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Review Article

Unsupervised Machine Learning for Anomaly Detection: A Systematic Review

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Abstract - *Anomaly detection has long been employed to consider and isolate abnormal components in data, with a variety of techniques developed for this purpose. One increasingly prominent approach is Machine Learning (ML), which has become instrumental in this field. In this article, we present a systematic literature review converging on anomaly detection using unsupervised machine learning algorithms. Our review examines anomaly detection models through three key dimensions: the applications of anomaly detection, the Unsupervised Machine Learning (UnML) techniques used, and the performance metrics for UnML models. We reviewed 169 research articles published between 2016 and 2024, all of which explore UnML techniques for anomaly detection. From this pool, 116 papers were selected for detailed analysis. Our review identified 58 distinct applications of anomaly detection and 34 unique UnML models employed across these studies. The frequency of various techniques highlights their application in anomaly detection and data processing. Autoencoder is the most frequently used technique, with 12 mentions. Isolation Forest follows with 5 times, while LSTM+Autoencoder appears 4 times. Methods such as IF+AE, LOF, COF, and k-Means are used twice. Hidden Markov Model, Random Histogram Forest, AutoGAN, DBSCAN, CNN+BiLSTM, DeepAE+CNN, Small Recurrent+CNN, PCA, GAN, CNN, LSTM, Autoencoder+Clustering, Hybrid CNN, COF, HBOS, OCSVM, SLOF, LDF, ORCA, LSTM+GAN, OCRF, OCSUM, OCCNN, OCNN, CVAE, C-Means, Entropy, and DAE+EIF are each mentioned once, showing a diverse range of techniques applied in the field. Notably, our findings highlight that the integration of heterogeneous methods is a promising avenue for future research. These advanced techniques offer substantial potential for enhancing the precision and effectiveness of anomaly detection in unsupervised machine learning contexts.*

Keywords - *Systematic review, Unsupervised machine learning, Anomaly detection, Accuracy, Evaluation.*

1. Introduction

Anomaly detection maneuver a key role in modern healthcare systems, aiding in the discovery of rare and potentially critical occurrences within extensive and varied medical datasets. [1] Finding patterns in data that differ from expected behavior is known as anomaly detection. A case in point within the medical domain is the application of heart rate monitors. These deviations can signify emerging diseases, unfavorable reactions to treatments, or irregular patient conditions demanding immediate attention.

Traditional methods for detecting anomalies often rely on tagged data, which can be scarce and expensive to procure within medical contexts. Consequently, the utilization of unsupervised learning algorithms has emerged as a potent approach to pinpoint anomalies within medical data, harnessing intrinsic patterns and deviations without necessitating labeled instances. In the realm of medical data, unsupervised learning algorithms hold a distinct advantage. In contrast to supervised techniques that mandate a labeled dataset encompassing both normal and anomalous samples, unsupervised methodologies enable the detection of anomalies devoid of such explicit guidance. This capability is particularly pertinent in healthcare, where anomalies can manifest in diverse forms and might lack complete comprehension or characterization. Through the adoption of unsupervised algorithms, medical experts and researchers can unveil concealed insights within intricate data, conceivably resulting in swifter disease diagnoses, enhanced patient care, and more efficacious medical interventions.

1.1. Anomaly

An anomaly is a departure from the regular pattern or behavior that stands out due to its uniqueness or difference

from the surrounding context. Anomalies can be found in various fields, such as science, statistics, technology, and even in everyday situations. Detecting anomalies can be valuable for identifying potential issues, uncovering hidden insights, or recognizing unusual occurrences [1].

Anomaly detection involves the identification of instances that fall outside the typical distribution; in simpler terms, it aims to spot examples that don't conform to the typical patterns observed within the dataset. [114] An anomaly is essentially described as a departure from the anticipated regular behavior pattern. These instances represent noteworthy deviations from the overall data behavior. These anomalies can be categorized into three primary classes.

1.1.1. Point Anomalies

A point anomaly occurs when one data instance stands out as unusual relative to the rest of the data. The most basic type of anomaly is this one. Among anomalies, this is the most basic type. For example, imagine the task of detecting instances of credit card fraud.

In this scenario, the datasets encompass an individual's various credit card transactions. Consider a single attribute: the amount spent in each transaction. Anomalies in this context refer to transactions where the expenditure deviates significantly from the person's usual spending patterns, indicating potential fraud.

1.1.2. Contextual Anomalies

When a data instance is deemed abnormal in one context but not in another, this is known as a contextual anomaly. Contextual and behavioral attributes are the two categories of characteristics that make up contextual anomalies. The former is used to define an instance's neighborhood or context. For example, time determines an instance's position within a time series, whereas longitude and latitude define contextual attributes in spatial datasets. In a spatial dataset that describes global rainfall patterns, the latter attributes specify the non-contextual features of an instance, such as the quantity of rainfall at a specific location.

The importance of contextual irregularities in the target domain and the accessibility of qualitative attributes determine whether contextual anomaly detection should be used. In some situations, determining context is simple, but in others, the lack of a clear context makes it difficult to apply particular detection techniques. Examine a temperature time series example that shows the monthly variations in temperature over the past year in a particular area. For example, in that region, a winter temperature of 35°F might not be noteworthy.

However, the same temperature reading in the summer, though, might point to an anomaly. An example from the field of credit card fraud detection is comparable to this. The time of purchase could be considered a contextual attribute in the context of credit card transactions. Assume that a person regularly spends $200 per week on shopping, with the exception of Christmas week, when the amount rises to $1000. It would be considered a contextual anomaly if a $1,000 transaction took place during a week in July. This is because, despite the fact that the same expenditure during Christmas week would be regarded as normal, it departs from the person's established spending pattern within the temporal context.

1.1.3. Collective Anomalies

Collective anomalies occur when a group of related data points are considered abnormal in the dataset as a whole. The collective behavior of the instances as a group is linked to the anomalous nature in these situations. Among the first algorithms used to identify anomalies, statistical techniques have endured over time [27].

By using these methods, a statistical model that captures the typical behavior of the given data is produced. To determine whether an instance fits or deviates from this model, a statistical inference test is then performed. Numerous methods, including proximity-based, parametric, non-parametric, and semi-parametric techniques, are available for statistical anomaly detection [112].

These techniques quantify the degree to which data instances deviate from the accepted statistical norms, making it possible to identify anomalies. Unlabeled data or prior knowledge of what an anomaly is are usually not required for the identification of anomalies in unsupervised anomaly detection.

Instead, after learning the data's typical patterns or structure, the algorithm marks as anomalies any instances that significantly deviate from the norm. This method is especially helpful when anomalies are uncommon and their exact characteristics are unknown beforehand.

1.2. Unsupervised Anomaly Detection

Unsupervised Anomaly Detection relates to the activity of distinguishing peculiar structures or deviations in a dataset without prior knowledge or labeled data. It involves detecting anomalies or deviations from the norm by comparing each collection constituent to the general distribution of the collection.

Since there is no labeled training data, the algorithm must rely on inherent patterns or structures in the data to differentiate between normal and anomalous instances**.** For example, in ECG anomaly detection, an unsupervised algorithm could be used to detect irregular heartbeats by identifying deviations in the ECG signal patterns, even when there are no labeled examples of what constitutes a "normal" or "abnormal" signal.

Typical strategies in unsupervised learning involve clustering, an approach that collects data points sharing similar characteristics, and dimensionality reduction, a technique that simplifies data by reducing the amount of variables. Key algorithms like k-means, hierarchical clustering, and PCA are often employed. Unsupervised learning is pivotal in domains such as anomaly detection, customer segmentation, and data compression.

Its primary challenge lies in evaluating the performance since there are no explicit correct outputs to compare against. This study was motivated by the fact that, as far as we are aware, there aren't many SLRs that concentrate on identifying anomalies through UnML techniques. The methodology of Kitchenham [121], the Parsif.al online platform [122], and the PRISMA framework for the article selection process diagram were all used in the meticulous reading, selection, and execution of the research articles. Among the selection criteria were

(i) Anomaly detection research,
(ii) UnML algorithms used in anomaly detection,
(iii) UnML model estimation and accuracy, and
(iv) The advantages and disadvantages of the UnML approaches used.

This paper's remaining content is divided into five sections: Section 2 describes the research methodology; Section 3 presents the findings and discussions; Section 4 addresses the review's limitations; and Section 5 provides conclusions and recommendations for additional study.

1.3. Literature Review

Anomalies in datasets can be detected through various approaches, including supervised, semi-supervised, and unsupervised learning methods. This review focuses on the unsupervised machine learning techniques used to identify abnormalities in diverse datasets, particularly emphasizing medical-related data. Both individual methods and hybrid models have been explored for anomaly detection across different networks.

In this systematic review, we have highlighted relevant studies that applied unsupervised learning algorithms, particularly in medical contexts. For instance, [69] outlined in their paper "Unsupervised Transformer-Based Anomaly Detection in ECG Signals" an unsupervised transformer-based technique for detecting anomalies in ECG signals. Promising results were obtained when their model, which included an embedding layer and a transformer encoder, was tested on two popular datasets: MIT-BIH Arrhythmia and ECG5000.

In the same way, [115] suggested a hybrid deep learning model that uses ECG data to identify and categorize arrhythmias by combining 2D CNN and LSTM networks. They highlight the significance of precise arrhythmia detection for cardiac diagnosis in their study, "A Hybrid Deep Learning Approach for ECG-Based Arrhythmia Classification," and show that their approach achieves high accuracy. S., Pandey, Bhatia, and [119] introduced an additional hybrid deep learning model for the classification of ECG heartbeats that combines CNN and BLSTM.

When compared to current techniques, their work, "Classification of Electrocardiogram Signals Based on Hybrid Deep Learning Models," performs better, obtaining high recall, precision, accuracy, and F-score. A thorough analysis by [114].

The article "A Review on the State of the Art in Atrial Fibrillation Detection Enabled by Machine Learning" focuses on machine learning models for atrial fibrillation (AF) auto-diagnosis. In order to achieve this, this paper also addresses the difficulties and contemporary technologies for ECG data collection, such as wearable sensors.

[112] examined cutting-edge deep learning techniques for time-series data anomaly detection, while Paragliola, G., along with Coronato, A. As part of their work on cardiovascular risk prediction, [120] offered insights into the assessment of hypertension using time-series classification models.

Another study found that [100], in their paper "Tensor-Based ECG Anomaly Detection Toward Cardiac Monitoring in the Internet of Health Things," investigated tensor-based techniques for identifying ECG abnormalities in cardiac monitoring within the Internet of Health Things (IoHT).

[107] Presented a hybrid CNN model that greatly outperformed other classification models on the MIT-BIH arrhythmia dataset for identifying abnormal arrhythmias from ECG signals. They demonstrated strong accuracy in the presence of noise in their study, "A Hybrid Deep CNN Model for Abnormal Arrhythmia Detection Based on Cardiac ECG Signal.". Furthermore, [1] created an unsupervised anomaly detection technique for Peripheral Venous Pressure (PVP) signals that may be used for PPG and ECG signals, among other time-series data.

Using a dynamic linear model with a Kalman filter proved to be effective in their study, "Unsupervised Anomaly Detection in Peripheral Venous Pressure Signals with Hidden Markov Models." [112] In their paper "Unsupervised Anomaly Detection in Multivariate Spatio-Temporal Data Using Deep Learning," they described how they used a deep learning framework for unsupervised anomaly detection in multivariate spatio-temporal data to find early indicators of the COVID-19 outbreak in Italy.

[104] In their paper "Deep Learning for Medical Anomaly Detection – A Survey," they offered a thorough analysis of

deep learning methods for medical anomaly detection, contrasting various strategies across medical domains and highlighting the importance of openness in model interpretations.

[116] In their study "Unsupervised Representation Learning and Anomaly Detection in ECG Sequences," they suggested an unsupervised learning method for ECG sequences that offers robust feature extraction by utilizing a variational autoencoder with recurrent neural networks.

[118] In their paper "Deep Learning: Current and Emerging Applications in Medicine and Technology," they explored the use of machine learning in deciphering intricate medical data, demonstrating its potential in biomedical research and molecular robotics.

[2] In "Machine Learning for Anomaly Detection: A Systematic Review," offers a thorough analysis of machine learning for anomaly detection, encompassing a variety of applications.

[119] Suggested a deep learning model to analyze physiological data and identify health risks. This model can detect anomalies in physiological data using unsupervised learning methods, such as the multivariate Gaussian distribution.

[117] Introduced a novel algorithm for arrhythmia detection in ECG signals based on various techniques, including DWT, ALMS, and SVM, in their paper “An Algorithm for ECG Analysis of Arrhythmia Detection.” This technique improves the precision and effectiveness of cardiac arrhythmia detection. The following are the review's goals.

1. To investigate new developments in unsupervised anomaly detection across a range of applications.
2. To identify anomaly detection applications using unsupervised machine-learning techniques.
3. To evaluate the strengths and weaknesses of related algorithms.
4. To analyze the performance metrics of unsupervised machine learning for anomaly detection.

1.4. Academic Contribution of the SLR Research

SLR offers valuable knowledge, insights, and advancements to the academic community. This contribution includes identifying gaps in existing research, synthesizing findings from multiple studies, proposing new research directions, and providing a framework for understanding or improving specific topics-in this case, anomaly detection using unsupervised learning.

Essentially, it reflects how the SLR adds to the body of academic knowledge and helps researchers build upon previous work. We identified research articles employing unsupervised learning for anomaly detection across a diverse range of fields, offering valuable insights into its broad applicability.

Our analysis uncovered 58 applications and 34 unsupervised machine learning algorithms with different types of data and use cases, presenting a cohesive and systematic body of knowledge that paves the way for deeper insights and future advancements in anomaly detection.

Our review of this topic is important for the following reasons:

- This review focuses solely on unsupervised learning, utilizing diverse datasets.
- Researchers will find related papers, applications, and algorithms to support further research and experimentation.
- Strengths and weaknesses of the algorithms have been identified to assist in applying them to specific domains.
- The performance metrics of various algorithms are presented to evaluate their effectiveness, allowing researchers to select the best algorithm.

