Representation Learning for Zero-Shot Anomaly Detection

Johannes Hölker

[1] University of Kassel
[2] Germany
johannes.hoelker@uni-kassel.de

Abstract. The abstract should briefly summarize the contents of the paper in 150–250 words.

Keywords: Representation Learning · Zero Shot Learning · Anomaly Detection.

1 Introduction

Nowadays sensors can be found everywhere and their usage is increasing in many fields. 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 situation. 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 2 the basic methodology used in this paper is described and the main research questions are formulated. First basic necessary terms are explained in section 3. 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 **??**

2 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 of the latest trends in representation learning and extracts the possible solutions addressing the problem described in 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.

2.1 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 multi variate 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 3. 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.

2.2 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: Is the method using a representation learning concept. The focus is on methods learning representations in data using machine learning concepts.
- IC2: Does the method handle time series data?
- IC3: Is the method used for Anomaly Detection. Sometimes the proposed methods perform well on different use cases. If one of them is Anomaly Detection, the paper is included in the review.
- IC4: Published in recent years (< 6 years)

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

2.3 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.

3 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 in 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.

3.1 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 in 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). A 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].

One solution to this 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 [60].

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.

3.2 Anomaly Detection

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.

Instead of dividing anomalies by their cause the shape of anomalies can vary in several ways. In real measurement data 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. Seasonal and shapelet anomalies change the values in a limited time window, trend anomalies are changing all following values [9, p. 9].

In this paper we want to focus on single time events, which are in any case anomalies. Potentially being caused by an unknown process, they cannot be classified [17]. This defines our goal as an Anomaly Detection (AD) task.

3.3 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 in 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 Detection followed by [55] who used semantic word vector representations to classify words in groups and to sort new words with an accuracy of 90% 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.

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. Here the inclusion criteria as described in 2.2 are applied.

The different RL strategies are listed, explained and compared. 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 methods that use 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 this representation error 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 (SRNN). This approach addresses the challenge of detecting anomalies in complex, high-dimensional time series data. Their method utilizes a SRNN 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. The SRNN learns to represent the normal patterns in the time series and identifies deviations from these patterns as anomalies. It relies on training with data that contains normal patterns, which the model uses to detect anomalies based on deviations from these patterns. 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 Convolutional Neural Networks (CNN) are normally used to classify 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 Zero Shot Learning. 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 1D 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 [70] 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. The inclusion of

a multivariate Gaussian model for error handling and the multi-scale feature mixture method enhances the robustness and accuracy of the anomaly detection process.

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 zero-shot learning scenarios. [36]

Contrastive Learning Learning representations in time series data is done in several different ways. One solution according to [69] is contrastive learning. By comparing pairs of data points and rating the similarities as distances between the two, CL gets less dependent on labeled data. The data can be more general and the extracted representations are more robust. The pairs of data points are labeled as positive and negative pairs with a distance according to their similarities. With this distance they are put into a feature space where they form groups of data points. To minimize the bias between representations multigranularity augmented view generation and expert knowledge are used during training. The proposed framework is applied on industrial fault detection. The two data sets consist of various vibration signals of industrial machines and stiction sensors with multiple variables. The effectiveness of the proposed framework is demonstrated through its application to these datasets, where it shows improved performance in fault detection compared to traditional methods.

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. Similar to 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.

The article by [38] introduces CL-TAD, a novel method for time series anomaly detection that leverages contrastive learning and reconstruction-based techniques to address the challenges of temporal dynamics, label scarcity, and data diversity in real-world applications. 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 (positive) and dissimilar (negative) samples to learn representations. This process helps the model map similar data points closer together in the feature space while distancing dissimilar points, making it easier to detect deviations indicative of anomalies. Extensive experiments on nine benchmark datasets show that CL-TAD outperforms ten other recent methods in detecting anomalies, highlighting its effectiveness in handling diverse and complex time series data [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. However, this would depend on the model's ability to generalize from the learned normal patterns to detect unseen anomalies. Further empirical studies would be needed to validate its performance in zero-shot learning scenarios.

To succeed on Zero-Shot Anomaly Detection, the method of One-Class Classification (OCC) can solve the problem. 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 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 [63].

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. To prevent representation collapse, the model incorporates a deterministic contrastive loss, which improves the network's ability to distinguish between normal and abnormal data.

