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ABSTRACT

Anomaly detection in time series data has gained substantial research interest due to its vital applications across domains like finance, healthcare, cybersecurity, and industrial IoT.This literature survey provides a comprehensive overview of unsupervised learning techniques for anomaly detection, with an emphasis on real-time applications. Key methodologies explored include clustering, dimensionality reduction, and density-based algorithms, supported by automation tools such as PyCaret. Algorithms commonly applied in these contexts include XGBoost, CatBoost, Isolation Forest, DBSCAN, and hybrid models that enhance anomaly detection performance.

Despite advancements, challenges persist in real-time anomaly detection, particularly in adapting to concept drift and ensuring computational efficiency in high-dimensional, resource-intensive environments. Additionally, high false positive rates and ethical concerns such as privacy, potential biases, and regulatory control are critical considerations for deploying these systems responsibly. This survey addresses these gaps, discussing adaptive learning and reinforcement learning as promising solutions to improve accuracy, scalability, and resilience against concept drift.

The objectives of this review are to synthesize existing methodologies, identify current gaps, and suggest directions for future research aimed at improving the accuracy, computational efficiency, and ethical deployment of anomaly detection systems. The insights from this review aim to guide further exploration of unsupervised learning approaches, fostering advancements in real-time, scalable, and ethical anomaly detection solutions.

Key Themes

Unsupervised Learning Techniques: Techniques like clustering, dimensionality reduction, and density-based algorithms are widely utilized for anomaly detection. Methods such as K-Means, DBSCAN, Principal Component Analysis (PCA), and auto-encoders are used to identify patterns and detect outliers in high-dimensional data. Hybrid models are also implemented to improve anomaly detection performance.
Tools and Libraries: Libraries such as PyCaret play a significant role in automating machine learning processes, making it easier to deploy clustering and regression-based methods for anomaly detection.
Algorithms: Commonly applied algorithms include XGBoost, CatBoost, Isolation Forest, and DBSCAN, often used within hybrid models to handle complex anomaly detection tasks.
Applications Across Domains: Anomaly detection has important applications in domains such as:
Finance: Detecting fraudulent transactions.
Healthcare: Monitoring patient vitals for anomalies.
Cybersecurity: Identifying unusual network activities.
Industrial IoT: Monitoring equipment sensor data to predict potential failures.
Ethical Considerations: Privacy, bias, and regulatory challenges are critical concerns in sensitive areas such as healthcare and surveillance. Continuous monitoring can infringe upon privacy, and biased data can lead to unfair targeting of specific groups.

Gaps in the Literature

Real-Time Detection and Concept Drift: Existing anomaly detection models struggle to adapt to dynamic changes in data distributions (concept drift), which affects their reliability in real-time environments.
Computational Efficiency: Handling high-dimensional data in real-time is resource-intensive, impacting the scalability and speed of these systems.
False Positives: High rates of false positives can reduce the effectiveness of anomaly detection systems, leading to overwhelmed monitoring systems and compromised decision-making.

Objectives of the Review

Synthesizing Existing Research: To provide a comprehensive summary of current unsupervised learning techniques and tools applied in real-time anomaly detection.
Identifying Gaps: To highlight areas requiring improvement, including handling concept drift, improving computational efficiency, and reducing false positives.
Suggesting Future Directions: To propose potential solutions, such as integrating reinforcement learning and adaptive learning methods, to enhance the accuracy, scalability, and ethical deployment of real-time anomaly detection systems.

INTRODUCTION

Anomaly detection in time series data is an essential field of research with wide-ranging applications in finance, healthcare, cybersecurity, and industrial IoT. The ability to detect unexpected patterns or deviations in data is crucial for tasks such as fraud detection, equipment failure prediction, cyber threat monitoring, and public health surveillance. In finance, for instance, detecting fraudulent transactions in real-time can prevent significant financial losses, while in healthcare, early identification of anomalies in patient data can lead to timely interventions. Similarly, cybersecurity applications benefit from anomaly detection by identifying abnormal network activities, helping to prevent data breaches and cyber-attacks. Time series data, known for its sequential nature, presents unique challenges and opportunities for anomaly detection, especially in real-time applications where timely response is critical.