1.5. PICOC

- Population: Studies involving various domains with the application of UnML techniques to detect anomalies. This includes but is not limited to computer networks, cybersecurity, healthcare, and manufacturing. However, our domain is anomaly detection in healthcare, especially heart disease-related.
- Intervention: The use of unsupervised machine learning algorithms for anomaly detection is an example of intervention. This includes many different approaches, including clustering-based techniques (e.g. DBSCAN, k-Means), and density estimation (e.g. GMM. All varieties of unsupervised anomaly detection algorithms will be investigated.
- Comparison: Performance metrics, computational efficiency, scalability, robustness to noise, interpretability, adaptability, and accuracy are all compared among various unsupervised anomaly detection algorithms.
- Outcome: Assessment of the effectiveness, accuracy, and precision of unsupervised machine learning techniques for anomaly detection. Evaluating metrics like accuracy, precision, recall and so on is assessed.
- Context: The context involves the specific application domains where anomaly detection is employed, such as health monitoring, fraud detection, network intrusion detection, fault diagnosis, and anomaly detection. Our exploration is about anomaly detection.

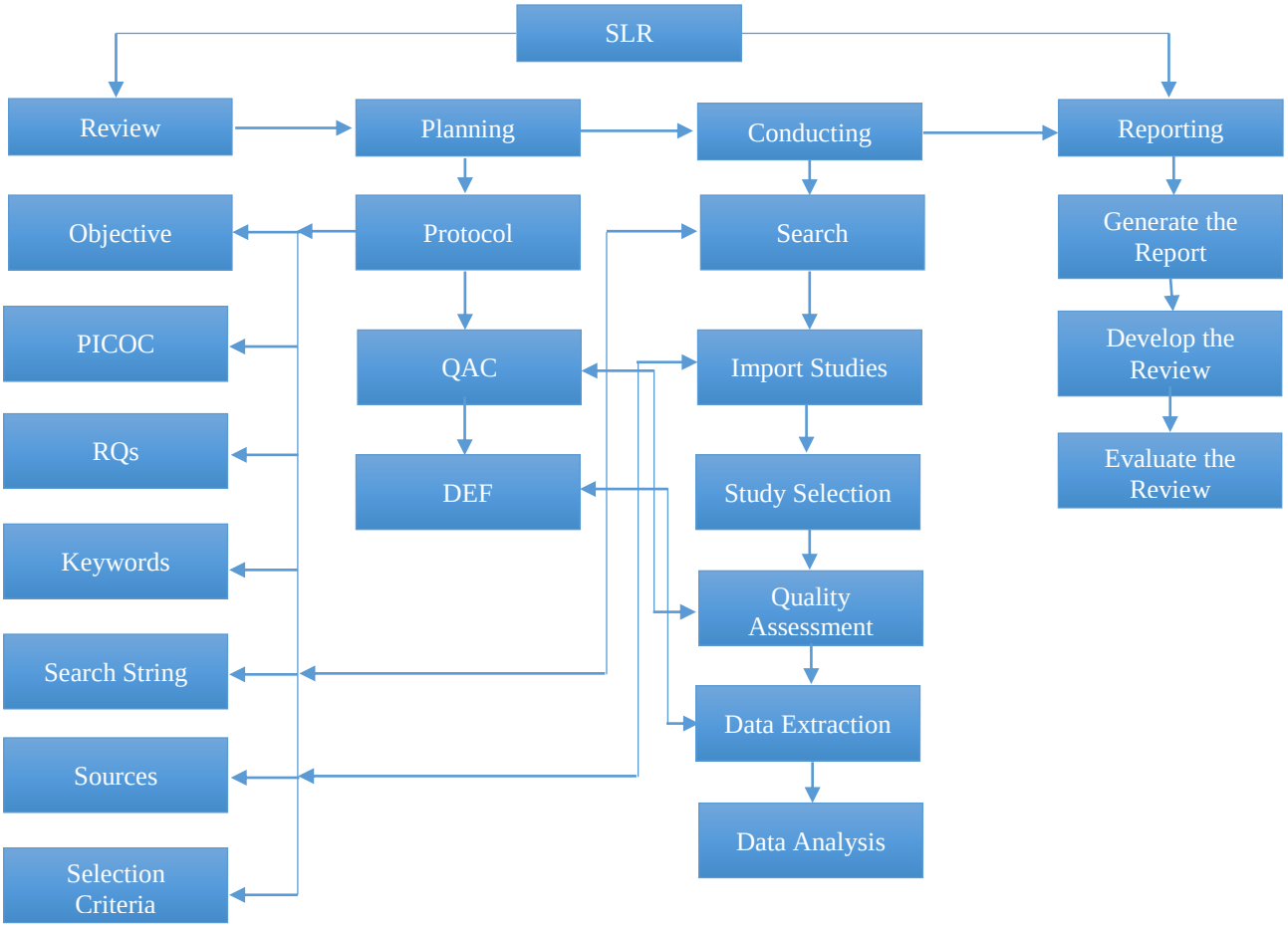

Fig. 1 Phases of systematic literature review

There are four main stages to the SLR process: Review, Planning, Conducting, and Reporting. In the review phase, the study is identified and described in detail. This involves a preliminary examination of the research area to outline the scope and relevance of the study, along with understanding its context and significance. This phase helps establish the foundation for the entire review process. In the Planning phase, a comprehensive protocol is developed, including the objectives, Research Questions (RQs), PICOC framework, keywords, search strings, sources, and selection criteria to guide the review. Additionally, Quality Assessment Criteria (QAC) are defined to assess the caliber of the studies, and a Data Extraction Form (DEF) is designed to systematically collect relevant information. Continuous feedback loops ensure that the protocol remains aligned with the objectives and other key components. In the Conducting phase, the search strategy is executed across the identified sources, and relevant studies are imported. Selection criteria are applied to filter the studies, followed by a quality assessment using the defined QAC. Data is then extracted using the DEF and analyzed to address the research questions. Finally, in the Reporting phase, the findings are compiled and documented, summarizing the key outcomes, conclusions, and recommendations for future research.

Table 1. Inclusion and exclusion criteria

Selection	Criteria	Details
Inclusion	Time Frame	Articles published between 2016 and 2024
	Application Focus	Anomaly detection applications
	Source Type	Journals and conference papers
	Content Focus	Studies comparing ML techniques
	Technique Focus	Use of ML to identify anomalies
Exclusion	Duplicate Papers	Remove duplicate papers
	Irrelevant Content	Exclude digital resources that do not discuss anomaly detection techniques
	Non-relevant ML Focus	Exclude articles which are not related to anomaly detection
	Publication Date	Exclude papers published before 2016
	Quality Assessment	Excluded papers quality scored <5

Inclusion criteria include articles published between 2016 and 2024, focus on anomaly detection applications, and be

sourced from journals and conference papers. The content should compare machine learning techniques specifically used for anomaly detection. Exclusion criteria include removing duplicate papers, excluding resources that do not discuss anomaly detection techniques, articles that use machine learning but are not related to anomaly detection, papers published before 2016, and papers with a quality score of less than 5.

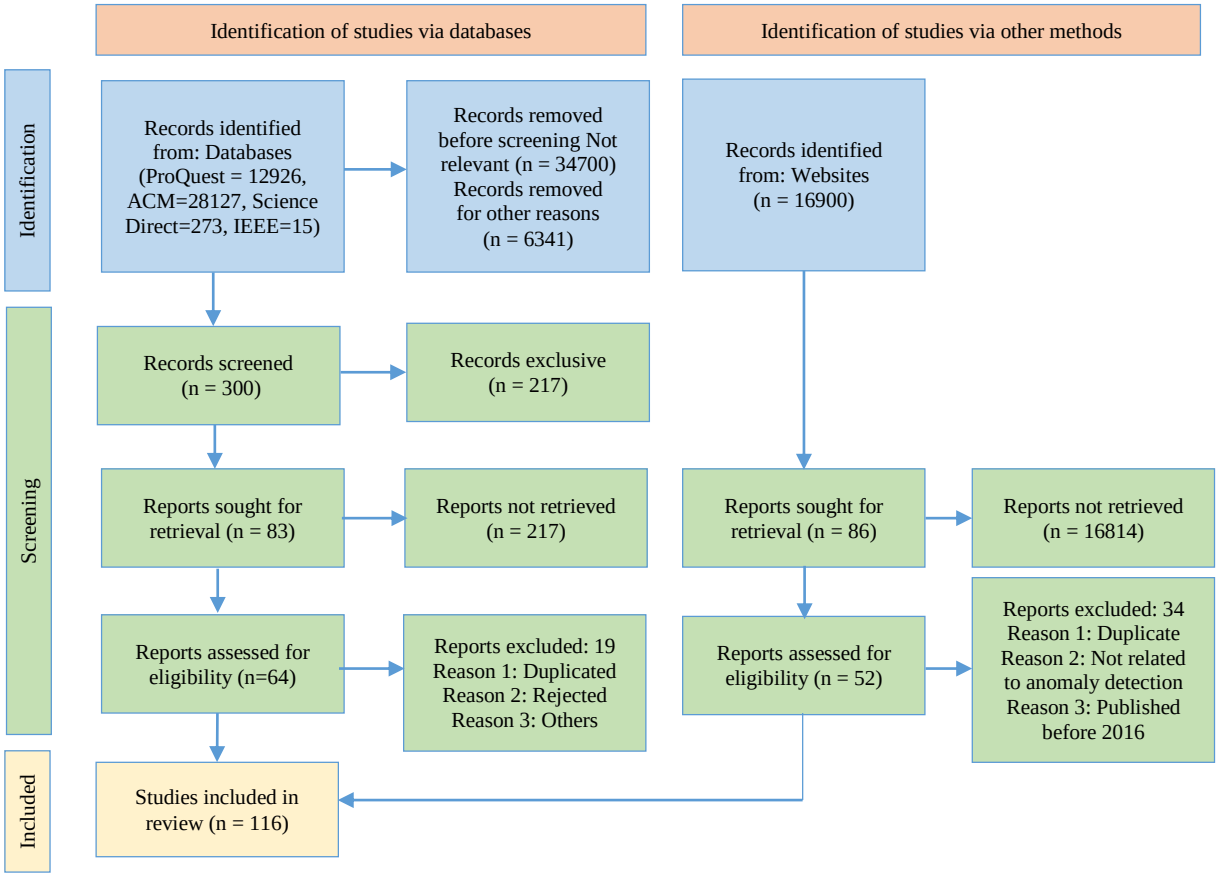

Fig. 2 Article selection process

The above flowchart provides a systematic review process for identifying relevant studies. It is divided into two main sections: identification of studies via databases and other methods. In the first section, "Identification of studies via databases," records were taken from various databases: Proquest (12926), ACM (28127), Science Direct (273), and IEEE (15), totaling 41341 records. Before screening, 34700 records were removed as they were not relevant, and an additional 6341 records were removed for other reasons, leaving 300 records to be screened. After screening, 217 records were excluded, and the remaining 83 reports were sought for retrieval. Out of these, 217 reports were not retrieved, and 64 reports were assessed for eligibility.

Ultimately, 19 reports were excluded for reasons such as duplication, rejection, or other unspecified reasons. In the second section, "Identification of studies via other methods," 16900 records were identified from websites (Google Scholar). After screening, 16814 records were not retrieved, leaving 86 reports to be assessed for retrieval. Out of these, 52 reports were assessed for eligibility, and 34 reports were excluded for reasons like duplication, irrelevance to anomaly detection, or being published before 2016. Consequently, 52 studies were included in the review from this method. Overall, 116 studies were included in the review from both identification methods combined.

2. Methodology

In the systematic literature review process, we followed kitchenham and Charters' methodology and used parsif.al online platform to conduct the whole SLR process. Moreover, we also used Prisma to draw the article selection process. The review phase involves defining the overall goal of the SLR using the PICOC framework and formulating research questions, followed by identifying relevant keywords and search strings to guide the search. The planning phase includes developing a detailed protocol, creating a QAC, designing DEF, and determining the sources and selection criteria. During the conducting phase, the search strategy is executed, studies are imported, selected based on predefined criteria, and assessed for quality using the QAC. Finally, in the

reporting phase, findings are compiled and reported, with data extracted using the DEF and analyzed to address the research questions, ensuring the review is thorough and aligned with its objectives through continuous feedback loops.

2.1. Research Questions

1. RQ1: What are the business applications of unsupervised anomaly detection are reported in the published literature?
2. RQ2: Which specific types of ML algorithms are reported in the published literature that predominantly applies in unsupervised anomaly detection?
3. RQ3: What is the overall accuracy and performance of unsupervised machine learning models for anomaly detection reported in the published literature?
4. RQ4: According to the published literature, what challenges are addressed in unsupervised anomaly detection methods, and are there any notable trends or patterns in their distribution across different research domains or periods?

2.2. Search String

The research questions help identify search terms Thus, we define the terms and boolean operators such as ("Unsupervised Learning") AND ("Anomaly") AND ("Medical data") AND ("Accuracy") AND ("Evaluation") and we used ACM Digital Library, Google Scholar, IEEE, ProQuest Database, and Science Direct digital libraries in this search.

2.3. Study Selection

During the study selection phase, we focused on articles published between 2016 and 2024 that pertain to anomaly detection applications, specifically examining journals and conference papers. The primary criterion was the use of ML techniques to identify anomalies, with a particular importance on studies that compare different machine learning methods. We removed duplicate papers and excluded digital resources that did not discuss anomaly detection techniques. Additionally, we excluded articles involving machine learning that were not related to anomaly detection and filtered out papers published before 2016 to ensure the relevance and contemporaneity of our selected studies. Moreover, we also excluded the papers that scored below less than 5.0 in the Quality assessment score. We have shown the article selection process in Figure 2.

Table 2. Import studies

Source	Number of Articles
ACM Digital Library	18
Google Scholar	86
IEEE	3
ProQuest Database	54
Science Direct	8
Total	169

The articles used in this study were sourced from various reputable databases, ensuring a diverse and comprehensive collection of research. Google Scholar contributed the highest number of articles, with a total of 86, followed by the ProQuest Database with 54 articles. The ACM Digital Library provided 18 articles, while Science Direct contributed 8 articles. The IEEE database added 3 articles to the collection. In total, 169 articles were gathered from these sources.

