Systematic Litterature Review of Anomaly Detection in Time series Data

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***Abstract*—Put abstract here**

***Index Terms*—Put Index Terms here**

I. Introduction

In the ever-evolving landscape of data analytics, the significance of time series data cannot be overstated. Understanding and spotting abnormalities within these sequences has grown critical since decision-making across different businesses and alike depends more and more on temporal data. This can be seen across many fields, like the gas, oil, or electricity industry, but also in places like elevators or temperature control in buildings to name a few. With anomaly detection being so important and widely used, it is no wonder why there are so many distinct models in this field that have very varying approaches to satisfying this niche. With the amount of data that is available today, however, many of these models now focus on machine learning, to, in various degrees, try to remove some of the human aspect of the detection. As a result, a wide range of strategies and approaches have been developed in the subject of anomaly identification in time series data due to a spike in interest and innovation. In this paper, we will take a look at some of these different methods of anomaly detection, and try to answer these questions:

RQ1: What are the state of the art methods for anomaly detection in time series data?

RQ2: How do different time series anomaly detection methods differ in terms of their performance?

The performance of anomaly detection methods working with time series data can often be extra important compared to those who do not, since some use cases involve real time monitoring the method used must be able to keep up with the output stream of the system supplying the data. Combine that with the possibility of anomalies being missed costing an extensive amount of money or worse, which could be a worst case scenario for the businesses like oil or gas companies, and it becomes pretty clear how important the performance of the anomaly detection method is. To answer our previously stated research questions, numerous papers on the subject have been found, proposing each their own method or insight on the topic. We explore the complexities of anomaly detection as we go through this wide range of applications, each with its own benefits and challenges. We aim to look at some of these methods and try to get a good understanding about the state of the art methods for anomaly detection in time series data, moreover, the differences in performance between various time series anomaly detection techniques.As such this is what you can expect from this paper:

- A listing of the different methods of anomaly detection, alongside some details about said method.
- An analysis and comparison of the different anomaly detection methods.
- A listing of possible optimal use cases for the different anomaly detection methods.
- A final discussion and conclusion on this paper, its findings and its applications.

The remainder of the paper is structured as follows: Chapter 2 takes a look at how the articles used in this paper were found and selected, chapter 3 then shows the results and analysis of said articles, chapter 4 is the discussion of the finding and lastly chapter 5 is the conclusion on this paper.

II. Research Method

This paper will conduct a Systematic Litterature Review (SLR), an empirical study where one or more research questions are investigated by collecting and synthesizing data from a number of *primary studies* through a search conducted systematically, followed by a data extraction process. We followed the guidelines proposed by Kitchenham [13] to accomplish this.

A. Search Process

The search process started off by constructing a mindmap of the different synonyms of the initial topic phrase in the topic, by taking each of the important words and separating them, finding their synonyms. By doing this it will include research which is the same topic but worded differently. The search query would include a boolean "OR" operator between each of the words. As the goal is to gain a current understanding of Anomaly Detection (AD) in Time Series Data (TSD), the dates are limited from 2017 to the current date (November 2023) ranging about 5 years back. The type of papers are limited to conference papers and article. The subject area is limited to 'Engineering', 'Computer Science' and 'Math'. All papers are found using Scopus.

TITLE-ABS-KEY (("Anomaly" OR "Outlier" OR "Irregularity") AND ("Detection" OR "Identification") AND ("Time series data" OR "Temporal data" OR "Sequence data")) AND PUBYEAR > 2017 AND PUBYEAR < 2024 AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "MATH")) AND (LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (SRCTYPE , "k"))

The search string was used in Scopus, and due to the availability of information Scopus provides about the studies was a combination of Google Sheets and Scopus used in the paper exclusion process.

B. Paper Exclusion Process

After the initial search yielded 1009 papers, then after, we followed several steps for excluding papers.

1) Firstly the papers were excluded based on the relevancy of their titles. Also, duplicate papers were removed. In this stage, each paper's title was read by two students each. A total of 348 papers passed this stage.
2) The second stage excluded papers based on the content of their abstracts in regard to the research questions. In this stage, each paper's abstract was read by two students each. A total of 131 papers passed this stage.
3) In the third stage papers were selected based on their Field-weighted Citation Impact (FWCI) score [6]. For the purpose of this SLR the 18 papers with the highest FWCI scores were selected. A total of 18 papers have passed this stage.
4) In the fourth and final stage papers were excluded based on the full text. In this stage, each paper was read by two researchers each. They were excluded based on their relevance in regard to the research questions stated before.