The significance of anomaly detection in time series data lies in its potential to support proactive decision-making, enhance operational efficiency, and avert catastrophic failures. Detecting anomalies in real time allows industries to act swiftly in response to suspicious patterns or outliers, reducing the risk of financial, operational, or security-related damages. For example, in finance, detecting unusual transaction patterns promptly can prevent fraudulent activity, saving considerable sums of money. In industrial IoT, real-time anomaly detection can prevent costly equipment failures by identifying potential issues before they escalate. The adaptability of unsupervised learning methods makes them particularly useful, as they do not rely on labeled datasets, which are often unavailable in real-time environments. Consequently, unsupervised approaches offer a powerful and flexible alternative to traditional supervised techniques, enabling the detection of unseen anomalies and adapting to evolving patterns in dynamic data streams.

Problem Statement or Research Question

Despite advancements in anomaly detection techniques, significant challenges remain in making real-time detection both scalable and robust across varying conditions. This research addresses the question*: How can real-time financial anomaly detection be optimized using hybrid unsupervised learning models*? By focusing on hybrid unsupervised models, this study aims to explore effective strategies to enhance accuracy, adapt to concept drift, improve computational efficiency, and mitigate false positives in real-time applications. Additionally, the study examines the ethical implications of these systems, particularly concerning privacy and potential biases in real-time anomaly detection for financial data.

Objectives of the Literature Survey

1. Review Current Methodologies: Provide a comprehensive overview of current methodologies used in real-time anomaly detection for time series data, with a focus on unsupervised learning techniques and hybrid approaches.

2. Identify Gaps and Challenges: Highlight the existing challenges in real-time anomaly detection, such as handling concept drift, enhancing computational efficiency, and reducing false positives in dynamic environments.

3. Discuss Ethical Implications: Examine the ethical implications associated with the deployment of real-time anomaly detection systems, particularly in relation to privacy, bias, and fairness.

4. Suggest Future Research Directions: Suggest future research directions, including the potential integration of reinforcement learning and adaptive methods to improve accuracy and scalability. Additionally, propose ethical guidelines for implementing anomaly detection in finance and other sensitive domains.

This research aims to provide valuable insights into how hybrid unsupervised models can address real-time anomaly detection challenges, focusing on practical applications within the financial sector. Through this literature survey, we seek to explore scalable solutions that enhance detection capabilities while maintaining ethical considerations for a broader, real-time deployment in financial anomaly detection systems.

LITERATURE REVIEW

1. Introduction to Anomaly Detection in Real-Time Data

Anomaly detection is the process of identifying unusual patterns or deviations from the norm within datasets. In real-time applications, anomaly detection is crucial in sectors like finance, cybersecurity, and industrial IoT, where it detects fraud, security threats, equipment malfunctions, and abnormal trends that need immediate action. Traditional supervised learning methods, which rely on labeled data, are often inadequate in real-time contexts due to the lack of labeled samples and the high volume, velocity, and variability of incoming data. Unsupervised learning, which does not require labeled datasets, has emerged as an effective approach for detecting anomalies across complex, dynamic environments.

2. Overview of Unsupervised Learning Approaches for Anomaly Detection

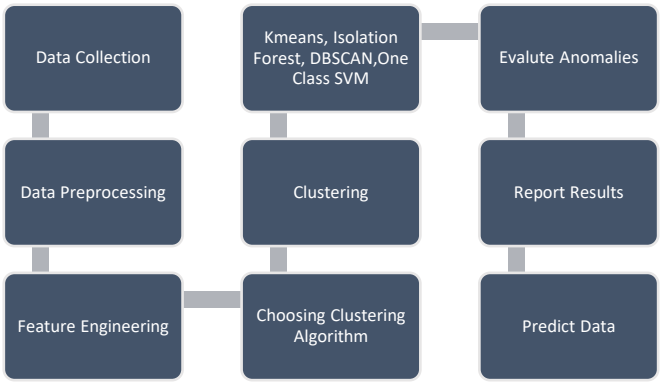
Unsupervised learning for anomaly detection encompasses several techniques, each suited to different data characteristics and detection needs.