[68] 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 unique characteristics of different time series instances and dynamic temporal patterns within each series. Extensive experiments show that TS2Vec outperforms state-of-the-art methods in classification, forecasting, and

anomaly detection tasks across 125 UCR and 29 UEA datasets, achieving average improvements of 2.4% and 3.0% in classification accuracy, respectively. The framework's efficiency in training time further underscores its practical utility. TS2Vec demonstrates its versatility by excelling in multiple time series analysis tasks, making it a significant contribution to the field. The framework's hierarchical contrastive learning at various scales encapsulates rich and meaningful patterns in time series data.

Another paper introduces an autonomous system for anomaly detection in multivariate time series data 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 [22].

The paper does not explicitly address zero-shot anomaly detection, which refers to detecting anomalies without having seen any labeled anomalies during training. However, the method is designed to function in a self-supervised manner, meaning it generates pseudo-negative samples from normal data to train the model, which suggests that it could be applied to scenarios where anomaly labels are not available. This approach allows the model to differentiate between normal and abnormal behaviors based on the learned representations, potentially making it useful for zero-shot anomaly detection in multivariate time series data. Nonetheless, further validation would be needed to confirm its effectiveness specifically for zero-shot tasks.

The ContrastAD framework presented by [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 by [66] 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 [66].

[47] present 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 effectively 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 jointly 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 identified where this prediction error exceeds a certain threshold, enabling unsupervised anomaly detection based on the structure of the data itself. Experimental results show that TRL-CPC outperforms traditional anomaly detection methods on several benchmark datasets, highlighting its effectiveness in capturing complex temporal dependencies and identifying anomalies in multivariate time series data [47].

CPC is also used by the method TiCTok presented by [23]. The model proposes a novel approach to 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 high-quality 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. Experimental results indicate that TiCTok performs effectively across multiple benchmark datasets, achieving results that are either superior or comparable to existing state-of-the-art methods. In their paper they do not test the model on Zero Shot Learning scenarios like the previous method.

A paper by [49] 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, outperforming existing methods on multiple real-world datasets

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, and it achieves significant improvements over state-of-the-art deep learning models in anomaly detection tasks [58].

Autoencoder "Autoencoders are robust to unclean training datasets" [1, p. 2487].

A paper by [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, showing its applicability across different domains. The LSTM autoencoder method in this paper focuses on unsupervised anomaly detection, where it is trained to recognize anomalies by learning the normal patterns in time series data. It can effectively detect outliers based on reconstruction error but does not inherently have the capacity for ZSL.

[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).

Realising few-shot anomaly detection of images is done by [52]. The method MAEDAY can detect objects newly added to the frames. To achieve this a masked autoencoder is used who recreates the former image but without the anomaly. The difference between the initial and reconstructed images is calculated and the object then visible. This method is useful for its ability to detect anomalies with very few examples, making it a powerful tool in scenarios where labeled data is rare. [52] demonstrate the effectiveness of MAEDAY in various applications, showcasing its potential for real-world anomaly detection tasks.

To detect anomalies in healthcare data a variational recurrent autoencoder is used by [45]. The model is trained on electrocardiogram (ECG) datasets. Their method tackles the challenge of finding anomalies in unlabelled time series data. They created an unsupervised framework where the model learns to represent the data and detect anomalies without needing labeled examples. The model is based on Variational Recurrent Autoencoders (VRAE) and 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. In their method, they use a two-level hierarchical latent space representation. First, they distill feature descriptors of normal data points into more robust representations using autoencoders (AEs). These representations are then refined using a variational autoencoder (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. Their method performs well on several benchmarks for anomaly detection [50].

The paper by [70] 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 method was tested on the NSL-KDD dataset, achieving an accuracy of 88.3%, outperforming traditional approaches in detecting unknown attacks. The research highlights the feasibility and effectiveness of zero-shot learning for cybersecurity applications.

[19]

[46]

[37]

[24]

[59]

[62]

[8]

[13]

[14]

[61]

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 well on 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. Mulitvariate! 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].

Transformer [65] use a Transformer architecture to detect anomalies on three different datasets. TODO

[64]

[10]

[44]

[33]

[54]

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 singify 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.

A method detecting anomalies in tabular data using LLMs is presented by [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].

Using Fourier Analysis and the transformer architecture [67] 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. This approach is particularly useful in scenarios where labeling data is difficult and expensive. 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, outperforming competing methods when the training data contains anomalies.

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 accurately. This approach is particularly suited for environments requiring immediate anomaly detection, such as finance, healthcare, and industrial monitoring.

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.