Table 3. Articles selection

Status	Number of Articles
Total paper	169
Accepted	116
Rejected	29
Duplicated	24

The study initially gathered a total of 169 papers. After a thorough review process, 116 articles were accepted for inclusion in the study. Meanwhile, 29 papers were rejected due to not meeting the necessary criteria, and 24 papers were identified as duplicates and subsequently excluded.

2.4. Quality Assessment Checklist

The QACs represented the final step in identifying the list of papers to be included in this review, serving a critical role in guaranteeing and assessing the superior of the research papers. To this end, 10 QACs were identified, with each criterion assigned a value of 1 mark, totaling 10 marks. The scoring for each QAC was determined based on the extent to which the criteria were met: “fully answered or yes” received a score of 1, “partial” received 0.5, and “no” received 0. Table 4 shows the answer criteria. The overall score of each article was the summation of the marks obtained for the 10 QACs, ensuring a comprehensive and systematic evaluation of the research quality [2]. Table 5 shows the QAS.

QAC 1 : Do the study goals have a clear understanding?
QAC 2 : Are the methods of analyzing the results appropriate?
QAC 3 : Are the anomaly detection techniques well outlined and emancipated?
QAC 4 : Is the particular application of anomaly detection understandably characterised?
QAC 5 : Does the paper cover practical experiments using the proposed technique?
QAC 6 : Are the experiments well-designed and justified?
QAC 7 : Are estimation precision criteria rumored?
QAC 8 : Are the scientific research applied to adequate datasets?
QAC 9 : Is the proposed approximation method compared with other methods?
QAC 10 : Does the study serve the donnish community or business as a whole?

Table 4. Answer criteria

Description	Weight	Quality Assessment Score	
Yes	1.0	Max Score	10.0
Partially	0.5	Cutoff Score	0.0
No	0.0		

In this study's quality assessment, each criterion was evaluated with a weighted scoring system. A response of "Yes" received a full weight of 1.0, "Partially" was given a half weight of 0.5, and "No" received a weight of 0.0. The maximum possible score for an article was 10.0, with a cutoff score of 0.0 indicating the minimum acceptable quality.

Table 5. Quality assessment scores

Paper Id	No. of Paper	Score
P133, P134 (Rejected)	2	4
P132 (Rejected)	1	4.5
P4, P7, P9, P10, P11, P15, P18, P26, P29, P31, P32, P39, P44, P46, P49, P50, P55, P58, P61, P66, P67, P80, P86, P88, P93, P97, P99, P100, P109, P116	30	5
P54, P56, P79, P81, P110, P111	6	5.5
P16, P112	2	6
P27, P37, P51, P74, P92, P105, P107	7	6.5
P3, P30, P96	3	7
P52, P63, P95, P105, P115	5	7.5
P20, P43, P83	3	8
P13, P14, P33	3	8.5
P2, P40, P62	3	9
P68, P103	2	9.5
P1, P5, P6, P8, P12, P17, P19, P21, P22, P23, P24, P25, P28, P34, P35, P36, P38, P41, P42, P45, P47, P48, P53, P57, P59, P60, P64, P65, P69, P70, P71, P72, P73, P75, P76, P77, P78, P82, P84, P85, P87, P89, P90, P91, P94, P98, P102, P106, P108, P110, P113, P114	52	10

2.5. Data Extraction Criteria

Our aim was to answer the questions; therefore, we assessed the year, machine learning model used, specific task, datasets employed, performance metrics, results, key findings, strengths, and weaknesses in a concise manner. There is a description in Table 6.

Table 6. Data extraction criteria

Data Extraction Field	Explanation
Anomaly Detection	Specifies whether the study focuses on anomaly detection (Yes/No)
Year	The year the study was published
ML Model	The ML models techniques used for AD
Task	The specific anomaly detection task (e.g., fraud detection, network intrusion, etc.)
Datasets	The datasets used in the study for training and testing the models
Performance Metrics	The metrics used to evaluate the demonstration of the ML models (e.g., accuracy)
Results	The outcomes of the study, including numerical results for performance metrics
Key Findings	Major conclusions and insights derived from the study
Strength	Strengths of the study, such as robustness of the model, comprehensive analysis, etc.
Weakness	Limitations or weaknesses identified in the study

The data extraction fields used in this study provided a structured framework for systematically gathering and evaluating relevant information from each article.

3. Results and Discussion

Here, we provide the outcomes of the designated articles included in this study. Detailed outcomes for from each one are presented in the subsequent four segments. Various anomaly detection applications, algorithms, datasets, and performance metrics are identified in the selected papers and are shown in the subsequent sections. A total of 119 studies were identified that applied UnML techniques for abnormality uncovering.

However, we finally accepted 116 papers, and these studies were published between 2016 and 2024. These papers' QAS was 5 or further (out of 10), which was our inclusion criteria. We show the QAS in Table 5. The complete list of papers, along with detailed information, can be found in the Appendix (Table 11). The performance metrics of the selected papers are also included in the Appendix (Table 12).

3.1. Anomaly Detection Applications

In this section, we address the application of AD that has been done in the selected papers, and it meets RQ1. We identified 58 unique utilizations in the designated articles. Table 7 provides a list of these applications. This table explains the list and frequencies that appear in the designated articles. It has been ascertained that time series data, medical, ECG, IoT, Brain, and network appeared multiple times to identify anomalies. Figure 3 shows the reappearance of anomaly detection-related applications per year.

3.2. Different Kinds of UnML Methods

In this subdivision, we address RQ2, focusing on identifying machine learning algorithms employed for anomaly detection between 2016 and 2024. We highlight the most frequently utilized UnML methods in this domain and

evaluate their effectiveness across different phases of experimentation, such as feature selection and extraction. Figure 6 illustrates the 34 UnML algorithms researchers applied in developing anomaly detection models, categorized into classification, ensemble, optimization, rule systems, clustering, and regression.

These algorithms were utilized either as standalone methods or integrated into hybrid models, combining multiple UnML approaches. Table 8 details the oftenness of these ML methods, indicating a prevalent trend among researchers to leverage combinations of UnML methods for enhanced anomaly detection capabilities. Table 9 identifies strengths and weaknesses of UnML techniques in various domains, and Table 10 provides a related work summary.

3.3. Unml Model Accuracy and Estimation

We address here RQ3, which is concerned with the overall estimation of the accuracy and performance of unsupervised machine learning models for anomaly detection, as reported in the systematic literature review.

This question focuses on performance matrices using unsupervised machine learning algorithms in anomaly detection on various datasets. The name and frequency of various datasets used in the paper are given in Figures 4 and 5, which demonstrate the frequency of performance metrics used in the paper. The details of datasets, performance metrics, and results have been given in the Appendix (Table 12).

3.4. Challenges of Unsupervised Anomaly Detection Methods

These methods developed techniques to work with unlabeled data, using autoencoders, variational autoencoders, clustering methods and so on to identify outliers without prior labeling, which demands large data sets and tuning according to the survey of weaknesses of the methods. We identify the weaknesses of machine learning techniques in Table 9. In addressing RQ4, the review found several key challenges: improving detection accuracy and reliability across diverse datasets, enhancing precision, recall, and F1-score to minimise false positives, and ensuring scalability and efficiency for large-scale, high-dimensional data.

They aim to capture intricate temporal dependencies and learn non-linear manifolds for more accurate anomaly identification, differentiate between local and global anomalies, and tailor models to specific domains such as medical diagnostics and network security. In summary, unsupervised anomaly detection methods address key challenges related to accuracy, scalability, handling complex data, and domain-specific applications. Trends indicate a dominance of deep learning models, improvements to existing techniques, diverse applications, and a standardized approach to performance evaluation, with recent years seeing a significant increase in research output.

Table 7. Anomaly detection applications observed in the selected papers

Application	Freq.	Application	Freq.
Time-series data	7	Offshore wells	1
Heart disease	2	Cybersecurity Logs	1
Multivariate spatio-temporal data	3	Video Impairments	1
COVID-19	1	I/O behaviours in HEP computing	1
Arrhythmia	1	Household electrical appliance	1
Brain	4	Acoustic	1
Social networks	1	Earthquake detection	1
Local anomaly point	1	Oil and Gas Sector	1
Medical	7	Cars CAN sensors time series	1
ECG	7	IoT	4
Network systems	1	Active sonar contact	1
Real-world data	2	sensor data	2
Medium-sized enterprize	1	Sensor Signals	1
Multidimensional data	1	Flight data	1
Mammography	1	Chest X-rays	1
Market	1	Video	1
Biological early warning systems	1	Network Anomaly	3
Transaction Order	1	Credit card fraud	1
Printed circuit boards	1	Time series data of spacecraft	1
High energy physics	1	KPIs Jitters in Network	1
Global Terrorism Data	1	Industrial screw tightening	1
Abnormal Pattern Mining	1	Text	1
Production HPC systems	1	Database systems	1
Academic plagiarism	1	Big data	1
Intrusion detection	1	Anomalous behavior	2
Wearables data	1	Cardiotocography signal	1
Chest radiographs	1	Distillated teacher-student network	1
Knowledge graphs	1	EEG	1
Industrial applications	1	Peripheral venous pressure signals	1

The application frequency indicates a diverse range of domains where anomaly detection and data processing techniques are applied. Medical, ECG, and time-series data are the most frequently cited applications, each with 7 mentions. Brain and IoT are mentioned 4 times, and multivariate spatio-temporal data and network anomaly each appear 3 times. Heart disease, real-world data, and sensor data are cited twice. Other applications like COVID-19, cybersecurity logs, video impairments, household electrical appliances, and many more are mentioned once, demonstrating the wide applicability of these techniques across various fields.

This research focuses on various fields from 2016 to 2024, with notable advancements in both methodology and application. The field has expanded its reach, covering medical data, time series analysis, heart disease detection, brain anomalies, and arrhythmia diagnosis. Between 2020 and 2023, a significant portion of research concentrated on healthcare, particularly in areas like ECG monitoring, wearable technologies, and brain-related studies, highlighting the crucial role of anomaly detection in medical settings. Beyond healthcare, it has also found applications in social networks (2021), local anomaly detection (2019), and IoT systems (2020-2024). Further, its techniques have been employed in market transactions (2024) and network anomaly detection (2023). This broad range of use cases illustrates its adaptability, with ongoing progress in multidimensional data analysis and wearable technology. The continuous focus on both healthcare and technological domains, such as ECG and IoT, underscores its significance in safeguarding human health and enhancing digital systems.

