and recurrent networks, and find that one dimensional CNNs perform particularly well for time series prediction tasks. Their approach successfully detects the majority of cyber attacks with minimal false positives, highlighting the effectiveness of CNNs in real-time anomaly detection in multivariate time series [26]. However, the paper does not discuss the usability on zero-shot learning. In the same area a method detecting unknown cyber-attacks is presented by [73] who use an Autoencoder which is discussed later on.

[20] use Temporal Convolutional Networks (TCN). TCNs restrict the output to be dependent on past and present time steps only. This enables them to capture temporal dependencies. By training on normal patterns, the network learns to predict future values. Significant deviations between these predictions and actual observations indicate potential anomalies. Since the model only learns the normal data, it is able to work in Zero Shot scenarios.

Another paper introduces a mask-based self-supervised representation learning approach to extract both short-term local dependencies and long-term global trends. By integrating forecasting and reconstruction-based models, the method effectively captures temporal contexts and feature correlations. An attention mechanism ensures feature importance, leading to better anomaly detection performance on various datasets. The method is designed for multivariate time series anomaly detection but does not explicitly address ZSL scenarios [36].

Contrastive Learning In [72] a framework using CL is proposed which is applied for industrial fault detection. Two data sets that consist of various vibration signals of industrial machines and stiction sensors with multiple variables are used for training. The effectiveness of the proposed framework is demonstrated through its application to these datasets.

CL is also used for anomaly detection in time series data by [9]. They use CL combined with synthetic anomaly injection. CL enables them to capture patterns in time series data and the framework shows good results on common real world datasets according to the authors. Like in the previous paper, dissimilar pairs, the anomalies, build distant data points and similar data points are close to each other. In order to train the model artificial anomalies are injected which build distant pairs. In the next stage the classification is done by the proximity of the neighbours in the representation space. Additionally anchor points representing the nearest and furthest neighbour are given from each representation. Their methodology is called CARLA and is not tested for Zero-Shot Learning. An implementation by the authors can be found [3].

CL-TAD, a method for time series anomaly detection that uses contrastive learning and reconstruction-based techniques addresses the challenges of temporal dynamics, label scarcity, and data diversity in real-world applications.

[3] github.com/zamanzadeh/CARLA

The method comprises two main components: positive sample generation and contrastive-learning-based representation learning. Positive samples are generated by reconstructing masked parts of the time series data, helping the model learn the underlying normal patterns. These samples, along with the original data, are then fed into a contrastive learning framework, which contrasts pairs of similar and dissimilar samples to learn representations [38]. While CL-TAD is not explicitly designed as a zero-shot learning method, its use of contrastive learning and reconstruction-based techniques suggests that it could have potential in zero-shot anomaly detection scenarios. A tutorial for implementation can be found [4].

To succeed on Zero-Shot Anomaly Detection, One-Class Classification (OCC) can be useful. By gathering all "normal" values into a single class the outliers are directly detected if they are outside of it. The COCA (Contrastive One-Class Anomaly Detection) method combines contrastive learning with OCC to improve anomaly detection in multivariate time-series data. By treating original and reconstructed representations as positive pairs, it optimizes a contrastive one-class loss function that enhances the detection of anomalies while preventing common issues like hypersphere collapse. Although COCA is designed for self-supervised anomaly detection, its ability to learn from unlabeled data suggests potential applicability in zero-shot learning scenarios, though this has not been explicitly tested [64]. An implementation script is provided by the authors [5].

The paper by [28] presents an approach for detecting anomalies also using OCC in industrial time series data, which typically lacks labels for supervised learning. They combine OCC with contrastive learning to define a new objective function that can simultaneously learn from both models. This method enhances feature extraction while preserving temporal characteristics. The paper demonstrates the method's effectiveness through high anomaly detection performance on datasets with similar normal and anomalous data forms, highlighting its potential in industrial applications.

Unlike traditional OCC methods that map all normal instances into a single hypersphere, the method presented by [7] focuses on local contextual information. By pulling each normal instance towards its recent context window, it aims to better detect context-based anomalies. The model incorporates a deterministic contrastive loss, which improves the network's ability to distinguish between normal and abnormal data.

[71] introduce TS2Vec, a framework for learning robust and universal time series representations at multiple semantic levels through hierarchical contrastive learning. This approach utilizes timestamp masking and random cropping to create augmented context views, enhancing position-agnostic and comprehensive representations. By combining instance-wise and temporal contrastive losses, TS2Vec captures characteristics of different time series instances and dynamic temporal patterns within each series. The method is tested on Zero Shot Learning

[4] github.com/nguhcv/cl-tad/tree/main

[5] github.com/ruiking04/COCA

and is applicable for multivariate time series data. The instructions on reproducing the outcomes are made publicly available by the authors [6].