TABLE I
EXTRACTED STUDY DETAILS

Extracted study details	
General Study Information	*Publication type, year, author, etc*
Study Setting	*Academic, industrial or semi-industrial*
Study type	*Case study, experiment, survey or literature review*
Dataset used	
Training data type	*Labeled, Not Labeled*
Supervision in production	*Supervised, Semi-supervised, Non supervised*
Focus level of AD in TSD	*The main focus of the study is AD in TSD* *One focus of the study is AD in TSD* *AD in TSD is not a focus of the study, but it is used to study something else*

C. Data Extraction Process

In the first step of the data extraction, the researchers focused on getting the study setting and domain, shown in Table I. Furthermore, extracting the dataset used for many of the studies was also a relatively straightforward approach, however, some of the studies were not using "named" datasets, and therefore the data was omitted from extraction, some of these being datasets from very specific scenarios which could likely favor the studies proposed solution on a new AD methods for TSD.

In the second step, the effects of AD in TSD were extracted. To rationalize all the remaining 18 different papers the researchers was tasked to generalize keywords of reading their assingned studies and find what affect AD has for TSD data, these keywords would be summarized to a common category and then accounted for to show the area of effect that shows the most frequent effect on AD in TSD. As mentioned in stage four in the paper exclusion process were all studies read by two researchers, during the readthrough both members noted down any effects "Positive", "Negative", or "Neutral". This was done with the mindset of lowering the chance of missing effects.

The noted effects were then compared, those that were noted from multiple studies passed immediately and those mentioned only in one study would the other researchers discuss whether the studies they read said otherwise that it was not an effect if no one argued against the effects' relevancy, it would also be passed on. This was to make sure that the claimed effect did not only apply to one specific case.

D. Data Synthesis

From the 11 AD in TSD effect areas were some limiting factors derived, these being the effect that impacts the performance of different AD methods for TSD, these being the following rules:

i) The effect area contained at least two studies, with observations of it having some degree of influence on AD methods for TSD
ii) The effect area was observed in at least one study performed in an academic setting.

TABLE II
EMPIRICAL STUDIES OF AD IN TSD

Study	Setting	Type	Dataset	Training Data	Supervision	Focus level
Bashar & Nayak (2020) [1]	Academic	Experiment	x	Not Labeled	Unsupervised	AD in TSD explicit primary focus
Canizo et. al (2019) [2]	Academic	Experiment	x	Labeled	Supervised	AD in TSD explicit primary focus
Chen et. al (2021) [3]	Academic	Experiment	SMD, SMAP, MSL, SWaT	Undefined	Unsupervised	AD in TSD explicit primary focus
Choi et. al et. al (2020) [4]	Industrial	Experiment	x	Labeled	Supervised	One focus of the study is AD in TSD
Deng & Hooi (2021) [5]	Academic	Experiment	SWaT, WADI	Labeled	Unsupervised	AD in TSD explicit primary focus
Geiger et. al (2020) [7]	Academic	Experiment	NASA, Yahoo, Numenta, Synthetic	Undefined	Unsupervised	AD in TSD explicit primary focus
Guo et. al (2018) [8]	Academic	Experiment	Intel Berkeley, Yahoo	Mix	Unsupervised	AD in TSD explicit primary focus
Hsieh et. al (2019) [9]	Academic	Experiment	Industrial	Not labeled	Unsupervised	AD in TSD explicit primary focus
Kieu et. al (2022) [12]	Academic	Experiment	x	Labeled	Supervised	AD in TSD explicit primary focus
Kieu et. al (2022) [10]	Academic	Experiment	x	Labeled	Unsupervised	AD in TSD explicit primary focus
Kieu et. al (2019) [11]	Academic	Experiment	x	Not labeled	Unsupervised	AD in TSD explicit primary focus
Munir et. al (2019) [14]	Academic	Experiment	x	Labeled	Unsupervised	AD in TSD explicit primary focus
Rewicki et. al (2023) [15]	Academic	Experiment	x	Not labeled	Unsupervised	AD in TSD explicit primary focus
Sabokrou et. al (2018) [16]	Academic	Experiment	x	Labeled	Unsupervised	AD in TSD explicit primary focus
Talagala et. al (2020) [17]	Academic	Experiment	Fiber optics & simulated	Labeled	Unknown	AD in TSD explicit primary focus
Zhang et. al (2019) [18]	Semi-Industrial	Experiment	Synthetic & modified Powerplant	Labeled	Unsupervised	One focus of the study is AD in TSD
Zhou et. al (2019) [19]	Academic	Experiment	x	Not labeled	Unsupervised	AD in TSD explicit primary focus
Zhou et. al (2019) [20]	Academic	Experiment	Simulated- and real world data	Not Labeled	Unsupervised	AD in TSD explicit primary focus