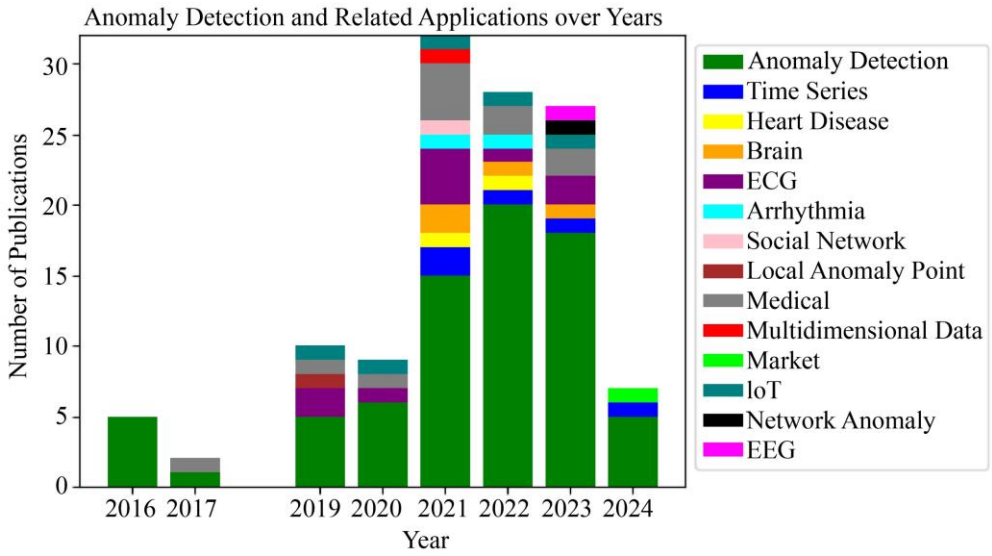

Fig. 3 Anomaly detection-related applications repetition per year

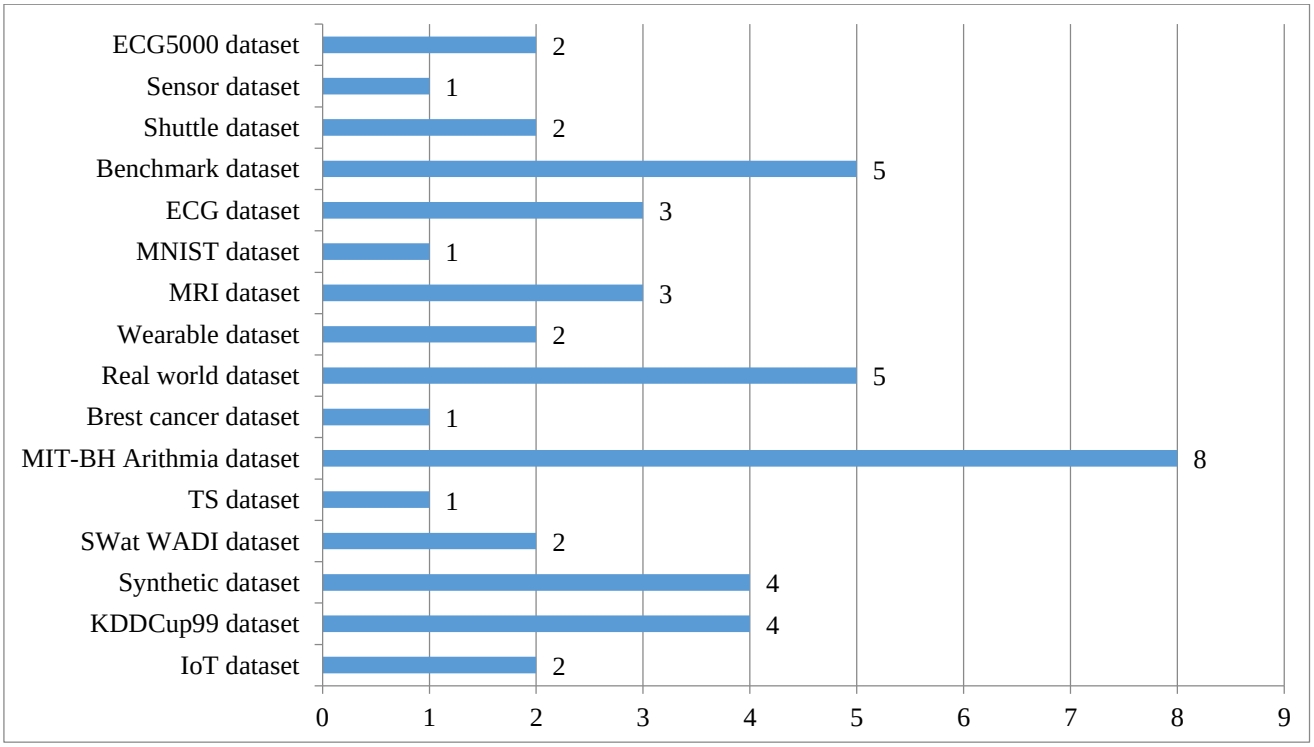

Fig. 4 Frequency of various datasets used in the selected paper

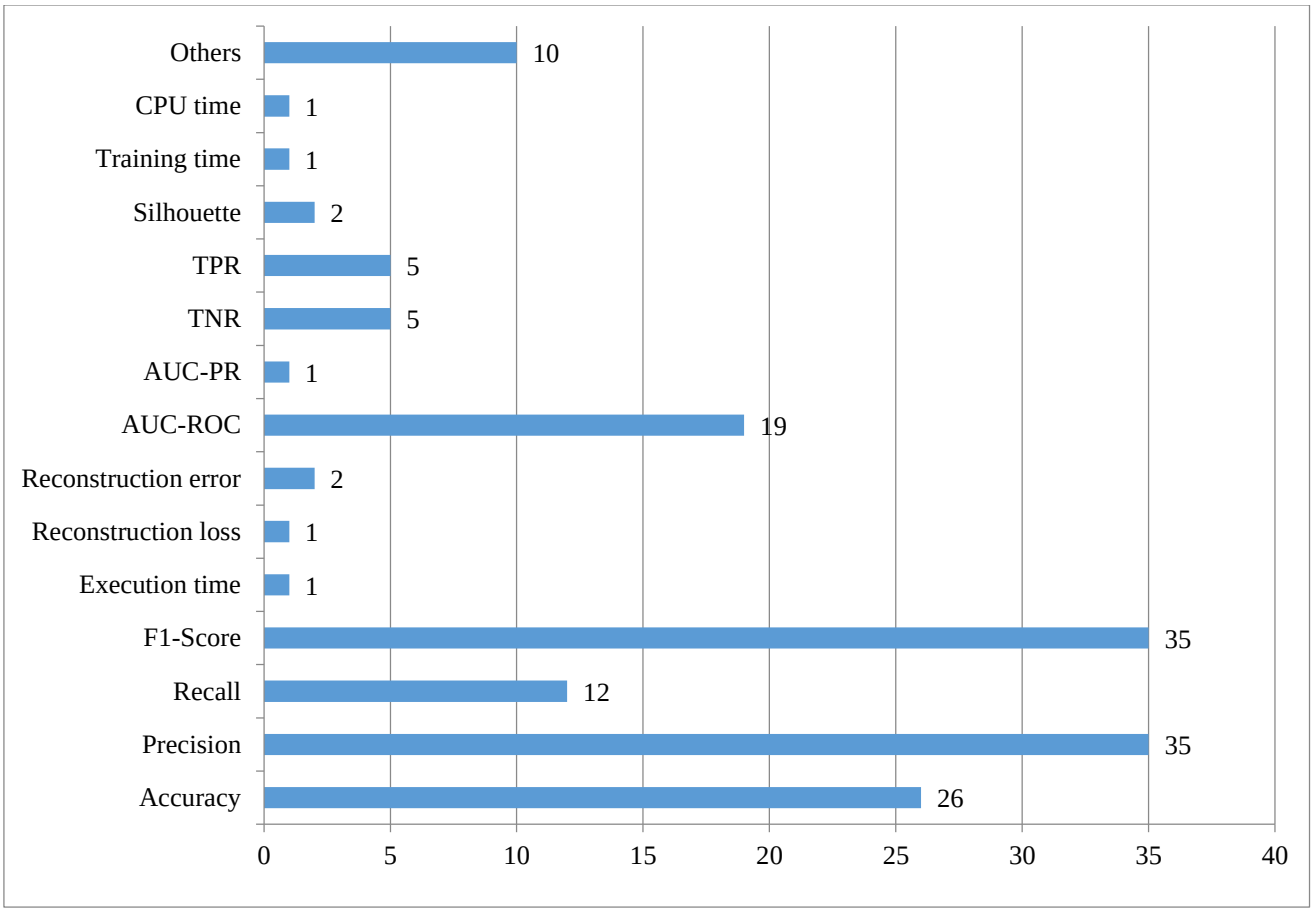

Fig. 5 Frequency of performance metrics used in the paper

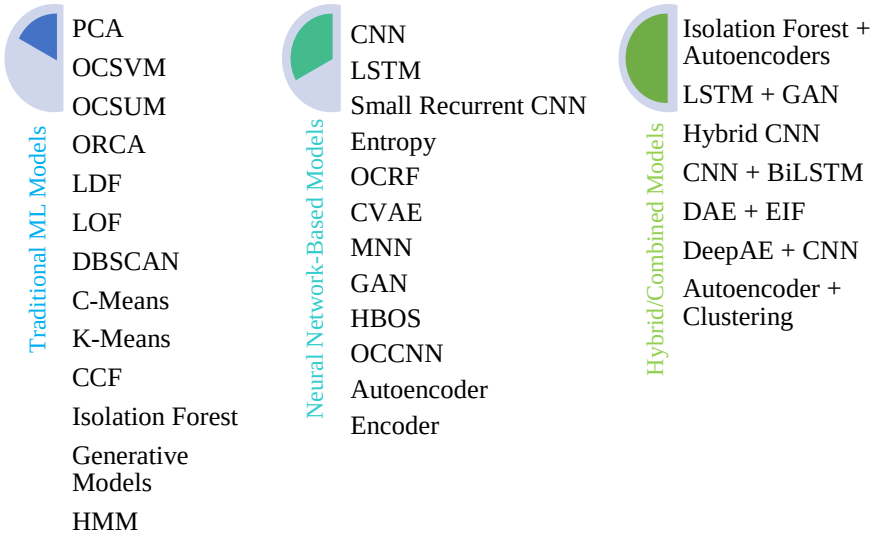

Fig. 6 Unsupervised machine learning techniques

Table 8. Machine learning techniques among accepted research articles were observed

Technique	Freq.	Technique	Freq.
Hidden Markov Model	1	Random Histogram Forest	1
Isolation Forest	5	LSTM+Autoencoder	4
AutoGAN	1	Isolation Forest+Autoencoders	2
Autoencoder	12	DBSCAN	1
CNN+BiLSTM	1	DeepAE+CNN	1
LOF, COF, k-Means	3	Small Recurrent+CNN	1
PCA	1	GAN	1
CNN	1	LSTM	1
Autoencoder+Clustering	1	Hybrid CNN	1
COF	1	HBOS	1
OCSVM	1	SLOF	1
LDF	1	ORCA	1
LSTM+GAN	1	OCRF	1
OCSUM	1	OCCNN	1
OCNN	1	CVAE	1
C-Means	1	MNN	1
Entropy	1	DAE+EIF	1

Table 9. Unsupervised machine learning techniques strength and weakness

Paper id	Technique	Strengths	Weaknesses
P1	Hidden Markov Model	Effective for modeling time-series data with hidden states.	Needs huge data for training; requires a lot of computing power.
P40	Random Histogram Forest	Robust against overfitting; effective for high-dimensional data.	Difficult to interpret; requires parameter tuning.
P21, P23, P24, P51, P57, P104	Isolation Forest	Efficient for AD in high-dimensional data.	Unsuitable for datasets that contain a large proportion of normal points relative to anomalies.
P47, P85	LSTM+ Autoencoder	Combines sequence learning with feature extraction; effective for time-series anomaly detection.	Computationally costly; training requires large datasets.
P5	AutoGAN	Generates high-quality synthetic data; useful for data augmentation.	Training is unstable; it requires extensive hyperparameter tuning.
P104	Isolation Forest+ Autoencoders	Enhances anomaly detection by combining unsupervised learning techniques.	Computationally intensive; requires expertise in both methods for effective implementation.
P65, P85	Autoencoder	Effective for dimensionality reduction and feature learning.	May not capture complex temporal dependencies; sensitive to the choice of architecture.
P61	DBSCAN	Detects clusters of varying shapes and sizes; robust to noise.	Unsuitable for high-dimensional data; sensitive to parameter selection.
P22	CNN+ BiLSTM	Captures spatial and temporal dependencies; effective for sequence data with spatial features.	Requires large datasets; computationally expensive.
P35	DeepAE+ CNN	Combines deep autoencoders with CNNs for powerful feature extraction.	Computationally intensive; requires expertise in both architectures.
P31	LOF, COF, k-Means	Effective for density-based and centroid-based clustering and anomaly detection.	Sensitive to parameter choices; k-means struggle with non-spherical clusters.
P80	Small Recurrent+ CNN	Combines temporal and spatial feature extraction; efficient for smaller datasets.	Limited scalability to larger datasets; Requires careful architecture design.
P32	PCA	Reduces dimensionality while preserving variance; computationally efficient.	Linear method; can’t capture complex nonlinear relationships.

P5	GAN	Generates realistic synthetic data; useful for data augmentation and generative tasks.	Training is unstable; and requires extensive hyperparameter tuning.
P110	CNN	Excels at capturing spatial hierarchies in images and grid-like data.	Requires large amounts of labeled data; computationally intensive.
P47, P132	LSTM	Effective for modeling temporal dependencies in sequence data.	Computationally expensive; requires large datasets for training.
P7, P60, P90	Autoencoder+Clustering	Combines feature learning with clustering; effective for anomaly detection and data segmentation.	Depends on the clustering method selected; Needs a lot of fine-tuning.
P110	Hybrid CNN	Combines strengths of various CNN architectures; versatile for multiple tasks.	Computationally expensive; and requires large datasets and extensive tuning.

Several techniques are effective in anomaly detection and data processing, each with strengths and weaknesses. Hidden Markov Models (HMM) are suited for time-series data but need extensive data and computational resources. Random Histogram Forests are prone to overfitting and effective for multi-dimensional data, yet require parameter tuning. Isolation Forests efficiently detect anomalies in high-dimensional data but struggle with datasets dominated by normal points. LSTM+Autoencoder models excel in time-series anomaly detection but are computationally intensive and require large datasets. Techniques like DBSCAN and AutoGAN have specific advantages, such as detecting clusters of various shapes and generating high-quality synthetic data, but come with sensitivities to parameter selection and training stability, respectively.

Table 10. Related work summary

Paper id	Study	Year	Summary	The difference between their review and ours
P2	A systematic review of machine learning for anomaly detection	2021	Extensive SLR on anomaly detection using machine learning techniques, except PICOC.	Our review includes an explanation of PICOC.
P26	Identifying anomalies in extensive, multi-dimensional data sets		Surveys challenges, techniques, and tools for big data anomaly detection.	Does not provide performance metrics; we do.
P128	A comprehensive meta-analysis of medical deep learning	2022	A comprehensive meta-analysis of deep learning surveys in medicine. (2017-2019).	We cover 2016-2024.
P44	A survey on explainable anomaly detection		Comprehensive survey on explainable anomaly detection techniques.	Focuses on XAD; we focus on AD.
P46	Academic plagiarism detection: a systematic review	2020	Review of computational methods for detecting academic plagiarism (2013-2018).	Focuses on plagiarism detection; we focus on anomaly detection.
P107	A survey of medical anomaly detection using deep learning	2021	Surveys deep learning-based medical anomaly detection.	Focuses on deep learning; we focus on unsupervised learning.
P111	Unsupervised ECG analysis: A review	2022	Reviews ECG clustering techniques using machine learning and deep learning.	Focuses on ECG analysis using unsupervised learning.
P4	Industrial anomaly detection using unsupervised machine learning	2022	Focuses on industrial anomaly detection using deep learning and unsupervised learning	Focuses on an unsupervised learning framework; we provide SLR.
P117	Atrial fibrillation detection with machine learning	2020	Reviews AF auto-diagnosis methods.	Focuses on AF detection; we focus on anomaly detection and future directions.
P86	Techniques for household electrical appliance anomaly detections	2023	SLR on anomaly detection and knowledge extraction for household appliances using machine learning.	Focuses on household appliances; we focus on unsupervised anomaly detection.