Another paper introduces an autonomous system for anomaly detection in multivariate time series data also using Contrastive Learning. The proposed TimeAutoAD automates model configuration and hyperparameter optimization, addressing challenges such as limited labeled anomaly data. It uses self-supervised contrastive learning to enhance the model's ability to differentiate normal and anomalous time series by generating pseudo-negative samples. The method is tested on real-world datasets, demonstrating improved performance over existing anomaly detection techniques, especially in scenarios where training data may be contaminated. The paper does not explicitly address zero-shot anomaly detection [22].

The ContrastAD framework presented in [30] is a self-supervised method for time series anomaly detection that leverages contrastive learning with temporal transformations. The key innovation is the use of anomaly-induced transformations to create representations that differentiate between normal and abnormal data. This approach targets both point anomalies and contextual anomalies in high-dimensional time series, which are often missed by other methods. By learning distinct representations for normal and anomalous data in the latent space, ContrastAD improves performance on noisy and complex datasets. However, the method is not trained or validated on entirely new types of anomalies.

Another model called DCdetector presented in [68] is a multi-scale dual attention contrastive learning framework designed for time-series anomaly detection. It utilizes a dual attention asymmetric design to create a permutation-invariant representation, guiding the learning process with pure contrastive loss. This approach enhances the model's ability to discriminate between normal and anomalous data. Extensive experiments demonstrate that DCdetector achieves state-of-the-art performance across multiple benchmark datasets. While the paper focuses on its effectiveness in anomaly detection, it does not explicitly address or test the model's applicability to zero-shot learning scenarios [68] In the article a repository containing bash scripts for implementation can be found [7].

[47] presents a novel approach for anomaly detection in multi-variate time series data using Contrastive Predictive Coding (CPC). Their method, named Time-series Representational Learning through Contrastive Predictive Coding (TRL-CPC), aims to capture the temporal dependencies and correlations across multiple variables in time series data. The TRL-CPC framework consists of an encoder, an auto-regressive model, and a non-linear transformation model. These components are optimized to learn the representations of multi-variate time series data by predicting future segments from past segments. The core idea is to maximize the mutual information between the encoded representations of past and future segments, thereby learning robust representations. To detect anomalies, TRL-CPC calculates the prediction error between actual future segments and the predicted segments generated by the CPC model. Anomalies are

[6] github.com/zhihanyue/ts2vec

[7] github.com/DAMO-DI-ML/KDD2023-DCdetector

identified where this prediction error exceeds a certain threshold, enabling unsupervised anomaly detection based on the structure of the data itself [47].

CPC is also used by the method TiCTok presented in [23]. The model proposes an approach to multivariate time-series anomaly detection by combining contrastive tokenization with a time-series token encoder. This encoder converts raw time-series data into latent embeddings that capture wide-ranging temporal information. The model employs contrastive learning to produce representations, which help distinguish between normal and anomalous data. Additionally, TiCTok introduces a new anomaly scoring method based on the contrastive loss used during training. In their paper they do not test the model on Zero Shot Learning scenarios.

Another paper introduces Multiview Graph Contrastive Learning for detecting anomalies in multivariate time-series data, particularly in IoT systems. The method constructs graph structures to model both temporal context and signal dependencies, while an adaptive data augmentation strategy generates graph views for contrastive learning. This approach enhances representation quality and improves performance in anomaly detection tasks except Zero Shot Learning [49]. The method is available on Github [8].

The paper by [58] introduces TriAD (Tri-domain Anomaly Detector), a self-supervised learning method for time-series anomaly detection. TriAD models features across three domains: temporal, frequency, and residual. Without relying on labeled anomalies. Unlike traditional contrastive learning, TriAD uses inter-domain and intra-domain contrastive losses to learn shared attributes among normal data and distinguish them from anomalies. The approach is designed to handle anomalies of varying lengths and shapes [58]. The authors provide a link to their implementation [9].

In summary methods using contrastive learning are mostly not tested on Zero-Shot Learning. Their robustness against noisy data is not ensured.

Autoencoder Autoencoders on the other hand are robust to unclean training datasets [1, p. 2487]. Due to their architecture noise is filtered from the input.