[34]

[31]

Other [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 approach is shown to effectively detect anomalies related to amplitude and shape changes in various application domains, such as healthcare and finance, and is optimized using Particle Swarm Optimization.

[40] [11]

5 Application for Zero Shot Anomaly Detection on Multi Variate Time Series Data

In this chapter the found articles are filtered using the exclusion criteria defined in chapter 2.2. 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.

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. In this chapter a selection of appropriate methods for Time Series Data Anomaly Detection out of 4 is extracted.

In order to achieve a successful implementation in the following chapter only models which are available and well documented are chosen for further examination.

Table 1. Representation learning methodologies matching the inclusion criteria and their classification by exclusion criteria. Single Letter abbreviations are introduced for Transformer (T) and Clustering (C) concerning the underlying concept. The check boxes show if the method is tested with multiple input variables (MV), tested on zero shot learning (ZSL) or have open source availability (OSA).

Method Name	Author	Concept	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	✓		
CL based method	Zhang et al.	CL		✓	✗
CARLA	Darban et al.	CL		✗	
CL-TAD	Ngu et al.	CL		✓	
COCA	Wang et al.	CL		✗	
CL based method	Lee et al.	CL			
CL based method	Chen et al.	CL		✗	
TS2Vec	Yue et al.	CL	✓	✓	✓
TimeAutoAD	Jiao et al.	CL		✗	
ContrastAD	Li et al.	CL		✗	
Dcdetector	Yang et al.	CL		✗	
TRL-CPC	Pranavan et al.	CL		✗	
TiCTok	Kang et al.	CL		✗	
MGCLAD	Qin et al.	CL		✗	
TriAD	Sun	CL		✗	
UCAE-TENN	Nivarthi et al.	AE			
MAEDAY	Schwartz et al.	AE			
VRAE based method	Pereira et al.	AE	✓	✓	✗
AE based method	Ramirez et al.	AE			
AE based method	Provotar et al.	AE	✓	✗	✗
FuSAGNet	Han et al.	AE, GNN	✓		
MSTVAE	Pham et al.	AE	✓		
deep AOC	Mou et al.	AE			
AE based method	Zhang et al.	AE		✓	
RANSynCoders	Abdulaal et al.	AE			✓
VRQRAE	Kieu et al.	AE			✗
TCN-AE	Thill et al.	AE			
MEGA	Wang et al.	AE	✓		
DAEMON	Chen et al.	AE	✓	✓	✗
TSMAE	Gao et al.	AE			
GRU-AE	Gong et al.	AE			
MSCVAE	Yokkampon et al.	AE	✓	✓	
AE based method	Wang et al.	AE			
MOMENT	Goswami et al.	AE		✓	✓
TranAD	Tuli et al.	T			✓
Transformer based method	Ye et al.	T			
AnomalyTransformer	Xu et al.	T			✓
DATN	Wu et al.	T			
LLM based method	Li et al.	T			
TiSAT	Doshi et al.	T			
TCF-Trans	Peng et al.	T			
DCT-GAN	Li et al.	T			
Transformer based method	Shin et al.	T	GAN		
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			
	Li et al.	C			
	Niu et al.	LSTM			

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.

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. The code for the implementions can be found here: https://github.com/johanneshoelker/Smart-Systems-Paper/tree/main/Implementation

TS2Vec An implemention of the model TS2Vec is done by the authors using Python. It is available under github.com/yuezhihan/ts2vec The paper providing TS2Vec claims the model to be prepared for multiple variables. However the anomaly detection training data was univariate [68].

Moment The method Moment presented by [16] 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. These 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.

CARLA

7 Conclusion

7.1 Discussion

The presented paper has a few limitations which are discussed in this section.

That the methods are not tested on Zero-Shot Scenarios in the paper they are presented doesn't mean they can not perform well on them. Further research and test with the most promising models need to be done in the future.

That is not the case for multivariate data. 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.

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 can be important for anomaly detection and the learned representations in general.

The transferability between time series datasets is difficult due to the fact that the data between domains is huge [35]

7.2 Future Work

This section presents ideas for further research.

The model selection 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 by [12].

The implemention is done without further analysis of the results. The correctness of the detection can be rated and compared.

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.