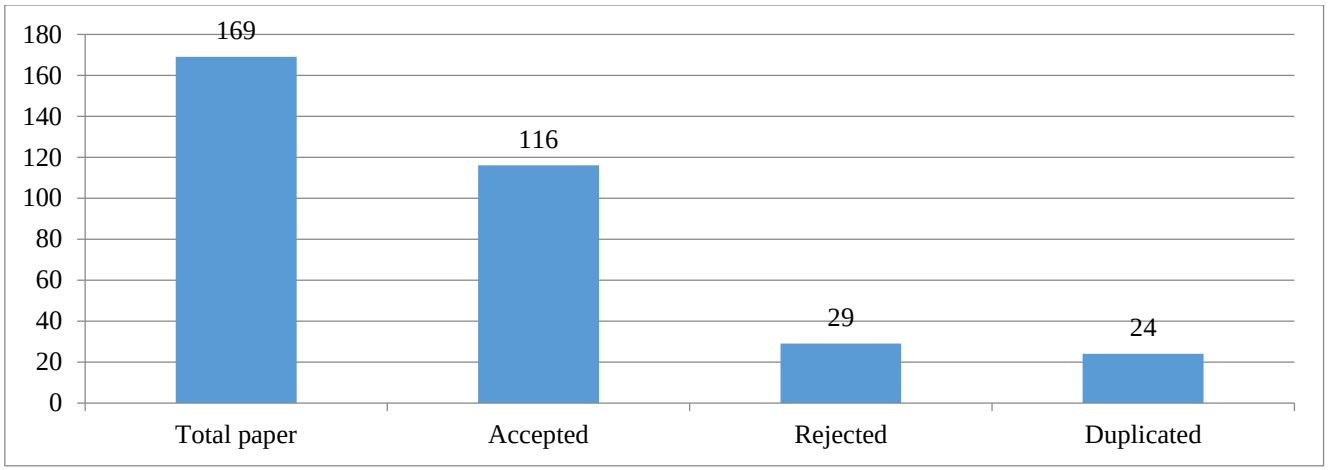

Fig. 7 Article selection from the total source

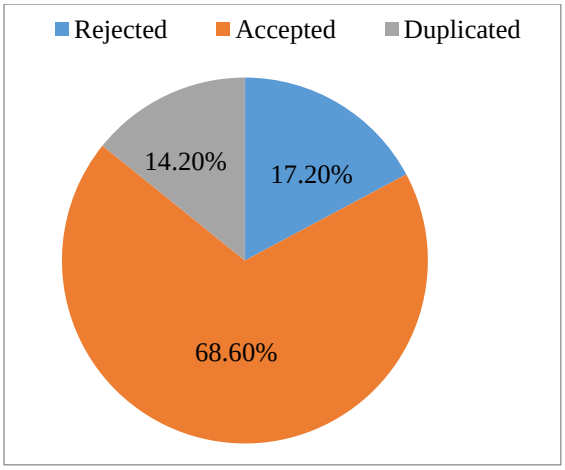

Fig. 8 Article selection rate

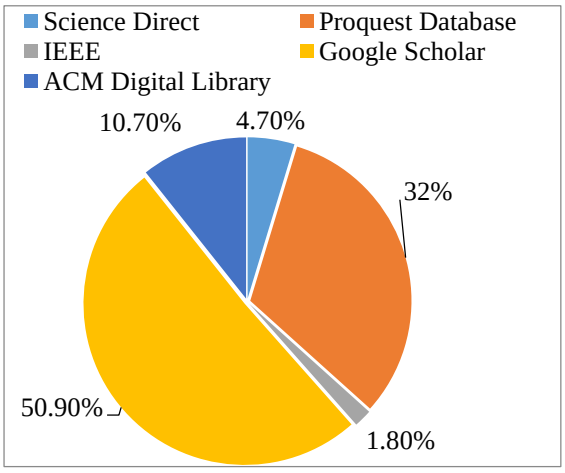

Fig 9. Articles per source

The figure consists of five pie charts that represent the distribution of articles sourced from different databases for various subsets of a study. The overall distribution shows that 50.9% of the articles (86 articles) were sourced from Google Scholar, 32% (54 articles) from the ProQuest Database, 10.7% (18 articles) from the ACM Digital Library, 4.7% (8 articles) from Science Direct, and 1.8% (3 article) from IEEE. The ACM Digital Library and Science Direct play notable roles, while IEEE has minimal representation. This uniformity indicates a reliance on certain databases, with Google Scholar and ProQuest being the available sources.

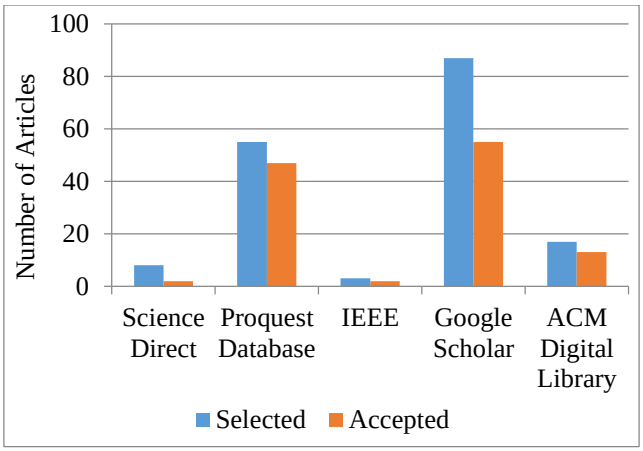

Fig. 10 Accepted articles per Source

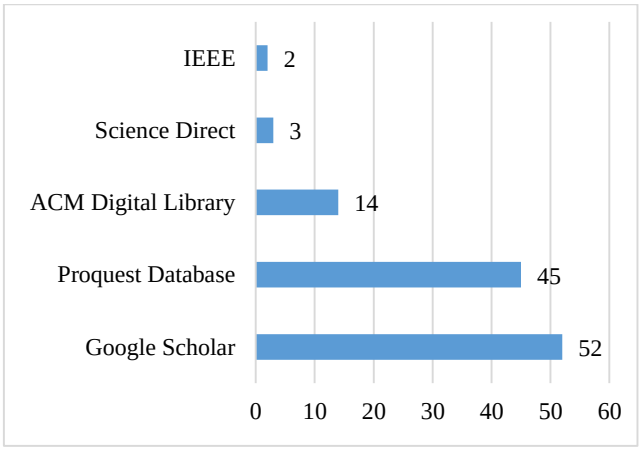

Fig. 11 Final article selection per source

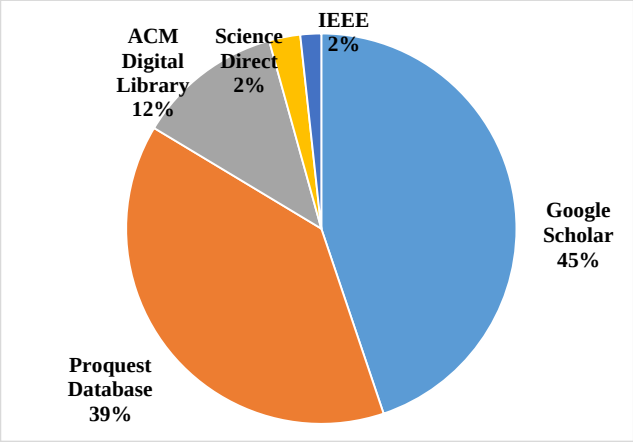

Fig. 12 Final articles selection rate per source

The pie chart depicts the sources of 116 selected articles. Google Scholar contributed the largest portion with 45% of the total, amounting to 52 articles. The Proquest Database follows, accounting for 39% with 45 articles. The ACM Digital Library provided 12%, equating to 14 articles.

Science Direct and IEEE each contributed a smaller fraction, with 2% each, translating to 3 articles from Science Direct and 2 articles from IEEE. This distribution indicates a heavy reliance on Google Scholar and Proquest Database for sourcing articles due to accessibility.

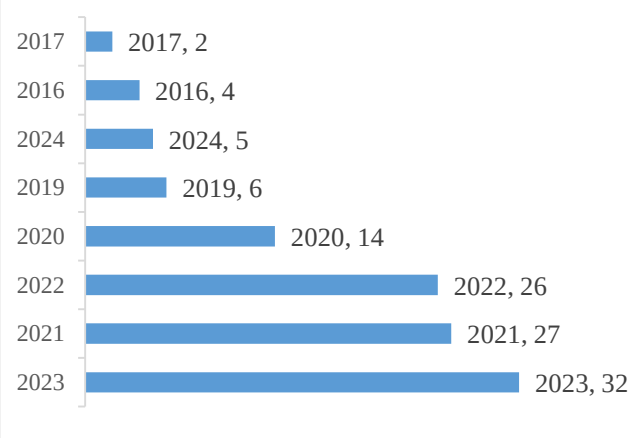

Fig. 13 Final articles per year (after study selection and quality assessment)

The bar chart illustrates the number of selected studies per year, totalling 116 studies. The breakdown is as follows: 4 studies were selected in 2016, 2 in 2017, 6 in 2019, 14 in 2020, 27 in 2021, 26 in 2022, 32 in 2023, and 5 in 2024. This distribution highlights a significant increase in selected studies in recent years, peaking in 2023 with 32 studies.

4. Limitations of this Review

This SLR focuses exclusively on articles in a limited manner concerning UnML in anomaly detection. In the first stages, we used a defined search strategy to weed out research papers that weren't relevant. As a result, the chosen papers were assured to meet strict research standards. Nevertheless, we admit that incorporating additional sources could have further enriched this review. Similarly, stringent QACs were applied to ensure rigorous evaluation.

5. Conclusion

UnML methods for anomaly detection were the main focus of this comprehensive review of the literature. It examined UnML models across four main perspectives: types of anomaly detection applications, types of UnML techniques utilized, methods for estimating UnML model accuracy, and challenges addressed in unsupervised anomaly detection. Four Research Questions (RQs) were addressed by 116 out of 169 research articles that were analyzed in this review, which covered studies published between 2016 and 2024. In answer to RQ1, the review found 58 different uses for anomaly detection, the most common of which were intrusion detection, network anomaly detection, general anomaly detection, and various data applications. Between 2020 and 2023, the adoption of anomaly detection applications significantly increased. Regarding RQ2, the authors applied 34 different UnML models, prominently featuring autoencoders and isolation forests, and showed interest in hybrid model development.

For RQ3, the review detailed the performance metrics used across the papers, showing the evaluation metrics on various parameters. It also identified different datasets used in experiments, with a preference for real-life datasets. In addressing RQ4, the review found several key challenges through the survey of the strengths and weaknesses of the methods. Based on these findings, the review recommends that researchers conduct more studies to further explore UnML-based anomaly detection, focusing on improving model performance and efficiency. It encourages the establishment of standardized experimental frameworks for UnML model evaluation. Additionally, enhancing consideration of feature selection/extraction techniques, using diverse and recent datasets, and employing a broader range of performance metrics are also suggested to advance the field. In addition, we reiterate the four questions proposed by Kitchenham et al. to summarize the contributions of this review paper. We believe our review positively satisfies the following criteria for evaluating the quality of literature reviews:

- Did the reviewers evaluate the quality/validity of the included studies?
- Were the basic data/studies adequately described?
- Were the inclusion and exclusion criteria described and appropriate?
- Is it likely that the literature search covered all relevant studies?

Our paper summarizes earlier studies and points out areas that require more investigation. This review aims to help new researchers navigate the field of anomaly detection using UnML and assist experienced researchers in finding related works. We hope our findings contribute to the development of more effective and efficient anomaly detection algorithms and methods, thereby facilitating the implementation of anomaly detection.

Abbreviations

UnML	Unsupervised Machine Learning
QAC	Quality Assessment Criteria
DEF	Data Extraction Form
VAE	Variational Autoencoders
IF	Isolation Forest
RF	Random Forest
DWT	Discrete Wavelet Transform
ALMS	Adaptive Least Mean Square
SLOF	Simplified Outlier Factor
LDF	Local Density Factor
CBLOF	Cluster-Based Local Outlier Factor
RDP	Random Distance Prediction
DAGMM	Deep Autoencoding Gaussian Mixture Model
LODA	Lightweight Online Detector of Anomalies
HBOS	Histogram Based Outlier Score
RHF	Random Histogram Forest
LOCI	Local Correlation Integral
ORCA	Online Representative Clustering Algorithm
DAE-KNNG	Deep Autoencoder-k Neural Networks Graph
ABOD	Angle-Based Outlier Detection
COPOD	Copula-Based Outlier Detection
RUAD	Robust Unsupervised Anomaly Detection
LNND	Local Nearest Neighbours Distance
CCB	Chain of Convolutional Block
OPTICS	Ordering Points to Identify the Clustering Structure
DAE	Deep Autoencoder
HTM	Hierarchical Temporal Memory
MDS	Multi-Dimensional Scaling
SWaT	Secure Water Treatment
WADI	Water Distribution
MSL	Mars Science Laboratory Rover
GRUs	Gated Recurrent Units
NMNs	Neural Memory Networks
RDA	Robust Deep Autoencoders
SNN	Spiking Neural Networks
MCD	Minimum Covariance Determinant
CLIP	Contrastive Language–Image Pre-training
ABIForest	Attention-based Isolation Forest
UCAD	Unsupervised Contextual Anomaly Detection
UGA-CAE	Unbalanced Generative-Adversarial-learning-based Convolutional Autoencoder
IREOS	Internal Relative Evaluation of Outlier Solutions
deep SVDD	Deep Support Vector Data Description
ORCF	Online Randomized Clustering Forests
OCCNN	One-Class Convolutional Neural Network
CVAE	Convolutional Variational Autoencoder
MNN	Mixture of Neural Networks
DAE	Denoising Autoencoder
EIF	Extended Isolation Forest
CNN	Convolutional Neural Network
PCA	Principal Component Analysis
XAD	Explainable Anomaly Detection
RNN	Recurrent Neural Network
GMM	Gaussian Mixture Model
GAN	Generative Adversarial Network
DBN	Deep Belief Network
KNN	K-Nearest Neighbors
NN	Neural Network
NB	Naive Bayes
ISOMAP	Isometric Mapping
DT-SVMNB	Decision Tree Support Vector Machine Naive Bayes
AnoGAN	Anomaly Detection Generative Adversarial Network
RBM	Restricted Boltzmann Machines
MAD	Median Absolute Deviation
DST	Distance from the Mean
CBSI	Clustering Based on Swarm Intelligence
MMC	Maximum Margin Clustering
EC	Ensemble Clustering
PDC	Permutation Distribution Clustering
DFFN	Deep Feed Forward Network
PSNR	Peak Signal to Noise Ratio
AP	Average Precision