[48] introduces an anomaly detection method using an autoencoder architecture based on Long Short-Term Memory (LSTM) networks. The core idea is that an LSTM autoencoder learns to compress and reconstruct the input time series data. During training, the model learns the normal patterns in the data by minimizing the reconstruction error. When fed new data, the model attempts to reconstruct it, and any significant reconstruction error (i.e. deviation between the original and reconstructed data) signals an anomaly. This approach is particularly effective because LSTMs are well-suited to capture temporal dependencies, making them ideal for time series data. The model works without requiring labeled datasets, making it an unsupervised solution. The authors test the model on both synthetic and real-world data, such as sound event detection.

[8] github.com/shuxin-qin/MGCLAD

[9] github.com/pseudo-Skye/TriAD

It can effectively detect outliers based on reconstruction error but does not have the capacity for ZSL.

Other methods that use LSTM networks are found in literature. All of them are designed for multivariate time series data but are not tested on Zero-Shot Learning. The authors did not provide instructions on how to replicate the outcomes [70] [13] [40].

[42] are the first to use a Unified Autoencoder (UAE) for time series data, namely the power forecast of wind and solar plants. They contribute to the challenge of predicting the possible outcome of renewable energy in a newly created plant, either wind or solar. To do so a UAE is combined with a Task Embedding Neural Network (TENN). They examine the usability divided in Single-Task, Multi-Task and Zero-Shot Learning. The method was first published in [41]. It is then extended by convolutional layers instead of the fully connected neural network layers (UCAE-TENN) and also Long Short-Term Memory layers (ULAE-TENN).

[46] proposes a Multi-Scale Temporal Variational Autoencoder (MST-VAE) for anomaly detection in multivariate time series data. MST-VAE combines short and long-scale convolutional kernels within a 1D CNN and a Variational Autoencoder to capture both short-term and long-term temporal patterns. The method is not directly tested in a Zero-Shot scenario. An implemention is provided by the authors [10].

To detect anomalies in healthcare data a variational recurrent autoencoder (VRAE) is used in [45]. They created an unsupervised framework where the model learns to represent the data and detect anomalies without needing labeled examples. The model works by learning to reconstruct the input sequences. During training, they add noise to the input data, and the model tries to reconstruct the original, uncorrupted data. This helps the model learn more robust representations of the data. To detect anomalies, they cluster these learned representations and calculate the distance to identify outliers. Their approach was tested on the ECG5000 dataset and showed that it could effectively detect unusual heartbeats, performing better than previous methods that required labeled data. The model is designed to capture temporal dependencies, making it applicable for MVTSD.

Another approach using VRAE involves creating synthetic anomalies to improve the detection process. A two-level hierarchical latent space representation is used. First, they distill feature descriptors of normal data points into more robust representations using AEs. These representations are then refined using a VAE that creates a family of distributions. From these distributions, they select those that lie on the outskirts of the normal data as generators of synthetic anomalies. By generating these synthetic anomalies, they train binary classifiers to distinguish between normal and abnormal data. Their hierarchical structure for feature distillation and fusion helps create robust representations, enabling effective anomaly detection without needing actual anomalies during training [50].

[10] github.com/tuananhphamds/MST-VAE

Kieu et al. propose Variational Quasi-Recurrent Autoencoders (VQRAEs) for unsupervised time series anomaly detection, using robust divergences to improve resilience against noisy data. VQRAEs utilize Quasi-Recurrent Neural Networks (QRNNs) for efficient temporal dependency capture, and a bi-directional version (BiVQRAEs) enhances accuracy by processing data in both forward and backward directions. However the method was not explicitly tested on Zero-Shot Learning [24] [11].

The paper by [73] addresses the challenge of detecting unknown cyberattacks by applying zero-shot learning. The proposed method maps the features of known attacks to a semantic space using a sparse autoencoder and restores them to the feature space by minimizing reconstruction errors, effectively creating a mapping between features and semantic attributes. This technique enables the model to detect previously unseen attacks by generalizing from known attack features. The research highlights the feasibility and effectiveness of zero-shot learning for cybersecurity applications.

A method called Fused Sparse Autoencoder and Graph Net (FuSAGNet) is used for anomaly detection in multivariate time series data, specifically targeting cyber-physical systems. The method combines a Sparse Autoencoder (SAE) to learn sparse latent representations and a Graph Neural Network (GNN) to forecast future time series behavior. It captures both temporal dependencies and complex inter-feature relationships by learning graph structures from the data. This joint optimization approach aims to improve anomaly detection performance by fusing reconstruction and forecasting tasks. The method was empirically tested on three real-world datasets related to industrial systems but not in Zero-Shot Learning scenarios [19] [12].