References

1. Abdulaal, A.: Practical Approach to Asynchronous Multivariate Time Series Anomaly Detection and Localization (2021)
2. Alshaer, M., Garcia-Rodriguez, S., Gouy-Pailler, C.: Detecting Anomalies from Streaming Time Series using Matrix Profile and Shapelets Learning. In: 2020 IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI). pp. 376–383. IEEE, Baltimore, MD, USA (Nov 2020). https://doi.org/10.1109/ICTAI50040.2020.00066, https://ieeexplore.ieee.org/document/9288261/
3. Aota, T., Tong, L.T.T., Okatani, T.: Zero-shot versus Many-shot: Unsupervised Texture Anomaly Detection. In: 2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV). pp. 5553–5561. IEEE, Waikoloa, HI, USA (Jan 2023). https://doi.org/10.1109/WACV56688.2023.00552, https://ieeexplore.ieee.org/document/10030870/
4. Beggel, L., Kausler, B.X., Schiegg, M., Pfeiffer, M., Bischl, B.: Time series anomaly detection based on shapelet learning. Computational Statistics **34**(3), 945–976 (Sep 2019). https://doi.org/10.1007/s00180-018-0824-9, http://link.springer.com/10.1007/s00180-018-0824-9
5. Bengio, Y., Courville, A., Vincent, P.: Representation Learning: A Review and New Perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence **35**(8), 1798–1828 (Aug 2013). https://doi.org/10.1109/TPAMI.2013.50, http://ieeexplore.ieee.org/document/6472238/
6. Bishop, C.M.: Pattern recognition and machine learning. Information science and statistics, Springer, New York (2006)
7. Chen, K., Feng, M., Wirjanto, T.S.: Time-series Anomaly Detection via Contextual Discriminative Contrastive Learning (Apr 2023), http://arxiv.org/abs/2304.07898, arXiv:2304.07898 [cs]
8. Chen, X., Deng, L., Zhao, Y., Zheng, K.: Adversarial Autoencoder for Unsupervised Time Series Anomaly Detection and Interpretation. In: Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining. pp. 267–275. ACM, Singapore Singapore (Feb 2023). https://doi.org/10.1145/3539597.3570371, https://dl.acm.org/doi/10.1145/3539597.3570371
9. Darban, Z.Z., Webb, G.I., Pan, S., Aggarwal, C.C., Salehi, M.: CARLA: Self-supervised Contrastive Representation Learning for Time Series Anomaly Detection (Apr 2024), http://arxiv.org/abs/2308.09296, arXiv:2308.09296 [cs]
10. Doshi, K., Abudalou, S., Yilmaz, Y.: TiSAT: Time Series Anomaly Transformer (Mar 2022), http://arxiv.org/abs/2203.05167, arXiv:2203.05167 [cs, eess, stat]
11. Duan, J., Xu, X., Wang, Y.: Unsupervised Time Series Anomaly Detection using Moving Memorial Dynamic Filter. In: 2021 40th Chinese Control Conference (CCC). pp. 3403–3408. IEEE, Shanghai, China (Jul 2021). https://doi.org/10.23919/CCC52363.2021.9549428, https://ieeexplore.ieee.org/document/9549428/
12. Fung, C., Qiu, C., Li, A., Rudolph, M.: Model Selection of Zero-shot Anomaly Detectors in the Absence of Labeled Validation Data (Feb 2024), http://arxiv.org/abs/2310.10461, arXiv:2310.10461 [cs]
13. Gao, H., Qiu, B., Barroso, R.J.D., Hussain, W., Xu, Y., Wang, X.: TS-MAE: A Novel Anomaly Detection Approach for Internet of Things Time Series Data Using Memory-Augmented Autoencoder. IEEE Transactions on Network Science and Engineering **10**(5), 2978–2990 (Sep 2023). https://doi.org/10.1109/TNSE.2022.3163144, https://ieeexplore.ieee.

org/document/9744555/?arnumber=9744555, conference Name: IEEE Transactions on Network Science and Engineering