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Appendix

Table 11. List of selected research articles along with source, publisher

ID	Title	Author	Journal/Conf.	Year	Source	Publisher	Ref.
P1	"Unsupervised anomaly detection in peripheral venous pressure signals with hidden Markov models"	Hayat et al.	Biomedical Signal Processing and Control	2020	Google Scholar	Elsevier	[1]
P2	"Machine learning for anomaly detection: A systematic review"	Nassif et al.	IEEE Access	2021	ACM Digital Library	IEEE	[2]
P3	"Deep isolation forest for anomaly detection"	Xu et al.	IEEE Transactions on Knowledge and Data Engineering	2023	Google Scholar	IEEE	[3]
P4	"A review of unsupervised machine learning frameworks for anomaly detection in industrial applications"	Usmani et al.	Intelligent Computing	2022	Google Scholar	Springer	[4]
P5	"Decision boundary-based anomaly detection model using improved AnoGAN from ECG data"	Shin et al.	IEEE Access	2020	Google Scholar	IEEE	[5]
P6	"Unsupervised anomaly detection in multivariate time series with online evolving spiking neural networks"	Bäßler, D. et al.	Machine Learning	2022	Proquest Database	Springer	[6]
P7	"Autoencoder and Incremental Clustering-Enabled Anomaly Detection"	Connelly et al.	Electronics	2023	Proquest Database	MDPI	[7]
P8	"Evaluation of unsupervised anomaly detection techniques in labeling epileptic seizures on human EEG"	Karpov et al.	Applied Sciences	2023	Proquest Database	MDPI	[8]
P9	"Unsupervised statistical concept drift detection for behaviour abnormality detection"	Friedrich et al.	Applied Intelligence	2023	Proquest Database	Springer	[9]
P10	"Unsupervised deep anomaly detection for medical images using an improved adversarial autoencoder"	Zhang et al.	Journal of Digital Imaging	2022	Proquest Database	Springer	[10]
P11	"Unsupervised anomaly detection in knowledge graphs"	Senaratne et al.	Proceedings of the 10th International Joint Conference on	2021	ACM Digital Library	ACM	[11]

			Knowledge Graphs				
P12	"Deep unsupervised anomaly detection"	Li et al.	Proceedings of the IEEE/CVF winter conference on applications of computer vision	2021	Google Scholar	IEEE Computer Society	[12]
P13	"Unsupervised anomaly detection with distillated teacher-student network ensemble"	Xiao et al.	Entropy	2021	Google Scholar	MDPI	[13]
P14	"Unsupervised brain imaging 3D anomaly detection and segmentation with transformers"	Pinaya et al.	Medical Image Analysis	2022	Google Scholar	Elsevier	[14]
P15	"Unsupervised deep anomaly detection in chest radiographs"	Nakao et al.	Journal of Digital Imaging	2021	Google Scholar	Springer	[15]
P16	"Denoising autoencoders for unsupervised anomaly detection in brain MRI"	Kascenas et al.	International Conference on Medical Imaging with Deep Learning	2022	Google Scholar	PMLR	[16]
P17	"Anobeat: anomaly detection for electrocardiography beat signals"	Ou et al.	2020 IEEE fifth international conference on data science in cyberspace (DSC)	2020	Google Scholar	IEEE	[17]
P18	"Unsupervised anomaly detection approach for time-series in multi-domains using deep reconstruction error"	Amarbayasgalan et al.	Symmetry	2020	Google Scholar	MDPI	[18]
P19	"Cardiotocography signal abnormality detection based on deep unsupervised models"	Bertieaux et al.	arXiv preprint arXiv:2209.15085	2022	ACM Digital Library	arXiv	[19]
P20	"A procedure for anomaly detection and analysis"	Koren et al.	Engineering Applications of Artificial Intelligence	2023	Google Scholar	Elsevier	[20]
P21	"An in-depth study and improvement of Isolation Forest"	Chabchoub et al.	IEEE Access	2022	Google Scholar	IEEE	[21]
P22	"CNN-BiLSTM Hybrid Model for Network Anomaly Detection in Internet of Things"	Omarov et al.	IJACSA	2023	Google Scholar	Science and Information (SAI)	[22]
P23	"Research and improvement of isolation forest in detection of local anomaly points"	Gao et al.	journal of physics: conference series	2019	Google Scholar	IOP Publishing	[23]
P24	"Anomalous behavior detection based on the	Fang et al.	Electronics	2022	Google Scholar	MDPI	[24]

	isolation forest model with multiple perspective business processes"						
P25	"A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data"	Goldstein et al.	PloS one	2016	Google Scholar	Public Library of Science San Francisco	[25]
P26	"A comprehensive survey of anomaly detection techniques for high dimensional big data"	Thudumu et al.	Journal of Big Data	2020	Google Scholar	Springer	[26]
P27	"Research on healthy anomaly detection model based on deep learning from multiple time-series physiological signals"	Wang et al.	Scientific Programming	2016	Google Scholar	Hindawi	[27]
P28	"Anomaly detection framework for wearables data: A perspective review on data concepts, data analysis algorithms and prospects"	Sunnyet al.	Sensors	2022	Google Scholar	MDPI	[28]
P29	"Online anomaly detection in ECG signal using hierarchical temporal memory"	Midani et al.	2019 Fifth International Conference on Advances in Biomedical Engineering (ICABME)	2019	IEEE	IEEE	[29]
P30	Regularised encoder-decoder architecture for anomaly detection in ECG time signals	Chandra et al.	2019 IEEE Conference on Information and Communication Technology	2019	IEEE	IEEE Computer Society	[30]
P31	"Outliers in rules-the comparision of LOF, COF and KMEANS algorithms."	Nowak-Brzezińska, A., et al.	Procedia Computer Science	2020	Science Direct	Elsevier	[31]
P32	"The entropy and PCA based anomaly prediction in data streams"	Hong et al.	Procedia Computer Science	2016	Science Direct	Elsevier	[32]
P33	"Unsupervised real-time anomaly detection for streaming data"	Ahmad et al.	Neurocomputing	2017	Science Direct	Elsevier	[33]
P34	"A comparative study on unsupervised anomaly detection for time series: Experiments and	Zhao et al.	arXiv preprint arXiv:2209.04635	2022	Google Scholar	arXiv	[34]

	analysis”						
P35	“Anomaly detection on medical images using autoencoder and convolutional neural network”	Siddalingappa et al.	IJACSA	2021	Google Scholar	SAI	[35]
P36	“Robust Anomaly Detection in Time Series through Variational AutoEncoders and a Local Similarity Score.”	Matias et al.	Biosignals	2021	Google Scholar	Tech Science Press	[36]
P37	“Unsupervised anomaly detection based on clustering methods and sensor data on a marine diesel engine”	Vanem et al.	Journal of Marine Engineering & Technology	2021	Google Scholar	Taylor \& Francis	[37]
P38	“Tensor-based ECG anomaly detection toward cardiac monitoring in the internet of health things”	Zhou et al.	Sensors	2021	Google Scholar	MDPI	[38]
P39	“Unsupervised two-stage anomaly detection”	Liu et al.	arXiv preprint arXiv:2103.11671	2021	Google Scholar	arXiv	[39]
P40	“Random histogram forest for unsupervised anomaly detection”	Putina et al.	2020 IEEE International Conference on Data Mining (ICDM)	2020	Google Scholar	IEEE Computer Society	[40]
P41	“Unsupervised anomaly detectors to detect intrusions in the current threat landscape”	Zoppiet al.	ACM/IMS Transactions on Data Science	2021	ACM Digital Library	ACM	[41]
P42	“An efficient framework for unsupervised anomaly detection over edge-assisted internet of things”	Liu et al.	ACM Transactions on Sensor Networks	2023	ACM Digital Library	ACM	[42]
P43	“Knowledge Extraction from Auto-Encoders on Anomaly Detection Tasks Using Co-activation Graphs”	Selani et al.	Proceedings of the 11th Knowledge Capture Conference	2021	ACM Digital Library	K-CAP	[43]
P44	“A survey on explainable anomaly detection”	Liet al.	ACM Transactions on Knowledge Discovery from Data	2023	ACM Digital Library	ACM	[44]
P45	“Internal evaluation of unsupervised outlier detection”	Marqueset al.	ACM Transactions on Knowledge Discovery from Data (TKDD)	2020	ACM Digital Library	ACM	[45]
P46	“Academic plagiarism	Folt`yneket al.	ACM Computing	2019	ACM	ACM	[46]

	detection: a systematic literature review"		Surveys (CSUR)		Digital Library		
P47	"Network anomaly detection using LSTM based autoencoder"	Said Elsayed et al.	Proceedings of the 16th ACM Symposium on QoS and Security for Wireless and Mobile Networks,	2020	ACM Digital Library	ACM	[47]
P48	"Unsupervised anomaly detection on microservice traces through graph VAE"	Xie et al.	Proceedings of the ACM Web Conference 2023,	2023	ACM Digital Library	ACM	[48]
P49	"Unsupervised contextual anomaly detection for database systems"	Liet al.	Proceedings of the 2022 International Conference on Management of Data	2022	ACM Digital Library	ACM	[49]
P50	"Prodigy: Towards unsupervised anomaly detection in production hpc systems"	Aksar et al.	Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis	2023	ACM Digital Library	ACM	[50]
P51	"Improved Anomaly Detection by Using the Attention-Based Isolation Forest"	Utkin et al.	Algorithms	2022	ACM Digital Library	MDPI	[51]
P52	"Unsupervised outlier detection in IoT using deep VAE"	Goudaet al.	Sensors	2022	Proquest Database	MDPI	[52]
P53	"Anomaly detection for internet of things based on compressed sensing and online extreme learning machine autoencoder"	Yu et al.	Journal of Physics: Conference Series	2020	Proquest Database	IOP Publishing	[53]
P54	"Analyzing the performance of anomaly detection algorithms"	Das et al.	IJACSA	2021	Proquest Database	SAI	[54]
P55	"Autoencoders in deep learning—a review with new perspectives"	Chen et al.	Mathematics	2023	Proquest Database	MDPI	[55]
P56	"Unsupervised Video Anomaly Detection Based on Similarity with Predefined Text Descriptions"	Kim et aa.	Sensors	2023	Proquest Database	MDPI	[56]
P57	"Isolation forests and deep autoencoders for industrial screw tightening anomaly detection"	Ribeiro et al.	Computers	2022	Proquest Database	MDPI	[57]
P58	"Unsupervised Learning and Online	Decker et al.	IJERTCS	2022	Proquest Database	IGI Global	[58]

	Anomaly Detection: An On-Condition Log-Based Maintenance System"						
P59	"Unsupervised abnormality detection in neonatal MRI brain scans using deep learning"	Raad et al.	Scientific Reports	2023	Proquest Database	Nature Publishing Group UK	[59]
P60	"Unsupervised anomaly detection based on deep autoencoding and clustering"	Zhang et al.	SCN	2021	Proquest Database	Hindawi Limited	[60]
P61	"Unsupervised Anomaly Detection via DBSCAN for KPIs Jitters in Network Managements."	Chen et al.	Computers, Materials & Continua	2020	Proquest Database	Tech Science Press	[61]
P62	"A Novel Unsupervised Outlier Detection Algorithm Based on Mutual Information and Reduced Spectral Clustering"	Huang et al.	Electronics	2023	Proquest Database	MDPI	[62]
P63	"Unsupervised anomaly detection for time series data of spacecraft using multi-task learning"	Yang et al.	Applied Sciences	2022	Proquest Database	MDPI	[63]
P64	"Unsupervised Anomaly Detection for Intermittent Sequences Based on Multi-Granularity Abnormal Pattern Mining"	Fan et al.	Entropy	2023	Proquest Database	MDPI	[64]
P65	"Autoencoders for unsupervised anomaly detection in high energy physics"	Finke et al.	Journal of High Energy Physics	2021	Proquest Database	Springer	[65]
P66	"Unsupervised anomaly detection in printed circuit boards through student--teacher feature pyramid matching"	Adibhatla et al.	Electronics	2021	Proquest Database	MDPI	[66]
P67	"Unsupervised Abnormal Transaction Order Detection Method Based on Deep Learning Time Factor"	Wang et al.	Journal of Physics: Conference Series	2023	Proquest Database	IOP Publishing	[67]
P68	"Anomaly detection using unsupervised methods: credit card	Rezapouret al.	IJACSA	2019	Proquest Database	SAI	[68]

	fraud case study"						
P69	"Unsupervised transformer-based anomaly detection in ECG signals"	Alamr et al.	Algorithms	2023	Proquest Database	MDPI	[69]
P70	"CRND: An Unsupervised Learning Method to Detect Network Anomaly"	Qu et al.	SCN	2022	Proquest Database	Hindawi	[70]
P71	"A Novel Unsupervised Video Anomaly Detection Framework Based on Optical Flow Reconstruction and Erased Frame Prediction"	Huang et al.	Sensors	2023	Proquest Database	MDPI	[71]
P72	"Unsupervised anomaly detection for posteroanterior chest X-rays using multiresolution patch-based self-supervised learning"	Kim et al.	Scientific Reports	2023	Proquest Database	Nature Publishing Group	[72]
P73	"Unsupervised anomaly detection in flight data using convolutional variational auto-encoder"	Memarzadeh et al.	Aerospace	2020	Proquest Database	MDPI	[73]
P74	"Anomaly Detection for Sensor Signals Utilizing Deep Learning Autoencoder-Based Neural Networks"	Esmaeili et al.	Bioengineering	2023	Proquest Database	MDPI	[74]
P75	"Unsupervised and non-parametric learning-based anomaly detection system using vibration sensor data"	Park et al.	Multimedia Tools and Applications	2019	Proquest Database	Springer	[75]
P76	"Unsupervised active sonar contact classification through anomaly detection"	Stinco et al.	EURASIP Journal on Advances in Signal Processing	2023	Proquest Database	Springer	[76]
P77	"Unsupervised Anomaly Detection for IoT-Driven Multivariate Time Series on Moringa Leaf Extraction"	Widyowati et al.	International Journal of Automation Technology	2024	Proquest Database	Fuji Technology Press Ltd.	[77]
P78	"An unsupervised data-driven anomaly detection approach for adverse health	Bijlani et al.	JMIR aging	2022	Proquest Database	JMIR	[78]