Deep Autoencoding One-Class (AOC), a method for time-series anomaly detection that combines autoencoder-based reconstruction and one-class classification in a single-stage approach to better capture normal patterns. The method is evaluated on public datasets, outperforming baseline models and proving effective for detecting various types of anomalies in both univariate and multivariate time-series data. However, zero-shot learning is not tested or addressed in the proposed framework [37] [13].

Another paper presents a method named RANSynCoders for detecting anomalies in asynchronous multivariate time series by combining spectral analysis with autoencoders. It leverages spectral analysis to synchronize the features, followed by multiple autoencoders using random feature subsets to detect anomalies via majority voting. This approach improves performance on high-dimensional, asynchronous data by reducing false positives and providing better localization of anomalies. The method in the paper does not specifically mention being tested in zero-shot scenarios [1]. An implemention of the method is provided by the authors [14].

[11] github.com/tungk/Bi-VQRAE
[12] github.com/sihohan/FuSAGNet
[13] github.com/alsike22/AOC
[14] github.com/eBay/RANSynCoders

Another proposed method is using a Temporal Convolutional Network Autoencoder (TCN-AE) designed for unsupervised anomaly detection in multivariate time series data. It employs dilated convolutions to capture long-range dependencies and compresses time series into representations using an autoencoder. The method detects anomalies by evaluating reconstruction errors, as anomalies are expected to have significantly higher reconstruction errors compared to normal patterns [59]. A Repository with a minimal working example can be found provided by the author but no implementation on new datasets is provided [15].

A framework called Multiscale Wavelet Graph AutoEncoder (MEGA) presented in [63] for anomaly detection in multivariate time series. It integrates Discrete Wavelet Transform (DWT) to decompose time series into different frequency components, reconstructing them to highlight anomalies across scales. Additionally, a dynamic graph convolution network is employed to model inter-variable relationships at different scales, enhancing the detection of anomalies caused by changes in variable dependencies. This method is tested in a zero-shot scenario and explicitly takes multivariate time series as input. The code can be found provided by the authors [16].

The method proposed in [8] introduces DAEMON, an adversarial autoencoder framework designed for unsupervised multivariate time-series anomaly detection and interpretation. The model employs two adversarial training processes: one to align the hidden variable's posterior distribution with a prior and another to minimize the difference between original and reconstructed data. This improves robustness and avoids overfitting while anomalies are detected based on reconstruction errors. There is no mentioning of testing in a zero-shot scenario. The authors of the method DAEMON published python scripts for replicating the results on all datasets they used. However, no explanation on how to use the method for entirely new datasets can be found [17].

The method proposed in [14] utilizes a Gated Recurrent Unit-based Autoencoder (GRU-AE) to detect anomalies in time-series data by reconstructing sequences and identifying large reconstruction errors as anomalies. It incorporates an attention mechanism to enhance performance and applies multi-timestamp stacking to reduce time steps for better training efficiency. The model is tested on real-world datasets from cellular networks, detecting anomalies at both single-day and multi-day scales. The method is applied to multivariate time-series data, but no mention of a zero-shot scenario is made.

The method proposed in [62] presents an attention-based encoder-decoder network for anomaly detection in time-series data, which focuses on learning representations in both principal and residual spaces without needing reconstruction. The attention mechanism is applied to rescale convolutional layers, highlighting the most contributive segments of the data for better representation learning. This approach improves anomaly detection by calculating belief

[15] github.com/MarkusThill/bioma-tcn-ae
[16] github.com/jingwang2020/MEGA
[17] github.com/Sherlock-C/DAEMON

scores in both spaces using kernel density estimation (KDE). The method is tested on multivariate time series and in a zero-shot scenario, specifically for detecting new faults.

To overcome the challenge of poorly available time series data sets [35], the model family MOMENT tries to learn general patterns on a pile of time series data. The pile is a collection of different datasets which they assembled for their pretraining. According to the paper minimal finetuning is needed to perform on multivariate time series tasks like anomaly detection. They published the model and made the usage easily accessible with its own python library. The time serie datasets the model is trained on consist of domains including weather measurements, sensor values and power consumption datasets. They also included tongue and finger movement of humans. The different tasks which the model is evaluated on are forecasting (long and short horizon), classification, anomaly detection and imputation. Except for short-horizon forecasting all tasks are managed well. However it cannot detect anomalies in vertically shifted time series [16]. The method is available as a Jupyter Notebook on Github [18].