14. Gong, X., Liao, S., Hu, F., Hu, X., Liu, C.: Autoencoder-Based Anomaly Detection for Time Series Data in Complex Systems. In: 2022 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS). pp. 428–433 (Nov 2022). https://doi.org/10.1109/APCCAS55924.2022.10090260, https://ieeexplore.ieee.org/document/10090260/?arnumber=10090260
15. Goodfellow, I., Bengio, Y., Courville, A.: Deep learning. Adaptive computation and machine learning, The MIT Press, Cambridge, Massachusetts (2016)
16. Goswami, M., Szafer, K., Choudhry, A., Cai, Y., Li, S., Dubrawski, A.: MOMENT: A Family of Open Time-series Foundation Models (May 2024), http://arxiv.org/abs/2402.03885, arXiv:2402.03885 [cs]
17. Gruhl, C.M.: Novelty Detection for Multivariate Data Streams with Probalistic Models (2022). https://doi.org/10.17170/KOBRA-202205106160, https://kobra.uni-kassel.de/handle/123456789/13902, publisher: Universität Kassel
18. Gärdenfors, P.: Conceptual spaces: the geometry of thought. MIT Press, Cambridge, Mass (2000)
19. Han, S., Woo, S.S.: Learning Sparse Latent Graph Representations for Anomaly Detection in Multivariate Time Series. In: Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. pp. 2977–2986. ACM, Washington DC USA (Aug 2022). https://doi.org/10.1145/3534678.3539117, https://dl.acm.org/doi/10.1145/3534678.3539117
20. He, Y., Zhao, J.: Temporal Convolutional Networks for Anomaly Detection in Time Series. Journal of Physics (2019)
21. Jeong, K.J., Shin, Y.M.: Time-Series Anomaly Detection with Implicit Neural Representation (Jan 2022), http://arxiv.org/abs/2201.11950, arXiv:2201.11950 [cs]
22. Jiao, Y., Yang, K., Song, D., Tao, D.: TimeAutoAD: Autonomous Anomaly Detection With Self-Supervised Contrastive Loss for Multivariate Time Series. IEEE Transactions on Network Science and Engineering **9**(3), 1604–1619 (May 2022). https://doi.org/10.1109/TNSE.2022.3148276, https://ieeexplore.ieee.org/document/9705079/
23. Kang, M., Lee, B.: TiCTok: Time-Series Anomaly Detection With Contrastive Tokenization. IEEE Access **11**, 81011–81020 (2023). https://doi.org/10.1109/ACCESS.2023.3301140, https://ieeexplore.ieee.org/document/10201844/
24. Kieu, T., Yang, B., Guo, C., Cirstea, R.G., Zhao, Y., Song, Y., Jensen, C.S.: Anomaly Detection in Time Series with Robust Variational Quasi-Recurrent Autoencoders. In: 2022 IEEE 38th International Conference on Data Engineering (ICDE). pp. 1342–1354 (May 2022). https://doi.org/10.1109/ICDE53745.2022.00105, https://ieeexplore.ieee.org/document/9835268/?arnumber=9835268, iSSN: 2375-026X
25. Kitchenham, B., Pearl Brereton, O., Budgen, D., Turner, M., Bailey, J., Linkman, S.: Systematic literature reviews in software engineering – A systematic literature review. Information and Software Technology **51**(1), 7–15 (Jan 2009). https://doi.org/10.1016/j.infsof.2008.09.009, https://linkinghub.elsevier.com/retrieve/pii/S0950584908001390
26. Kravchik, M., Shabtai, A.: Detecting Cyberattacks in Industrial Control Systems Using Convolutional Neural Networks (Dec 2018), http://arxiv.org/abs/1806.08110, arXiv:1806.08110 [cs]
27. Lavrač, N., Podpečan, V., Robnik-Šikonja, M.: Representation Learning: Propositionalization and Embeddings. Springer International Publishing, Cham (2021).

https://doi.org/10.1007/978-3-030-68817-2, https://link.springer.com/10.1007/978-3-030-68817-2