III. RESULTS AND ANALYSIS

This review covers the 18 studies concerning AD in datasets that are TSD. 14 of those proposes a new-, altering existing-, or combination of some methods and 3 proposed a framework. This section provides the details of the studies included, as well as an analysis of the factors affecting performance, based on the stated factors in the studies affecting the performance of AD for TSD.

This review covers two research questions, although these are relatively closely related they still deviate to some degree, therefore it was necessary to evaluate the included studies' relevancy separately to each research question.

A. Empirical studies of AD state-of-the-art methods

An overview of the studies concerning AD for TSD is given in Table II. Out of the 18 included studies, 1 settled in an industrial setting, 16 academic settings and 1 was semi-industrial. All of the 18 studies were experiments and none were case studies, surveys, or literary reviews. The majority were 10 training data labeled, 5 were not labeled, and 3 were either mixed or unknown. When it comes to the level of supervision under production 14 were unsupervised whereas 3 were supervised and 1 was unknown. When it comes to The level of focus in the selected academic papers is categorized based on the focus level of AD in TSD, "The main focus of the study is AD in TSD, "One focus of the study is AD in TSD is not a focus of the study, but it is used to study something else" that is 89%, 11%, and 0% respectively.

In concerns to the Requirements of state-of-the-art methods and the performance methods used in AD in TSD, the prior has 0 amount of the studies that were exclusive to state-of-the-art as the primary focus, whereas the latter have 17 focus exclusively on performance and 1 are overlapping, with none have neither requirements as the primary focus.

B. Reported Effects on performance of AD for TSD

Table V provides a general overveiw over the litertures agreed on areas in the subject, by having a higher count indicate the variable has higher importance and or in more need of research in the views of the experts in the field, the count is the sum of positive and negative effects.

TABLE III
AREAS OF EFFECT OF AD FOR TSD

No.	Description	Count
1	Labeled training data	11
2	Not labeled training data	9
3	Supervised	6
4	Semi-supervised	1
5	Not supervised	12
6	Physical & non-Physical environment	6
7	Data velocity	2
8	Data structure	9
9	Found anomalies	10
10	False positives	10
11	Availability of expert knowledge	5

Table IV provides an in-depth view of the included studies relative to the areas of effect.

C. Factors limiting performance of AD for TSD

Based on the effect areas arrived from the previous section, 8 factors limiting the performance of AD for TSD

TABLE V
LIMITING FACTORS FOR AD IN TSD EFFIENCY

No.	Description
1	Labeling training data
2	Labeled training data
3	Supervision
4	Physical & non-Physical environment
5	Data velocity
6	Data structure
7	Target Rating
8	Availability of expert knowledge

These limiting factors are further explained based on the observations and results in the included studies.