Statistical Methods: Statistical techniques like ARIMA are often applied in time-series anomaly detection. For univariate data, models such as Auto Regression (AR), Moving Averages (MA), and ARIMA are used to predict values based on historical patterns, flagging significant deviations as anomalies. For multivariate time-series data, Vector-based methods like VAR (Vector AutoRegressive) or VARMA (Vector AutoRegressive Moving Average) help capture relationships among multiple variables.

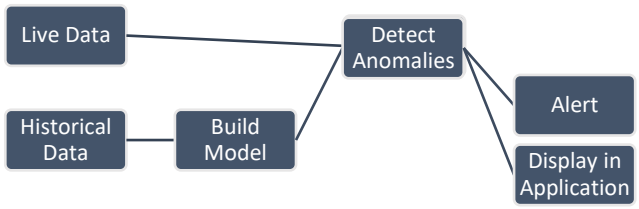
Clustering-Based Methods: Clustering techniques group data points based on similarity. Anomalies are identified as points that do not fit into any cluster or belong to small, distinct clusters. Common algorithms include K-means and DBSCAN (Density-Based Spatial Clustering of Applications with Noise). K-means is effective for well-defined clusters, while DBSCAN is more flexible, handling arbitrary-shaped clusters and identifying noise points as potential anomalies.

Density-Based Methods: Density-based techniques, such as Isolation Forest and Local Outlier Factor (LOF), assess the density of data points to identify anomalies. Isolation Forest, for example, isolates data points through recursive partitioning, identifying anomalies as points that are easier to isolate (lower density) compared to normal points. LOF compares the local density of each point to that of its neighbors, marking points with significantly lower density as outliers.

Dimensionality Reduction Techniques: Dimensionality reduction helps to simplify high-dimensional data, making anomalies easier to detect. Techniques like PCA (Principal Component Analysis) reduce the number of features while preserving the underlying data structure, enabling the detection of anomalies that deviate significantly from principal components. Autoencoders, a neural network-based approach, compress and reconstruct data, identifying anomalies as instances with high reconstruction error



Steps in clustering-based anomaly detection



Real-Time Anomalies Detection

3. Applications of Unsupervised Learning in Real-Time Anomaly Detection

Real-time anomaly detection using unsupervised learning has practical applications across various fields. Each application benefits from different methodologies tailored to specific data types and anomaly characteristics.

Financial Fraud Detection: Banks and financial institutions use real-time clustering and density-based methods to detect anomalies in transaction data. DBSCAN, for instance, helps group transactions by similar attributes, flagging any that deviate as potential fraud. Isolation Forest identifies sparse, low-density transactions that may indicate fraudulent activity.

Cybersecurity Threat Detection: In network security, real-time anomaly detection identifies abnormal network traffic patterns, indicative of potential threats. Hybrid approaches combining K-means clustering with One-Class SVM detect unusual patterns, such as sudden spikes in outbound traffic or irregular access attempts, allowing organizations to proactively respond to threats.

Industrial IoT (IIoT): Anomaly detection in IIoT settings involves monitoring sensor data from machinery to detect malfunctions early. Techniques like PCA and LOF are used to reduce data dimensions and highlight deviations in sensor readings, allowing for predictive maintenance and minimizing downtime.

4. Methodological Advances and Key Algorithms

Key advancements in unsupervised learning techniques for anomaly detection include clustering, dimensionality reduction, and hybrid models, each contributing unique strengths.