28. Lee, Y., Byun, Y., Baek, J.G.: Time Series Anomaly Detection Using Contrastive Learning based One-Class Classification. In: 2023 International Conference on Artificial Intelligence in Information and Communication (ICAIIC). pp. 330–335. IEEE, Bali, Indonesia (Feb 2023). https://doi.org/10.1109/ICAIIC57133.2023.10067089, https://ieeexplore.ieee.org/document/10067089/
29. Li, A., Zhao, Y., Qiu, C., Kloft, M., Smyth, P., Rudolph, M., Mandt, S.: Anomaly Detection of Tabular Data Using LLMs (Jun 2024), http://arxiv.org/abs/2406.16308, arXiv:2406.16308 [cs]
30. Li, B., Müller, E.: Contrastive Time Series Anomaly Detection by Temporal Transformations. In: 2023 International Joint Conference on Neural Networks (IJCNN). pp. 1–8. IEEE, Gold Coast, Australia (Jun 2023). https://doi.org/10.1109/IJCNN54540.2023.10191358, https://ieeexplore.ieee.org/document/10191358/
31. Li, G., Choi, B., Xu, J., Bhowmick, S.S., Mah, D.N.y., Wong, G.L.: IPS: Instance Profile for Shapelet Discovery for Time Series Classification. In: 2022 IEEE 38th International Conference on Data Engineering (ICDE). pp. 1781–1793 (May 2022). https://doi.org/10.1109/ICDE53745.2022.00179, https://ieeexplore.ieee.org/document/9835498/?arnumber=9835498, iSSN: 2375-026X
32. Li, J., Izakian, H., Pedrycz, W., Jamal, I.: Clustering-based anomaly detection in multivariate time series data. Applied Soft Computing **100**, 106919 (Mar 2021). https://doi.org/10.1016/j.asoc.2020.106919, https://linkinghub.elsevier.com/retrieve/pii/S1568494620308577
33. Li, Y., Peng, X., Zhang, J., Li, Z., Wen, M.: DCT-GAN: Dilated Convolutional Transformer-Based GAN for Time Series Anomaly Detection. IEEE Transactions on Knowledge and Data Engineering **35**(4), 3632–3644 (Apr 2023). https://doi.org/10.1109/TKDE.2021.3130234, https://ieeexplore.ieee.org/document/9626552/?arnumber=9626552, conference Name: IEEE Transactions on Knowledge and Data Engineering
34. Liang, Z., Zhang, J., Liang, C., Wang, H., Liang, Z., Pan, L.: A Shapelet-based Framework for Unsupervised Multivariate Time Series Representation Learning (Aug 2024). https://doi.org/10.14778/3632093.3632103, http://arxiv.org/abs/2305.18888, arXiv:2305.18888 [cs]
35. Ma, Q., Liu, Z., Zheng, Z., Huang, Z., Zhu, S., Yu, Z., Kwok, J.T.: A Survey on Time-Series Pre-Trained Models (May 2023), http://arxiv.org/abs/2305.10716, arXiv:2305.10716 [cs]
36. Miao, Q., Xu, C., Zhan, J., Zhu, D., Wu, C.: An Unsupervised Short- and Long-Term Mask Representation for Multivariate Time Series Anomaly Detection (Aug 2022), http://arxiv.org/abs/2208.09240, arXiv:2208.09240 [cs]
37. Mou, X., Wang, R., Wang, T., Sun, J., Li, B., Wo, T., Liu, X.: Deep Autoencoding One-Class time Series Anomaly Detection. In: ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp. 1–5 (Jun 2023). https://doi.org/10.1109/ICASSP49357.2023.10095724, https://ieeexplore.ieee.org/document/10095724/?arnumber=10095724, iSSN: 2379-190X
38. Ngu, H.C.V., Lee, K.M.: CL-TAD: A Contrastive-Learning-Based Method for Time Series Anomaly Detection. Applied Sciences **13**(21), 11938 (Oct 2023). https://doi.org/10.3390/app132111938, https://www.mdpi.com/2076-3417/13/21/11938