TABLE IV
MAPPING BETWEEN EFFECTS OBSERVED AND PRIMARY STUDIES

Study \ Effect	*Labeled training data*	*Not labeled training data*	*Supervised*	*Semi-supervised*	*Not supervised*	*Physical & non-Physical environment*	*Data velocity*	*Data structure*	*Found anomalies*	*False positives*	*Availability of expert knowledge*
Bashar & Nayak (2020) [1]		+			+				+	-	
Canizo et. al (2019) [2]	.	.	+	-	-	+		+	+	-	+
Chen et. al (2021) [3]	+	-			+	.		+	+	+	
Choi et. al et. al (2020) [4]	-	+				+	+				
Deng & Hooi (2021) [5]	+		-		+			+	+	+	
Geiger et. al (2020) [7]	+		+		+			+			
Guo et. al (2018) [8]	-	+	.	.	+			+		+	
Hsieh et. al (2019) [9]	-	+	.	.	.	+		+	+	-	
Kieu et. al (2022) [12]	+	-	+	.	-	+					+
Kieu et. al (2022) [10]	+	-			+				+	+	+
Kieu et. al (2019) [11]											
Munir et. al (2019) [14]											
Rewicki et. al (2023) [15]	-	+	-		+					+	+
Sabokrou et. al (2018) [16]											
Talagala et. al (2020) [17]							+	+	+		
Zhang et. al (2019) [18]	+		-		+	+		+	+	+	
Zhou et. al (2019) [19]	.	+	.		+				+		
Zhou et. al (2019) [20]	-		.		-	+		+	+	-	+

Positive View : $+$ | *Negative View :* $-$ | *Neutral View :* .

1) LF1: Need for labeling training data:

Description: By labeling training data, we refer to unlabeled data which due to training reason has to be labeled.
Observations: 9 of the chosen articles use labeled data in thier research.
Discussion: Labeling training data requires an expert in the field which the data originates. The reason for labeling the data is to train or test an algorithm to perform AD. The reason why one would avoid the labeling their own data is due to the required expert knowledge in the field the data originates, the likely high cost for such expert knowledge and the time such a task would consume. Some technologies tries to use different approaches to achieve an algorithm without the use of labeled training data, such an instance could be graph relations.[5]

2) LF2: Not labeled training data:

Description: Unlabeled data referse to data, meaning data where humans have not labeled any data as anomalies.
Observations: 6 of the chosen articles use Unlabeled data in their research.
Discussion: Unlike labeled data, using unlabeled data requires very little effort in comparison. However, an unlabeled dataset for training can be unpredictable in the sense that it has nothing to compare to, and in most cases it has to learn by errors, failures or other misbehaviours in the system. Futhermore, it is very hard to verify weather the algorithem is right or wrong in its predictions, due to the lack of labels in training dataset.

3) LF3: Supervision:

Description: By supervision, we refer to an AD method that requires supervision, semi-supervised, or no supervision.
Observations: 3 of the chosen articles use a supervised approach in their research, while 14 used unsupervised.
Discussion: The advantage with supervised is that it is possible to catch an anomaly which has passed through the algorithm unnoticed, which the superviser can then

report to the algorithm for furture improvements. The disadvantage is that it requires manpower and that the superviser also can miss an anomaly by human error. This results in increased cost, and the algorithms inability to further improve itself by furture data.

4) LF4: Physical & non-Physical environment:

Description: By Physical & non-Physical environment we refer to the device, framework and other technology which the algorithm runs on for the experiment.

Observations:

The environment which the algorithm are running on can have a profound effect on the final result. If one compare en algorithm which ran on a different machine, even with replicated process the results will differ.

5) LF5: High data velocity:

Description: By high data velocity, we refer to real time data which has to be analyzed upon entering the system.

Observations: 2 of the studies used discuss data velocity.

Discussion: When data has to be analyzed in real time, performance is of high importance and accuracy might have to be compromised for speed. Other things such as the architecture, its ability to scale and its ability to communicate over multiple threads, can have a determining factor in the algorithms ability to process the incomming data.

6) LF6: Complex data structures:

Description: By complex data structure, we refer to a specific structure of the data which makes it different from single vector with its time and variable.

Observations: 9 of the included studies in the review discuss their data structure

Discussion: Many problems arise which requires multiple variables to be analyzed, the solution is different and more complex in these situations.

7) LF7: Target Rating:

Description: By Target Rating we refer to whether the algorithms goal is to have, high performance, low quantity of false positivs or high accuracy of true positives.

Observations: 12 of the included studies in the review discuss their target rating.

Discussion: It is a depending on the target which the system developers wants to reach, defining this is often important for the system which the researchers/developers try to develop. It depends on the qualitive attributes which the system has to fulfill.

8) LF8: Availability of expert knowledge:

Description: By Availability of expert knowledge we refer to the researchers having an expert in the field of their dataset available.

Observations: 5 of the included studies in the review discuss their Availability of expert knowledge.

Discussion: Having an expert can help one in labeling the datasets for anomalies.

IV. Discussion

V. Conclusion

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