Transformer A method called "Anomaly Transformer", which detects anomalies in time series by comparing a time point's learned associations with a Gaussian-based prior association to compute the Association Discrepancy. The model uses a minimax strategy to amplify the difference between normal and anomalous points based on this discrepancy. The method is tested in a zero-shot scenario and supports multivariate time series as input [66] [19].

TranAD is a transformer-based model designed for anomaly detection in multivariate time-series data. It leverages self-attention mechanisms and adversarial training to enhance both accuracy and training stability. The method includes meta-learning to perform well even in low-data scenarios. The paper does not explicitly mention testing the method in a zero-shot learning scenario [60] [20].

The proposed method, Decompose Auto-Transformer Network (DATN), focuses on time-series anomaly detection by decomposing the input into seasonal and trend components, followed by an auto-attention mechanism for feature extraction. The method takes multivariate input, where the decomposition and attention mechanisms operate on multivariate time-series data. The paper does not mention zero-shot learning explicitly [65].

Time Series Anomaly Transformer (TiSAT), introduces a transformer-based approach that captures long-range temporal dependencies in time-series anomaly detection using a probabilistic attention mechanism, which improves computational efficiency by focusing on key query-value pairs. The model takes multivariate input and applies non-parametric k-nearest neighbors (kNN) for anomaly detection. The paper does not mention zero-shot learning, too [10] [21].

The TCF-Trans method enhances anomaly detection in multivariate time-series data by using a feature fusion decoder that combines shallow and deep

[18] github.com/moment-timeseries-foundation-model/moment/blob/main/tutorials/anomaly_detection.ipynb
[19] github.com/thuml/Anomaly-Transformer
[20] github.com/imperial-quore/TranAD
[21] github.com/kevaldoshi17/TiSAT

layers to capture important anomaly details while resisting noise. It also introduces a temporal context fusion module to adaptively merge predictions for more robust results. Although the method was tested on various datasets, it is not explicitly evaluated in a strict zero-shot scenario [44].

The DCT-GAN method proposed in [33] integrates Dilated Convolutional Networks with Transformers within a GAN framework to enhance the detection of anomalies in time series data, improving generalization and accuracy. It employs multiple generators and a single discriminator, using a weight-based mechanism to balance contributions from different generators, which capture coarse-grained and fine-grained information. There is no specific mention in the document about testing the method on zero-shot learning tasks.

The AnoFormer method is a Transformer-based GAN framework for unsupervised multivariate time series anomaly detection, utilizing a two-step masking strategy to improve normal data representation and anomaly detection. The model masks parts of the data randomly, then re-masks uncertain regions based on entropy to refine its focus. While the method excels in unsupervised learning, it is not explicitly tested in a ZSL scenario [54].

A method detecting anomalies in tabular data also using LLMs is presented in [29]. In order to perform tasks that LLMs are not directly build for they generate synthetic datasets. Using these datasets LLMs and specifically GPT-4 have comparable performance with transductive learning methods [29, p. 6]. Concerning different batches, the method is tested in ZSL. The model is trained on some batches and evaluated on new ones. Due to the fact that the prompt contains data of one variable, the method is not used for multivariate time series.

Using Fourier Analysis and the transformer architecture [69] detect anomalies in time series data. The encoder of a transformer is used to capture temporal features of time series. They detect frequencies by using Fourier Analysis.

Shapelet Learning [4] address the problem of detecting anomalies in time series data using a novel unsupervised method based on shapelet learning. Their method learns representative features that describe the shape of time series data from the normal class and simultaneously learns to accurately detect anomalies. The objective function encourages the learning of a feature representation in which normal time series lie within a compact hypersphere, while anomalous observations lie outside the decision boundary. This is achieved through a block-coordinate descent procedure. The advantage of their approach is that it can efficiently detect anomalies in unseen test data without retraining the model, by reusing the learned feature representation. Experimental results on multiple benchmark datasets demonstrate the robustness and reliability of the method in detecting anomalous time series. They suggest to extend their method on multivariate time series in future works.

In contrast, [2] propose a method combining matrix profiles with shapelet learning to handle streaming time series data. The matrix profile efficiently identifies potential anomalies in real-time, and shapelet learning characterizes these anomalies. This approach is particularly suited for environments requiring immediate anomaly detection. The authors provide code examples for implementation in their paper but furhter open source repositories were not found. As the previous work they didn't use the method for multivariate time series and suggest expanding the method for this.