39. Nielsen, M.: Neural Networks and Deep Learning p. 224 (2015)
40. Niu, Z., Yu, K., Wu, X.: LSTM-Based VAE-GAN for Time-Series Anomaly Detection. Sensors **20**(13), 3738 (Jul 2020). https://doi.org/10.3390/s20133738, https://www.mdpi.com/1424-8220/20/13/3738
41. Nivarthi, C.P., Vogt, S., Sick, B.: Unified Autoencoder with Task Embeddings for Multi-Task Learning in Renewable Power Forecasting. In: 2022 21st IEEE International Conference on Machine Learning and Applications (ICMLA). pp. 1530–1536. IEEE, Nassau, Bahamas (Dec 2022). https://doi.org/10.1109/ICMLA55696.2022.00240, https://ieeexplore.ieee.org/document/10068974/
42. Nivarthi, C.P., Vogt, S., Sick, B.: Multi-Task Representation Learning for Renewable-Power Forecasting: A Comparative Analysis of Unified Autoencoder Variants and Task-Embedding Dimensions. Machine Learning and Knowledge Extraction **5**(3), 1214–1233 (Sep 2023). https://doi.org/10.3390/make5030062, https://www.mdpi.com/2504-4990/5/3/62
43. Palatucci, M., Pomerleau, D., Hinton, G.E., Mitchell, T.M.: Zero-shot Learning with Semantic Output Codes (2009)
44. Peng, X., Li, H., Lin, Y., Chen, Y., Fan, P., Lin, Z.: TCF-Trans: Temporal Context Fusion Transformer for Anomaly Detection in Time Series. Sensors **23**(20), 8508 (Oct 2023). https://doi.org/10.3390/s23208508, https://www.mdpi.com/1424-8220/23/20/8508
45. Pereira, J., Silveira, M.: Learning Representations from Healthcare Time Series Data for Unsupervised Anomaly Detection. In: 2019 IEEE International Conference on Big Data and Smart Computing (BigComp). pp. 1–7. IEEE, Kyoto, Japan (Feb 2019). https://doi.org/10.1109/BIGCOMP.2019.8679157, https://ieeexplore.ieee.org/document/8679157/
46. Pham, T.A., Lee, J.H., Park, C.S.: MST-VAE: Multi-Scale Temporal Variational Autoencoder for Anomaly Detection in Multivariate Time Series. Applied Sciences **12**(19), 10078 (Oct 2022). https://doi.org/10.3390/app121910078, https://www.mdpi.com/2076-3417/12/19/10078
47. Pranavan, T., Sim, T., Ambikapathi, A., Ramasamy, S.: Contrastive predictive coding for Anomaly Detection in Multi-variate Time Series Data (Feb 2022), http://arxiv.org/abs/2202.03639, arXiv:2202.03639 [cs]
48. Provotar, O.I., Linder, Y.M., Veres, M.M.: Unsupervised Anomaly Detection in Time Series Using LSTM-Based Autoencoders. In: 2019 IEEE International Conference on Advanced Trends in Information Theory (ATIT). pp. 513–517 (Dec 2019). https://doi.org/10.1109/ATIT49449.2019.9030505, https://ieeexplore.ieee.org/document/9030505/?arnumber=9030505
49. Qin, S., Chen, L., Luo, Y., Tao, G.: Multiview Graph Contrastive Learning for Multivariate Time-Series Anomaly Detection in IoT. IEEE Internet of Things Journal **10**(24), 22401–22414 (Dec 2023). https://doi.org/10.1109/JIOT.2023.3303946, https://ieeexplore.ieee.org/document/10214266/
50. Ramirez Rivera, A., Khan, A., Bekkouch, I.E.I., Sheikh, T.S.: Anomaly Detection Based on Zero-Shot Outlier Synthesis and Hierarchical Feature Distillation. IEEE Transactions on Neural Networks and Learning Systems **33**(1), 281–291 (Jan 2022). https://doi.org/10.1109/TNNLS.2020.3027667, https://ieeexplore.ieee.org/document/9228891/
51. Sabokrou, M.: Deep-anomaly_ Fully convolutional neural network for fast anomaly detection in crowded scenes. Computer Vision and Image Understanding (2018)
52. Schwartz, E., Arbelle, A., Karlinsky, L., Harary, S., Scheidegger, F., Doveh, S., Giryes, R.: MAEDAY: MAE for few and zero shot AnomalY-Detection (Feb 2024), http://arxiv.org/abs/2211.14307, arXiv:2211.14307 [cs]