Clustering Approaches: K-means and DBSCAN are foundational in clustering-based anomaly detection. K-means is straightforward but less effective in non-spherical data distributions. DBSCAN, on the other hand, does not require a predefined number of clusters and can detect anomalies as noise points. However, DBSCAN's performance may degrade with high-dimensional data.

Deep Learning Techniques: LSTM and CNN models are increasingly used in time-series anomaly detection due to their ability to learn complex temporal patterns. Autoencoders, specifically, have gained traction for their ability to detect subtle anomalies based on reconstruction error. LSTM, with its memory capacity, captures long-term dependencies, making it suitable for sequential anomaly detection in time-series data.

Hybrid Models: Hybrid approaches that integrate clustering and dimensionality reduction are emerging as promising techniques. Combining Isolation Forest with PCA or using Autoencoders with DBSCAN allows for more robust anomaly detection by leveraging both global and local anomaly detection capabilities. These models benefit from dimensionality reduction for processing efficiency while maintaining clustering accuracy.

5. Critical Analysis and Comparative Evaluation of Methods

5.1 Comparison of Clustering-Based Techniques

K-means and DBSCAN: K-means clustering has long been used for anomaly detection due to its simplicity and efficiency in identifying clusters. However, its effectiveness is limited in non-spherical data distributions and high-dimensional datasets. Niu et al. (2020) evaluated K-means for sales forecasting and found that it struggles to manage complex data structures, often leading to false positives in identifying anomalies in high-velocity streams.

DBSCAN: DBSCAN, on the other hand, does not require a predetermined number of clusters and is highly effective for irregularly shaped data. Ahmad et al. (2017) demonstrated DBSCAN's efficacy in real-time streaming environments, such as network traffic, due to its ability to label isolated points as noise, thus reducing false positives. However, as Wu et al. (2020) point out, DBSCAN's performance deteriorates when applied to high-dimensional data, making it less suitable for complex, multi-attribute IoT datasets.

5.2 Evaluation of Density-Based Methods

Isolation Forest: Isolation Forest has gained prominence in anomaly detection for high-dimensional data, owing to its scalability and efficiency. Bergmann et al. (2019) and Zhong et al. (2019) have both highlighted Isolation Forest's ability to detect rare events by isolating data points based on density. Its effectiveness in network traffic and cybersecurity is noted in its capability to rapidly detect sparse anomalies, such as Distributed Denial of Service (DDoS) attacks, by isolating outliers in large datasets.

Local Outlier Factor (LOF): LOF offers an alternative to Isolation Forest by comparing local densities, which enables it to detect anomalies in regions with varying data density. Gupta and Tripathy (2024) found LOF particularly effective in identifying contextual anomalies, such as unusual financial transactions, by analyzing densities across local neighborhoods. However, LOF is computationally intensive, and its performance in high-velocity applications is limited, which restricts its use in real-time data streams.

5.3 Dimensionality Reduction Techniques and Challenges

Principal Component Analysis (PCA): PCA is widely used in anomaly detection for high-dimensional data. According to Habeeb et al. (2019), PCA reduces data complexity by focusing on principal components, which effectively highlights anomalies that deviate from expected patterns. Despite its benefits, PCA's reliance on linearity can limit its effectiveness in detecting non-linear anomalies in complex datasets, such as those in healthcare and cybersecurity.

Autoencoders: Autoencoders, a type of neural network, provide a non-linear approach to dimensionality reduction and anomaly detection. Wu et al. (2020) reported

that autoencoders excel in detecting subtle anomalies with minimal manual tuning, especially in image and video data. While autoencoders achieve high accuracy in domains like industrial IoT, they require substantial computational resources, and their efficacy can diminish in high-frequency streaming data, where low latency is crucial.