While both methods utilize shapelet learning, Beggel et al. focus on static datasets and robust feature representation, whereas Alshaer et al. emphasize real-time detection in dynamic, streaming environments.

The IPS (Instance Profile for Shapelet Discovery) method addresses time series classification by using shapelets-discriminative subsequences of time series. This method was tested extensively on various datasets but was not explicitly tested in a zero-shot scenario [31].

The method proposed in the paper focuses on using shapelet-based representations for unsupervised learning of multivariate time series. It employs contrastive learning, multi-scale alignment, and a shapelet transformer to enhance MVTSDno representations without requiring labeled data. The method was tested in scenarios where labeled data is sparse or unavailable (partially labeled scenarios), but it does not appear to be tested explicitly in a traditional zero-shot setting [34] [22].

Combinations [32] propose a method for detecting anomalies in multivariate time series by combining clustering and reconstruction techniques. The authors use a sliding window approach to generate subsequences from the multivariate time series, then apply extended fuzzy clustering to reveal the underlying structure of the subsequences. By reconstructing these subsequences with optimal cluster centers, the method detects anomalies based on how well the reconstructed data fits the original subsequences. A confidence index quantifies the level of detected anomalies. The method does not seem to have been explicitly tested in a ZSL scenario.

A Fourier transformation isolates seasonal components in a method called Moving Memory Dynamic Filter (MMDF). While the distance transformation captures both the data values and their temporal dependencies. Anomalies are detected when the center-to-center distance exceeds the threshold. The authors primarily discuss the proposed method in the context of univariate time series anomaly detection and do not explicitly mention its applicability to MVTSD [11].

In contrast, the method DCFF-MTAD, a multivariate time-series anomaly detection method. It leverages a dual-channel feature extraction that combines spatial short-time Fourier transformation for spatial features and a graph attention network for temporal features. These features are then fused using a Gated Recurrent Unit for robust anomaly detection. THe method is not tested on Zero-Shot Learning and is not available as open source [67].

[22] github.com/real2fish/CSL

5 Application on Zero-Shot Anomaly Detection in Multivariate Time Series

The found articles are filtered using the exclusion criteria defined in subsection 3.2. By excluding methods that haven't been tested with multiple input variables we answer RQ2. Methods that are not tested in Zero-Shot Learning Scenarios are also excluded which covers RQ4. In order to achieve a successful implementation in the following chapter only models which are publicly available and well documented are chosen for further examination.

More precisely we want to know by the defined filter process which of the proposed RL types are best suited for Zero Shot Anomaly Detection in multivariate time series data. A selection of appropriate methods for Time Series Data Anomaly Detection out of section 4 is extracted.

All found representation learning methodologies from section 4 are listed in Table 1. Their evaluation on the exclusion criteria is marked and a short description on the underlying concepts is given.

6 Proof of Concept

The best fitting strategies extracted in section 5 are implemented on a small test data set in order to demonstrate how and if they work. First the used dataset ant the purpose of anomaly detection for the specific use case is described. Later the process of implemention and the results are presented.

6.1 Inverter data including Anomalies

While NLP and image processing tasks are common and a variety of data sets exists, time series data sets are not available that much [35]. Thanks to the employees of SMA a multivariate time series dataset is provided. The specific use case and the structure of the chosen data is described in this section.

SMA developes and manufactures inverters for home and commercial use. The inverters convert direct to alternating current or vice versa depending on the use case. They also act as home managers controlling all energy flows in a power plant. Inverters are equipped with several sensors measuring the surroundings and internal states in order to maximize the efficency and to avoid system failures. Sometimes system failures appear still which raises the question if this could have been foreseen by analyzing the gathered sensor data during runtime. The first step to reach such a forecasting tool is to detect the anomalies in recorded sensor data. The implementation of the chosen methods is therefore done on inverter data provided by the company.

The variables contain measurements of current and voltage of all phases in AC and the generated DC sources. Additionally temperatures, CPU usage, internal parameter settings and many other measurements are included. The total number of features is 137.