	conditions in people living with dementia: Cohort study"						
P79	"Unsupervised anomaly detection for cars CAN sensors time series using small recurrent and convolutional neural networks"	Cherdo et al.	Sensors	2023	Proquest Database	MDPI	[79]
P80	"An Unsupervised Anomaly Detection Based on Self-Organizing Map for the Oil and Gas Sector"	Concetti et al.	Applied Sciences	2023	Proquest Database	MDPI	[80]
P81	"Unsupervised anomaly detection for earthquake detection on Korea high-speed trains using autoencoder-based deep learning models"	Seo et al.	Scientific Reports	2024	Proquest Database	Nature Publishing Group	[81]
P82	"Deep autoencoders for acoustic anomaly detection: experiments with working machine and in-vehicle audio"	Coelho et al.	Neural Computing and Applications	2022	Proquest Database	Springer	[82]
P83	"A robust unsupervised anomaly detection framework"	Luo et al.	Applied Intelligence	2022	Proquest Database	Springer	[83]
P84	"Unsupervised outlier detection for time-series data of indoor air quality using LSTM autoencoder with ensemble method"	Park et al.	Journal of Big Data	2023	Proquest Database	Springer	[84]
P85	"Systematic literature review of the techniques for household electrical appliance anomaly detections and knowledge extractions"	Raufet al.	Journal of Electrical Systems and Information Technology	2023	Proquest Database	Springer	[85]
P86	"Anomaly detection of I/O behaviours in HEP computing cluster based on unsupervised machine learning"	Wanget al.	Journal of Physics: Conference Series	2023	Proquest Database	IOP Publishing	[86]
P87	"On Novel System for Detection Video Impairments Using Unsupervised Machine Learning Anomaly Detection Technique."	Goran et al.	TEM Journal	2023	Proquest Database	UIKTEN	[87]
P88	"Design and Evaluation	Sánchez-Zas, C.,	Mathematics	2022	Proquest	MDPI	[88]

	of Unsupervised Machine Learning Models for Anomaly Detection in Streaming Cybersecurity Logs"	et al.			Database		
P89	"Unsupervised machine learning model for predicting anomalies in subsurface safety valves and application in offshore wells during oil production"	Aranha et al.	Journal of Petroleum Exploration and Production Technology	2024	Proquest Database	Springer	[89]
P90	"Anomaly detection in biological early warning systems using unsupervised machine learning"	Grekov et al.	Sensors	2023	Proquest Database	MDPI	[90]
P91	"Unsupervised anomaly detection with generative adversarial networks in mammography"	Park et al.	Scientific Reports	2023	Google Scholar	Nature Publishing Group	[91]
P92	"Unsupervised outlier detection in multidimensional data"	Brahim et al.	Journal of Big Data	2021	Google Scholar	Springer Nature BV	[92]
P93	"A Comparative Study of Unsupervised Anomaly Detection Algorithms used in a Small and Medium-Sized Enterprise"	Petrariu et al.	IJACSA	2022	Google Scholar	SAI	[93]
P94	"Unsupervised anomaly detection of implausible electronic health records: a real-world evaluation in cancer registries"	Röchner, P., et al.	BMC Medical Research Methodology	2023	Google Scholar	Springer	[94]
P95	"Unsupervised anomaly detection algorithms on real-world data: how many do we need?"	Bouman et al.	Journal of Machine Learning Research	2024	Google Scholar	Microtome Publishing	[95]
P96	"Unsupervised anomaly detection: methods and applications"	Putina, Andrian	HAL Open Science	2022	Google Scholar	Institut Polytechnique de Paris	[96]
P97	"An unsupervised anomaly detection framework for detecting anomalies in real time through network system's log files analysis"	Zeufack et al.	High-Confidence Computing	2021	Google Scholar	Elsevier	[97]
P98	"Electrocardiogram quality assessment	Seeuws et al.	IEEE Transactions on Biomedical	2021	Google Scholar	IEEE	[98]

	using unsupervised deep learning"		Engineering				
P99	"A novel method of QRS detection using time and amplitude thresholds with statistical false peak elimination"	Modak et al.	IEEE Access	2021	Google Scholar	IEEE	[99]
P100	"Anomaly detection with robust deep autoencoders"	Zhou et al.	Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining	2017	Google Scholar	ACM	[100]
P101	"Anomaly Detection using combination of Autoencoder and Isolation Forest"	Almansoori et al.	proceedings of the 1st Workshop on Intelligent Infocommunication Networks, Systems and Services (WINS 2023)	2023	Google Scholar	BME (Budapest University of Technology and Economics)	[101]
P102	"MADGAN: Unsupervised medical anomaly detection GAN using multiple adjacent brain MRI slice reconstruction"	Han et al.	BMC bioinformatics	2021	Google Scholar	Springer	[102]
P103	"Distributed anomaly detection using minimum volume elliptical principal component analysis"	O'Reilly et al.	IEEE Transactions on Knowledge and Data Engineering	2016	Google Scholar	IEEE	[103]
P104	"Deep learning for medical anomaly detection--a survey"	Fernando et al.	ACM Computing Surveys (CSUR)	2021	Google Scholar	ACM	[104]
P105	"An efficient hybrid system for anomaly detection in social networks"	Rahman et al.	Cybersecurity	2021	Google Scholar	Springer	[105]
P106	"Unsupervised anomaly detection using generative adversarial networks in 1H-MRS of the brain"	Jang et al.	Journal of Magnetic Resonance	2021	Google Scholar	Elsevier	[106]
P107	"A hybrid deep CNN model for abnormal arrhythmia detection based on cardiac ECG signal"	Ullah et al.	Sensors	2021	Google Scholar	MDPI	[107]
P108	"Unsupervised ECG analysis: A review"	Nezamabadi et al.	IEEE Reviews in Biomedical Engineering	2022	Google Scholar	IEEE	[108]
P109	"Unsupervised anomaly detection in multivariate spatio-	Karadayi et al.	IEEE Access	2020	Google Scholar	IEEE	[109]

	temporal data using deep learning: early detection of COVID-19 outbreak in Italy"						
P110	"Using machine learning for heart disease prediction"	Salhi et al.	Proceedings of the 4th Conference on Computing Systems and Applications	2021	Google Scholar	Springer International Publishing.	[110]
P111	"Anomaly detection in heart disease using a density-based unsupervised approach"	Nanehkaran et al.	Wireless Communications and Mobile Computing	2022	Google Scholar	Hindawi	[111]
P112	"Deep learning for anomaly detection in time-series data: Review, analysis, and guidelines"	Choi et al.	IEEE access	2021	Google Scholar	IEEE	[112]
P113	"Autoencoders"	Bank et al.	Machine learning for data science handbook: data mining and knowledge discovery handbook	2023	Google Scholar	Springer	[113]

This collection of studies provides a comprehensive overview of recent advancements in unsupervised anomaly detection using machine learning techniques across various applications. These studies collectively highlight the versatility and effectiveness of machine learning in identifying anomalies across different types of data and use cases.

Table 12. Performance metrics among selected papers

ID	Year	ML Model	Datasets	Performance Metrics	Results
P2	2021	29 distinct ML models	22 different datasets	Acc, P, R, F1, and AUC-ROC	Results vary across different models and datasets
P20	2023	IF, LOF, OC- SVM, MAD, DST, Tukey Fences	Five datasets, both supervised and unsupervised	Noise Ratio (NR), percentage of non-anomalous values	The proposed method showed consistent results across various algorithms
P22	2023	CNN-BiLSTM, SVM, Logistic Regression, RF, AdaBoost, KNN, NB, DT	Various IoT datasets	Accuracy, Precision, Recall, F1-Score, Execution Time	Accuracy: 96.28%, Precision: 96.17%, Recall: 95.14%, F1-Score: 95.09%, Execution Time: 47.16s
P113	2021	VAE, Disentangled Autoencoders	Not specified explicitly	Reconstruction loss (e.g., $\ell 2$-norm), Regularization terms (e.g., KL divergence)	Achieved compressed and meaningful representations, Reconstruction close to the original input
P3	2023	Deep Isolation Forest	Tabular (Analysis, Backdoor, DoS, Exploits, R8, Cover, Fraud, Pageblocks, Shuttle, Thrombin), Graph, TS	AUC-ROC, AUC-PR	Analysis: AUC-ROC: 0.931±0.006, AUC-PR: 0.404±0.051 Backdoor: AUC-ROC: 0.918±0.002, AUC-PR 0.453±0.051 DoS: AUC-ROC: 0.932±0.003, AUC-PR: 0.440±0.023 Exploits: AUC-ROC:

					0.858±0.010, AUC-PR: 0.273±0.020 R8: AUC-ROC: 0.930±0.008, AUC-PR: 0.145±0.031 Cover: AUC-ROC: 0.972±0.010, AUC-PR: 0.246±0.069 Fraud: AUC-ROC: 0.953±0.002, AUC-PR: 0.387±0.039 Pageblocks: AUC-ROC: 0.903±0.010, AUC-PR: 0.547±0.020 Shuttle: AUC-ROC: 0.941±0.006, AUC-PR: 0.150±0.017 Thrombin: AUC-ROC: 0.913±0.003, AUC-PR: 0.468±0.020
P21	2022	Isolation Forest	Shuttle, KDDCup99 HTTP, KDDCup99 SMTP, Forest Cover, and two-dimensional synthetic datasets	CPU Time, ROC AUC, FAR (%), Specificity, Recall	MVIForest has a shorter execution time than IForest, with almost the same accuracy
P23	2019	Isolation Forest , Cluster Based Isolation Forest	kddcup-99, breast cancer, credit card from UCI	Accuracy, F1-Score	CBIF algorithm can better identify local anomalies than OC-SVM, LOF
P24	2022	Isolation Forest model	Real event logs	Anomalous Behavior Recognition Rate, Model Quality Improvement, Anomaly Score, Detection Rate, Precision, Recall	The algorithm effectively detects unusual behaviors improves acc.
P25	2016	Various Alg.	10 different datasets from multiple application domains	Anomaly detection performance, computational effort, impact of parameter settings, global/local anomaly detection behavior	Evaluate of nineteen different UnML algorithms
P26	2020	PCA,Subspace approach and MDS	na	na	na
P1	2020	Dynamic Linear Model DLM) with Kalman Filter and HMM	Clinical data from a cohort of 24 pediatric patients	True Positive Rate, True Negative Rate, Precision, F1 Score, Accuracy	True Positive Rate: 71.65%, True Negative Rate: 81.21%, Precision: 74.60%, F1 Score: 73.09%, Accuracy: 77.05%
P27	2016	CNN, AE, multivariate Gauss distribution	Eight physiological signals on DEAP dataset	Threshold Value use	A significant performance in physiological signals anomaly detection
P112	2021	RNN, CNN, HTM, ConvLSTM,	SWaT, WADI, MSL	Precision, Recall, and F1-score	Omni anomaly for SWaT (precision 99.01, Recall:

		Transformer, Self Attention			77.06, F1-Score: 86.67), WADI (precision 26.52, Recall: 97.99, F1-Score: 41.74), MSL (precision: 88.67, Recall: 91.17, F1-Score: 89.90)
P109	2020	OCSVM, IF, LOF and LDBSCAN , Hybrid spatio-temporal autoencoder (proposed)	Italian COVID-19 time series dataset	The threshold level, the reconstruction errors as anomaly scores	Result performed based on region
P111	2022	KNN, SVM, NN, DT, NB, Proposed method	UCI standard data repository	F-measure, Precision, Recall, TNR, Accuracy	F: 97.25, P: 99.99, R: 94.65, TNR: 93.57 Acc: 95.14
P108	2022	Various clustering methods including CBC, HC, GMM, DBC, SC, CBSI, MMC, EC, PDC, and clustering with deep learning (Deep AE, Deep FFN, VAE, GANs), k-Means, Max-Min, SOM	MIT-BIH Arrhythmia, PhysikalischTechnische Bundesanstalt (PTB), St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia (CTAD), UCR Arrhythmia, and BIDMC Congestive Heart Failure datasets.	Accuracy	Self-Organizing Map MIT-BIH: 98.5% acc, Max-Min MIT-BIH 98.6% acc, Affinity Propagation MIT-BIH 98.4% acc, K-means + SVD MIT-BIH 99.98% acc, Ant Colony MIT-BIH 94.4% sensitivity, Maximum Margin Clustering MIT-BIH 95.9% acc, Tensorization + Gaussian Mixture Model 0.93 Jaccard coefficient, Symbolization + Gaussian Mixture Model PTB 94.4% accuracy; 0.97 NMI, Autoencoder + Permutation Distribution UCR 80.6% acc; VDE-BIDMC: 96.0% acc, Silhouette coefficient 0.31
P110	2021	NN, SVM, KNN	Data set from Mohand Amokrane EHS Hospital	Accuracy	Accuracy:NN: 93%, , SVM: 90%, KNN: 85.5%
P107	2021	1D, 2D CNN	arrhythmia database	Accuracy	Acc: 97.38%, 99.02% with 1D and 2D model
P105	2021	DT-SVMNB	synthetic and real datasets from social network.	Recall, Precision, F-Measure, Accuracy	Recall, Precision, F-Measure, Accuracy respectively -KNN (K=10): 0.936120, 0.983026, 0.959000, 0.951073
P104	2021	AE, GANs, Multitask Learning, RNN, LSTM Networks, GRUs, NMNs	Various bio-medical datasets	na	na
P28	2022	na	wearables-assoc.	na	na
P106	2021	na	wearables-assoc.	na	na
P5	2020	AnoGAN	MIT-BIH arrhythmia ECG	AUC, F-Measure	AUC: 0.9475, F-Measure: 0.9143
P4	2022	RBM, AE, RNN			na
P103	2016	PCA	Real-World data	AUC-ROC	na
P102	2021	GAN	MRI dataset	AUC	na
P100	2017	RDA, IF	MNIST	precision, recall, and F1-scores	RDA, λ: 0.00065 with an F1-score: 0.64, IF, F1-score:

					0.37
P99	2021	Novel method	MIT-BIH database, Fantasia database	Detection Error Rate (DER)	DER: 0.45
P101	2023	AE, IF	Real-world	F1-score	F1-score (AE): 0.33, F1-score (IF): 0.34
P98	2022	AE	ECG	na	na
P97	2021	OPTICS	HDFS log data sets	Precision, Recall, F-Measure	P:71, R:100, F: 83
P95	2024	33 ML Model	Real-world data	na	na
P96	2022	Different UnML	na	na	na
P13	2021	LOF, iForest, LODA, DAGMM and RDP	10 publicly available datasets	AUROC	IF:130.4%, LODA: 34.6%, RDP: 7.2%, LOF :77.2%, DAGMM: 30.4%
P12	2021	OC-NN, OC-SVM, DAGMM, Proposed (Deep end-to-end Unsupervised Anomaly De-section)	KDDCUP,,MNIST, CIFAR-10, CatVsDog and UCF-Crime	AUROC	OC-SVM: 0.79, DAGMM: 0.61, Proposed: 0.93
P93	2022	KNN, CBLOF, HBOS, LOCI, LOF	employee datasets	precision, ROC, and accuracy.	KNN-ROC: 0.9786, Precision: 0.7500, Accuracy: 72.97 LOF -ROC: 0.9100, Precision: 0.5000, Accuracy: 90.74 CBLOF -ROC: 0.9893, P recision: 1.0000, Accuracy: 82.43 HBOS -ROC: 0.8429, Precision: 1.0000, Accuracy=98.64 LOCI -ROC: 0.9643, Precision: 0.5000, Accuracy: 87.83
P94	2023	A pattern-based approach (FindFPOF) and a compression-based approach (AE)	Medical datasets	Precision, sensitivity, specificity	Precision: 28% (both). the sensitivity of the autoencoder: 22% and FindFPOF: 26%. specificity: 94%(both)
P92	2021	Various outlier algorithm	AUROC	AUROC	na
P91	2023		Mammography from Asan Medical Center	Accuracy, Sensitivity, Specificity, PPV, NPV, AUC-ROC	Acc:64.0%, Sen:78.0%, Spec:52.0%, PPV:61.4%, NPV:70.2%, ROC: 70.0%
P90	2023	Elliptic Envelope, iForest, OC-SVM, LOF	Chernaya River water	F1-Score	na
P88	2022	k-Means, Hierarchical Clustering, GMM, PCA, ISOMAP, t-SNE		Within Set Sum of Squared Error (WSSSE), Silhouette	K-Means: 87, 393.66, 0.61 GMM: None, 0.57
P87	2023	Unsupervised learning model	TV Show	Structural Similarities (SSIM),	na

				MSE/PSNR	
P89	2023	Proposed model	Oil well	ACCb, F1-Score	ACCb: 0.9910, F1-Score: 0.9969
P86	2023	IF, t-SNE	Lustre file system	na	na
P85	2023	CNN, DAE, DBN, RNN, MLP, Semi-SVM, DAE-KNNG, OCRF, OCSVM, OCNN	Electrical Appliances	Accuracy, Recall, Precision, F-Score	Accuracy: 99.31 Precision: 99.8 f-score:98.97 Recall: 97.21
P82	2022	Dense AE, CNN, (CNN) AE, (LSTM) AE.	Audio data in machine and vehicle	ROC, pROC	pAUC respectively ToyCar: 81.36, 68.40, 83.87, 72.64, 81.59, 71.88, 80.97, 66.67
P84	2023	LSTM-AE	Indoor Environment data	Accuracy	Accuracy: 0.9766
P81	2024	Deep-Autoencoder	vibration data	TP, FP, TN, FN	F1 score:0.987
P78	2022	ABOD, COPOD, LODA	Dementia people	Precision, Recall	LODA -Recall: 85.7, Precision:6.2 COPOD: Recall: 79.1, Precision:5.9 ABOD:Recall:77.7, Precision:7.1
P83	2021	RUAD, Deep AE, GMM	public datasets: KDDCup99 etc.	Precision, Recall, F1	RUAD: 0.8556, 0.8648, 0.8601, 0.7609, 0.7778, 0.7692
P77	2023	Various alg.	Public datasets-Secure Water Treatment Server Machine Dataset	P, R, F1, AUPR	PCA: 0.996, 0.642, 0.781, 0.827, 0.730 IF: 0.998, 0.617, 0.762, 0.854, 0.766 OC-SVM 0.959 0.644 0.771 0.826 0.746 VAE: 0.996, 0.642, 0.781, 0.827, 0.730 MLP-AE: 0.996, 0.620 ,0.764, 0.836 ,0.738 CNN-AE: 0.976, 0.643, 0.775, 0.842, 0.753 GRU: 0.996, 0.643, 0.782, 0.844, 0.752 LSTM: 0.998, 0.643, 0.782, 0.862, 0.777 LSTM-AE: 0.856, 0.610, 0.712, 0.822, 0.604 ConvLSTM: 0.998, 0.643, 0.782, 0.863, 0.765 USAD: 0.989, 0.614, 0.758, 0.808, 0.706 DAGMM: 0.971, 0.614 ,0.752, 0.807, 0.707 MAD-GAN: 0.912, 0.589, 0.716, 0.801, 0.700
P79	2023	LSTM	Alpine Renault car during driving tests	TPR, FPR, TNR, FNR	TPR: 0.84, FPR: 0.068, TNR: 0.63, FNR: 0.008
P80	2023	SOM	Experimental plant at Università Politecnica delle Marche	Acc.	Acc.: 90

P76	2023	CNN	Sonar	P, R, F1	na
P75	2018	Novel	Vibration data	na	na
P73	2020	CVAE	Benchmark	P, R	Precision: 36.8 pp, Recall: 27.3 pp higher.
P71	2023	GAN	Benchmark UCSD Ped2, CUHK Avenue, and ShanghaiTech datasets	AUROC	AUROC Score: 97.7%, 89.7%, and 75.8%
P6	2022	SNN, SPIRIT	Numenta Anomaly Benchmark-NAB	F1-Score	SPIRIT: 0.42, OeSNN-A: 0.22 , OeSNN-B: 0.44, OeSNN-C: 0.61, OeSNN-D: 0.61
P7	2023	AE, IC	Power consumption	Reconstruction Error	na
P75	2023	Vanilla,ULSTM, BiLTM, Autoencoders		Recall, Precision, F1-Score, Accuracy	accuracy VAE, ULSTM & VAE, and BLSTM & VAE: 71%, 80% and 77%, Accuracy : ULSTM and BLSTM: 57%.
P72	2023	Self-supervised learning	PadChest	Accuracy, Precision, Sensitivity, Specificity, AUROC	Acc: 0.73, P: 0.83, Sen: 0.59, Spec:0.89, AUROC: 0.75
P70	2022	CRND	CICIDS2018	Accuracy, F1-score	Accuracy: 96.13%, F1-score: 0.9
P9	2022		Home	F1 –Score, Accuracy, precision, Recall	F1-Score:1.0, Acc: 1.0, P: 1.0, R: 1.0
P10	2022	CCB	CIFAR-10, ILD, HAM10000	AUC, ACC, F1	na
P69	2023	Unsupervised transformer-based method	ECG5000 and MIT-BIH Arrhythmia.	AUC, ACC, F1, Precision, Recall	In the ECG5000 dataset, 99% acc. 99% F1, 99% AUC, 98.1% R., and P.,100%
P68	2019	AE, OCSVM, and robust Mahalanobis outlier detection	Credit card transaction	TP, FP, TN, FN	na
P67	2022	LSTM	Yahoo Webscope S5 dataset	Precision, Recall, F1-score, AUC, Kappa	Dataset one: Traditional structure P: 0.4554, R: 0.5275, F1: 0.4055, AUC: 0.8980, Kappa: 0.3995
P66	2021	Deep ResNet CNN	PCB Data Set	Accuracy, Misclassification Rate, TPR, FPR, TNR, Precision, Prevalence	Cross-validation 1: Acc: 97.20%, MCR: 0.02, TPR: 0.99, FPR: 0.06, TNR: 0.93, Precision: 0.96, Prevalence: 0.65
P65	2021	Autoencoder	Top jet, QCD jet images	AUC	na
P64	2023	Proposed approach	Before and after-sales demands datasets	Precision, Recall, F1-Score	na
P63	2022	MTAD	In-orbit spacecraft	P, R, and F1-score	MTAD: P:0.9966, R:1.0, F1:0.9980
P61	2020	DBSCAN	KPIs (time series data)	F-score	na
P59	2023	AE, VAE	MRI	MSE	na
P58	2022	OC-SVM, IF, LOF.	User log events	Accuracy	Acc. (IF): 69.5%
P62	2023	MISC-OD	public datasets of ODDS-	ROC-AUC, AP	ROC: 0.795,

			Lympho		AP: 0.62
P55	2023	AE	na	na	na
P54	2021	LOF, IF, MCD, OC-SVM	public datasets.	Precision, Model Score, Computation Time, ROC (Training dataset), and ROC (Test dataset)	Precision: 0.8888, 0.9028, 0.8880, 0.9164, Model Score: 0.802, 0.835, 0.814, Computation Time: 0.3, 0.3, 0.3, <0.1, ROC (Training dataset): 0.9833, 0.9864, 0.9838, 0.8863, ROC (Test dataset): 0.9804, 0.9832, 0.88, 0.8123,
P56	2023	CLIP	ShanghaiTech and UCFcrime datasets	AUC	92.14 (Micro), 81.27 (Micro)
P57	2022	IF, DeepAE	Assembled products	Inference Time (s), AUC, EER, Train Time (s)	IF-Product A: 0.998, 0.840, 115.933, 0.018, DAE-Product A: 0.996, 0.793, 61.250, 0.005
P52	2022	VAE	IoT data	precision, F1-score	Precision: 90%, F1-score: 79%.
P51	2022	ABIForest	synthetic and real datasets	F1-Score(Circle Dataset)	ABIForest: 0.916
P49	2022	UCAD	Real-world data	P, R, F1	P: 0.86713, R: 0.92884, F1: 0.89693
P50	2023	Prodigy	Eclipse, HPC testbed	F1-Score	F1-Score: 0.95, F1-Score: 0.88
P11	2021	OCSVM	knowledge graphs	na	na
P48	2023	Dual-variable graph,VAE	Internet company	F-Score	F1: 0.954
P47	2020	LSTM Based AE, OC-SVM	InSDN	Precision, Recall, F1-measure, Acc.	Precision: 0.7111, Recall: 0.983, F1: 0.825, Acc: 0.741 (Threshold: 0.07)
P19	2022	IF, AE, GANomaly	CTG signals	F1-score, Balanced accuracy, Precision, Recall	IF: 0.687 ± 0.045, 0.687 ± 0.046, 0.591 ± 0.058, 0.579 ± 0.085, AE: 0.699 ± 0.018, 0.697 ± 0.013, 0.613 ± 0.043, 0.589 ± 0.021 GANomaly: 0.752 ± 0.011, 0.750 ± 0.001, 0.682 ± 0.041, 0.663 ± 0.042
P43	2021	AE	ECG	Accuracy score	Accuracy score: 95
P41	2021	IF, OCSVM, SOM	public-Netflow_IDS, AndMal17,CICIDS17..	na	na
P42	2023	UGA-CAE	Real-world, sWaT	P, R, F1	P: 0.9372, R: 0.9239, F1: 0.9305
P45	2020	IREOS	Synthetic and real	ROC AUC	ROC: 0.805
P44	2023	Various ML	na	na	na
P46	2019	Various ML	Textual, Non-textual	na	na
P15	2021	auto-encoding generative adversarial network (α-GAN)	Frontal chest radiographs	AUROC	AUROC: 0.752
P14	2022	Transformers	Synthetic and real pathological lesions	AUROC	AUROC: 1.00
P16	2022	DAE	MRI	AUPRC	AUPRC: 0.816±0.005
P18	2020	RE-ADTS	Benchmark datasets	P, R, F-measure, AUC	P: 10.0, R: 0.74, F: 16.2, AUC: 52.6

P40	2020	RHF	Benchmark	AP	AP: 0.513 ± 0.100
P39	2021	Unsupervised two-stage anomaly detection	MVTec AD	mean IoU (IoU) and mean AUROC	Mean Iou: 0.53, meanAUROC: 0.90
P37	2019	K-means, Mixture of Gaussian models, DBC, SOM, SVM	sensor data	na	Cluster-based methods are found good
P38	2021	GADF, MPCA, deep SVDD	Real-world ECG	Acc., AUROC, F-Score	Acc: 0.9752, AUROC: 0.9849, F-Score: 0.9771
P36	2021	VAE, Local Similarity Score	ECG5000, MIT-BIH Arrhythmia.	AUC, Acc, F1	AUC: 98.79, Acc: 97.11, F1: 96.01
P17	2020	Anobeat,	MIT-BIH intra-patient, inter-patient dataset	ROC-AUC	ROC-AUC (intra): 0.960, ROC-AUC (inter): 0.89
P34	2022	LOF, IF, OC-SVM, AE	Numenta Anomaly Benchmark (NAB)	Precision, Recall, F1 score, ROC-AUC, and PR-AUC	IF: 0.1451, 0.1951, 0.1664, 0.5411, 0.2269, OCSVM: 0.2296, 0.0791,0.117,7 0.5134, 0.2149, LOF: 0.1715, 0.1051, 0.1303, 0.5068, 0.2139 , MP: 0.191, 0.0363, 0.061, 0.5006, 0.2434, DL:0.1535, 0.2009, 0.174, 0.5333, 0.2278
P35	2021	AE, CNN	CT scan images	Accuracy	98% - outlier detection, 97.2% - classification task
P33	2017	HTM	NAB	NAB Score	NAB Score: 70.1
P32	2016	PCA, information entropy theory, support vector regression	WFGD (Wet Flue Gas Desulfurization)	na	na
P31	2020	LOF, COF and k-Means	Six different knowledge bases	Silhouette	LOF: 88.90%, 11.10%, 0%, COF: 83.30%, 16.70%, 0%, k-Means: 72.20%, 22.20%, 5.60%
P30	2019	LSTM (MSE + KL Div.)	ECG database	F1	F1: 0.90
P29	2019	HTM	Arrhythmia	P, R, FPR, F1 score	P: 0.9, R: 0.16, FPR: 0.2, F1: 0.26

The dataset covers various machine learning models and their applications in anomaly detection across multiple domains. The dataset highlights a broad range of ML applications and their evolving effectiveness in various anomaly detection tasks.