5.4 Hybrid Models for Enhanced Anomaly Detection

Combining Clustering and Dimensionality Reduction: Hybrid models that integrate clustering with dimensionality reduction have shown significant promise in recent studies. For instance, by combining DBSCAN with PCA, Stoian (2020) observed improved scalability and a reduction in false positives, making it suitable for detecting anomalies in high-dimensional IoT data. However, tuning parameters for hybrid models remains complex and data-specific, which can be a limitation in real-time applications.

Isolation Forest with PCA: Demertzis et al. (2020) propose a combination of Isolation Forest with PCA for anomaly detection in Industry 4.0 environments, demonstrating that PCA pre-processing helps Isolation Forest achieve faster anomaly detection with fewer false positives. This hybrid model shows potential in applications that require both local and global anomaly detection, as it leverages Isolation Forest's efficiency in isolating sparse anomalies while PCA highlights multi-dimensional outliers.

5.5 Real-Time Constraints: Latency and Throughput

Latency Considerations: The need for low-latency anomaly detection is critical in real-time applications such as cybersecurity and fraud detection. Studies by Bhatia et al. (2019) and Tripathy (2024) both emphasize that while clustering methods like DBSCAN offer low false positives, they are relatively slower and require high computational resources, making them challenging to implement in high-frequency environments.

Throughput Optimization: Gupta and Tripathy (2024) report that dimensionality reduction techniques like PCA and autoencoders help manage large data streams efficiently, but their high computational overhead can increase latency in real-time applications. They suggest using incremental learning approaches to update model parameters dynamically, enhancing throughput without retraining the entire model.

5.6 Challenges in Adaptive Learning and Concept Drift

Concept Drift: The ability to adapt to changing data patterns, known as concept drift, is vital in real-time anomaly detection. Ahamed et al. (2019) stress the importance of developing adaptive models to handle dynamic, non-stationary data, such as real-time transaction data, which is prone to frequent shifts. Models that fail to adapt to concept drift often show higher false positive rates and may overlook emerging patterns in data streams.

Incremental and Reinforcement Learning: To address concept drift, several studies propose incremental learning methods that allow models to learn from new patterns continuously. For example, Demertzis et al. (2020) suggested combining reinforcement learning with unsupervised methods to allow for continuous adaptation based on feedback, which enhances robustness in real-time applications like cybersecurity and fraud detection.

5.7 Performance Evaluation Metrics

Precision and Recall: Metrics like precision, recall, and F1-score are standard for evaluating anomaly detection models. The work of Gupta and Tripathy (2024) demonstrated that hybrid models generally achieve higher precision and recall scores compared to traditional clustering and density-based methods, especially in multi-source data environments.

Detection Latency: Detection latency, or the time taken to detect anomalies, is particularly important in real-time settings. Bergmann et al. (2019) and Zhong et al. (2019) both note that Isolation Forest has lower detection latency than clustering methods, making it ideal for applications that require immediate anomaly detection. However, clustering-based approaches like DBSCAN offer higher accuracy at the cost of increased latency.

6. Trends, Gaps, and Future Directions

Emerging Trends: Hybrid models are becoming more popular, combining clustering with dimensionality reduction to address challenges in high-dimensional, high-velocity data environments. Additionally, adaptive models that learn from new patterns without retraining are gaining attention.

Research Gaps: Despite the effectiveness of unsupervised methods, issues such as high false-positive rates and the need for frequent hyperparameter tuning hinder their application. Most methods also struggle with multi-source data, which is common in real-time IoT and cybersecurity environments.

Future Research Opportunities: Future research should explore reinforcement learning to enable models to learn from feedback and improve detection accuracy over time. Additionally, ethical considerations such as privacy and bias in anomaly detection models should be addressed to ensure responsible deployment in sensitive areas like surveillance and healthcare.

Theoretical Framework

Key Theories, Models, and Concepts
In the realm of real-time anomaly detection, particularly within dynamic and high-velocity data environments, several key theories, models, and concepts emerge as foundational. This section discusses these elements and links them to relevant literature.