Table 1. Abbreviations: Transformer (T), Clustering (C), multiple input variables (MV), open source availability (OSA). Legend: yes: ✓, no: ✗

Method Name	Author	Concepts	MV	ZSL	OSA
INRAD	Jeong et al.	MLP	✓	✗	✓
OmniAnomaly	Su et al.	RNN	✓	✗	✓
CNN based method	Kravchik et al.	CNN	✓	✗	✗
CNN based method	He et al.	CNN	✓	✓	✗
SLMR	Miao et al.	CNN	✓	✗	✗
Debiased CL	Zhang et al.	CL	✓	✓	✗
CARLA	Darban et al.	CL	✓	✓	✓
CL-TAD	Ngu et al.	CL	✓	✗	✓
COCA	Wang et al.	CL, OCC	✓	✗	✓
CL based method	Lee et al.	CL, OCC	✓	✓	✗
CL based method	Chen et al.	CL	✓	✗	✗
TS2Vec	Yue et al.	CL	✓	✓	✓
TimeAutoAD	Jiao et al.	CL	✓	✗	✗
ContrastAD	Li et al.	CL	✓	✗	✗
Dddetector	Yang et al.	CL	✓	✗	✓
TRL-CPC	Pranavan et al.	CPC	✓	✗	✗
TiCTok	Kang et al.	CPC	✓	✗	✗
MGCLAD	Qin et al.	CL	✓	✗	✓
TriAD	Sun	CL	✗	✗	✓
AE based method	Provotar et al.	AE, LSTM	✓	✗	✗
LSTM-based VAE-GAN	Niu et al.	AE, LSTM	✓	✗	✗
TSMAE	Gao et al.	AE, LSTM	✓	✗	✗
UCAE-TENN	Nivarthi et al.	UAE, LSTM	✓	✓	✗
VRAE based method	Pereira et al.	VRAE	✓	✓	✗
AE based method	Ramirez et al.	VRAE	✓	✓	✗
Bi-VRQRAE	Kieu et al.	VRAE	✓	✗	✓
FuSAGNet	Han et al.	AE, GNN	✓	✗	✓
MSTVAE	Pham et al.	VAE, CNN	✓	✗	✓
deep AOC	Mou et al.	AE, OCC	✓	✗	✓
AE based method	Zhang et al.	AE	✗	✓	✗
RANSynCoders	Abdulaal et al.	AE	✓	✗	✓
TCN-AE	Thill et al.	AE, TCN	✓	✓	✗
MEGA	Wang et al.	AE, GCN	✓	✓	✓
DAEMON	Chen et al.	AE	✓	✓	✓
GRU-AE	Gong et al.	AE, GRU	✓	✗	✗
MSCVAE	Yokkampon et al.	VAE	✓	✓	✗
AE based method	Wang et al.	AE	✓	✓	✗
MOMENT	Goswami et al.	AE	✓	✓	✓
TranAD	Tuli et al.	T	✓	✗	✓
AnomalyTransformer	Xu et al.	T	✓	✗	✓
TiSAT	Doshi et al.	T	✓	✗	✓
TCF-Trans	Peng et al.	T	✓	✗	✗
DCT-GAN	Li et al.	T, GAN	✓	✗	✗
AnoFormer	Shin et al.	T, GAN	✓	✗	✗
LLM based method	Li et al.	T, LLM	✗	✓	✗
DATN	Wu et al.	T, LLM	✓	✗	✗
Transformer based method	Ye et al.	T, Fourier	✓	✗	✗
SL based method	Beggel et al.	SL	✗	✗	✗
SL based method	Alshaer et al.	SL	✗	✗	✗
SL based method	Liang et al.	SL	✓	✗	✓
IPS	Li et al.	SL	✗	✗	✗
Clustering based	Li et al.	C	✓	✗	✗
MMDF	Duan et al.	MMDF	✗	✗	✗
DCFF-MTAD	Xu et al.	DCFF	✓	✗	✗

The values are collectively stored at a 7 minute interval over several months. 19 inverters that had system failures at some point are taken into account. These failure time stamps are known and added as an additional feature with a binary value of 1. Every other error bit is 0. The data is collected between 2018 and 2020 and the locations of the inverters cannot be provided.

6.2 Implemented Methods

The main goal is to detect the labeled anomalies in the SMA dataset. If the methods find the timestamp of the system failure, they perform correctly. First the models are taken as is and a forward pass is applied. The given output is evaluated if the model already detects the failure time points in the inverter time series data. If possible, the model is trained afterwards using a set of 12 inverters and tested on the remaining 7 inverters. This way the Zero-Shot scenario like in section 2 is created. The code for the implementions can be found on link [23].

CARLA An implemention of the model CARLA is done by the authors using Python available on footnote 3. The repository contains scripts for replicating the results, but no further information on how to adapt the model on new datasets is given.