53. Shi, Z., Chen, J., Li, K., Raghuram, J., Wu, X., Liang, Y., Jha, S.: The Trade-off between Universality and Label Efficiency of Representations from Contrastive Learning (Feb 2023), http://arxiv.org/abs/2303.00106, arXiv:2303.00106 [cs]
54. Shin, A.H., Kim, S.T., Park, G.M.: Time Series Anomaly Detection Using Transformer-Based GAN With Two-Step Masking. IEEE Access **11**, 74035–74047 (2023). https://doi.org/10.1109/ACCESS.2023.3289921, https://ieeexplore.ieee.org/document/10164104/
55. Socher, R., Ganjoo, M., Sridhar, H., Bastani, O., Manning, C.D., Ng, A.Y.: Zero-Shot Learning Through Cross-Modal Transfer (Mar 2013), http://arxiv.org/abs/1301.3666, arXiv:1301.3666 [cs]
56. Su, J., Jiang, C., Jin, X., Qiao, Y., Xiao, T., Ma, H., Wei, R., Jing, Z., Xu, J., Lin, J.: Large Language Models for Forecasting and Anomaly Detection: A Systematic Literature Review (Feb 2024), http://arxiv.org/abs/2402.10350, arXiv:2402.10350 [cs]
57. Su, Y., Zhao, Y., Niu, C., Liu, R., Sun, W., Pei, D.: Robust Anomaly Detection for Multivariate Time Series through Stochastic Recurrent Neural Network. In: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. pp. 2828–2837. ACM, Anchorage AK USA (Jul 2019). https://doi.org/10.1145/3292500.3330672, https://dl.acm.org/doi/10.1145/3292500.3330672
58. Sun, Y., Pang, G., Ye, G., Chen, T., Hu, X., Yin, H.: Unraveling the "Anomaly" in Time Series Anomaly Detection: A Self-supervised Tri-domain Solution (Nov 2023), http://arxiv.org/abs/2311.11235, arXiv:2311.11235 [cs]
59. Thill, M., Konen, W., Wang, H., Bäck, T.: Temporal convolutional autoencoder for unsupervised anomaly detection in time series. Applied Soft Computing **112**, 107751 (Nov 2021). https://doi.org/10.1016/j.asoc.2021.107751, https://linkinghub.elsevier.com/retrieve/pii/S1568494621006724
60. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I.: Attention is All you Need (2017)
61. Wang, B., Tsung, F., Yan, H.: Attention-based Representation Learning for Time Series with Principal and Residual Space Monitoring. In: 2022 IEEE 18th International Conference on Automation Science and Engineering (CASE). pp. 1833–1839. IEEE, Mexico City, Mexico (Aug 2022). https://doi.org/10.1109/CASE49997.2022.9926721, https://ieeexplore.ieee.org/document/9926721/
62. Wang, J., Shao, S., Bai, Y., Deng, J., Lin, Y.: Multiscale Wavelet Graph AutoEncoder for Multivariate Time-Series Anomaly Detection. IEEE Transactions on Instrumentation and Measurement **72**, 1–11 (2023). https://doi.org/10.1109/TIM.2022.3223142, https://ieeexplore.ieee.org/document/9954430/?arnumber=9954430, conference Name: IEEE Transactions on Instrumentation and Measurement
63. Wang, R., Liu, C., Mou, X., Gao, K., Guo, X., Liu, P., Wo, T., Liu, X.: Deep Contrastive One-Class Time Series Anomaly Detection (Apr 2023), http://arxiv.org/abs/2207.01472, arXiv:2207.01472 [cs]
64. Wu, B., Fang, C., Yao, Z., Tu, Y., Chen, Y.: Decompose Auto-Transformer Time Series Anomaly Detection for Network Management. Electronics **12**(2), 354 (Jan 2023). https://doi.org/10.3390/electronics12020354, https://www.mdpi.com/2079-9292/12/2/354
65. Xu, J., Wu, H., Wang, J., Long, M.: Anomaly Transformer: Time Series Anomaly Detection with Association Discrepancy (Jun 2022), http://arxiv.org/abs/2110.02642, arXiv:2110.02642 [cs]

66. Yang, Y., Zhang, C., Zhou, T., Wen, Q., Sun, L.: DCdetector: Dual Attention Contrastive Representation Learning for Time Series Anomaly Detection. In: Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. pp. 3033–3045 (Aug 2023). https://doi.org/10.1145/3580305.3599295, http://arxiv.org/abs/2306.10347, arXiv:2306.10347 [cs]
67. Ye, Y., He, Q., Zhang, P., Xiao, J., Li, Z.: Multivariate Time Series Anomaly Detection with Fourier Time Series Transformer (2023)
68. Yue, Z., Wang, Y., Duan, J., Yang, T., Huang, C., Tong, Y., Xu, B.: TS2Vec: Towards Universal Representation of Time Series (Feb 2022), http://arxiv.org/abs/2106.10466, arXiv:2106.10466 [cs]
69. Zhang, K., Cai, R., Zhou, C., Liu, Y.: Debiased Contrastive Learning for Time-Series Representation Learning and Fault Detection. IEEE Transactions on Industrial Informatics **20**(5), 7641–7653 (May 2024). https://doi.org/10.1109/TII.2024.3359409, https://ieeexplore.ieee.org/document/10443248/
70. Zhang, Z., Liu, Q., Qiu, S., Zhou, S., Zhang, C.: Unknown Attack Detection Based on Zero-Shot Learning. IEEE Access **8**, 193981–193991 (2020). https://doi.org/10.1109/ACCESS.2020.3033494, https://ieeexplore.ieee.org/document/9239385/

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, 15.09.2024

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 GPT reassured the correctness of paragraphs. The AI-based translator "DeepL" was used to formulate sentences and to find a proper wording.

Kassel, 15.09.2024