TS2Vec An implemention of the model TS2Vec is done by the authors using Python which is available on footnote 6. A function for preprocessing the data to fit as an input for the model was written. Using the function a successful forward pass was made. The learned representations can be used for further evaluation.

MEGA According to [63] the model MEGA is trained and evaluated on three different datasets. The code for reproduction is provided by the authors. They implement the model using Python on footnote 16. No further information on how to adapt the model on new datasets is given but the scripts are adapted to run successfully with SMA data as multivariate input. The output was not further reviewed.

DAEMON The authors of the method DAEMON published python scripts for replicating the results on all datasets they used [8]. However, no explanation on how to use the method for entirely new datasets can be found on this footnote 17.

MOMENT A detailed instruction on how to reproduce the outcomes of MOMENT presented by [16] is provided on this GitHub footnote 18. The method takes a three dimensional input tensor, containing batches, channels and time points. The maximal number of points is 512. It reconstructs the given input and returns a tensor containing the reconstructions.

[23] github.com/johanneshoelker/Smart-Systems-Paper/tree/main/Implementation

For the implementation on SMA data the provided tutorial is used as a guide. The SMA data is preprocessed to match the requested input tensor. The reconstructions are further compared with the inputs by calulating the Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

The error is further normalized using the Min-Max Normalization:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{2}$$

Every timestamp that exceeds a certain threshold then represents the found anomalies.

One sensor needed to be excluded because the values didn't change. The threshold was decreased until 0.005 but with an untrained model no anomalies are found.

7 Discussion and Future Work

The presented paper has a few limitations which are discussed in this chapter. Additionally ideas for further research are given.

Some of the found methods are not tested in Zero-Shot Scenarios in the article they are presented. The authors didn't focus on Zero-Shot Learning and didn't use appropriate datasets for this use case. This doesn't mean they can not perform well on ZSL. Further research in generating ZSL scenarios with benchmark datasets need to be done with these methods.

In comparison the adaptability of univariate methods for multivariate data is restricted. If a method designed for time series data with a single input variable needs to be used for multiple input variables a redesign is necessary. This can be extensive or rather simple depending on the architecture. To know how much redesign is necessary every method has to be reviewed in further research. However, nearly all of the found methods are trained and tested with MVTSD.

Some models like MOMENT are handling input variables seperately. The interconnection between the different channels is not considered directly. The influence of one variable on the other can provide informations that may be important for anomaly detection and the learned representations in general.

Another important evaluation point is the selection of datasets. The transferability between time series datasets is difficult due to the fact that the data between domains is huge [35]. Time series can have a similar shape across different domains but that does not have to be true in general. For a good model fitting to the specfic context, it should be trained on similar data. This way robust representations can be learned that hold information about the specific domain.

The model selection in this paper could have been more systematically. Several models were excluded that could possibly be adapted to the presented use case. A model selection process with generating synthetic anomalies simplifies the search for an appropriate dataset. Such a model selection process for zero shot anomaly detection is presented in [12].

Not only the methods available as open source should be implemented and tested. Methods without a code example provided by the authors can be implemented based on the architecture presented in the paper. THis needs to be done in future development.

Testing pretrained models that are not trained on the domain of inverter data is an interesting attempt, which could potentially have an advantageous outcome. This way domains that have no data available can be tested on anomalies. However in this case it is not ensured to find all anomalies successfully. For robust representations that contain information about the data, they need to be trained and finetuned for the specfifc use case in future works.

During the research on how to use the methods for entirely new datasets, several difficulties occured. The code provided by the authors was mainly provided for replicating the found results. Given scripts took the main benchmark datasets that were mentioned in the paper as an input. Preparing entirely new datasets in order to train and use the models was tricky because of the missing knowledge of their software architecture. Providing additional data preprocessing guidelines for generalization is necessary for further development. However, preprocessing SMA inverter data for some methods and a forward pass through the models was successful. This work can be used for further development.

Additionally the implemention in this paper is done without further analysis of the results. The correctness of the detection can be rated and compared in future works.

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8 Originality Statement

I hereby declare that the content of this paper is written on my own and sources from literature are declared as such.

Kassel, 23.09.2024

9 AI Assistance Statement

Artificial intelligence is used for learning the foundations to write this paper. During literature research the GPT "Consensus" helped in finding and summarizing relevant papers. The output was reviewed and checked for correctness. The AI-based translator "DeepL" was used to formulate sentences and to find a proper wording.

Kassel, 23.09.2024