Unsupervised Learning:

Clustering algorithms, such as K-means and DBSCAN, are pivotal in unsupervised learning for anomaly detection. These methods group similar data points, making it easier to identify outliers that deviate from the norm. For instance, DBSCAN has been effectively used in network traffic anomaly detection but struggles with high-dimensional data.

Dimensionality Reduction:

Techniques like Principal Component Analysis (PCA) are employed to reduce the dimensionality of data, which helps in identifying anomalies by focusing on the most significant features. Dimensionality reduction is crucial for handling large datasets efficiently.

Density-Based Methods:

Isolation Forest is a prominent density-based method used for anomaly detection. It excels in identifying anomalies by isolating observations in the feature space. However, it requires careful tuning to avoid high false positive rates.

Hybrid Models:

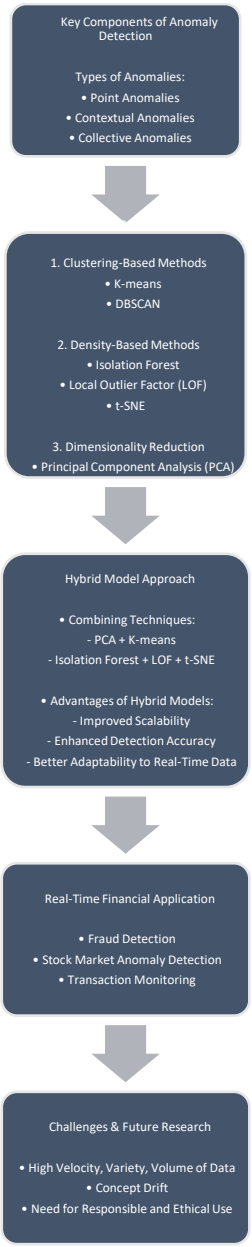
Hybrid models combine various unsupervised techniques to enhance the robustness and accuracy of anomaly detection systems. For example, integrating clustering with dimensionality reduction improves scalability and real-time detection efficiency.

Adaptability and Scalability:

The ability to adapt to changing data patterns (concept drift) and scale with increasing data volumes is critical. Current research emphasizes developing models that can handle these aspects effectively.

Linking Theoretical Framework to Literature

The theoretical framework outlined above is grounded in extensive literature on unsupervised learning and real-time anomaly detection. Recent advancements have highlighted the limitations of supervised learning models due to their reliance on labeled datasets, which are often unavailable in real-time scenarios. Unsupervised learning methods offer a promising alternative by detecting anomalies without requiring pre-labeled data.



For instance, studies have shown that clustering algorithms like DBSCAN can effectively detect network anomalies, though they face challenges with high-dimensional data. Similarly, Isolation Forest has been applied successfully in industrial IoT settings but needs careful parameter tuning.

Hybrid models that integrate clustering and dimensionality reduction techniques have demonstrated improved performance in handling large data streams and adapting to dynamic environments. These models address the scalability and adaptability issues that plague traditional methods.

In conclusion, the theoretical framework for real-time anomaly detection leverages unsupervised learning techniques to overcome the limitations of supervised models. By incorporating clustering, dimensionality reduction, and hybrid approaches, researchers aim to develop scalable and adaptable systems capable of detecting anomalies in high-velocity data environments.

METHODOLOGY

1) Sources of Data

To conduct a comprehensive literature review on anomaly detection, we accessed a range of databases and journals to ensure a thorough exploration of relevant research in this field. Our primary data sources included established academic databases such as Google Scholar, IEEE Xplore, PubMed, and ScienceDirect, each providing a broad scope of scholarly articles. The focus of the research was primarily on unsupervised machine learning techniques for anomaly detection, particularly in real-time or time series contexts. Key journals reviewed in this study included the International Journal of Information Management, Symmetry, Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, IEEE Transactions on Knowledge and Data Engineering, International Journal of Computer Vision, Neural Computing and Applications, Applied Energy, Expert Systems with Applications, Environmental Modelling & Software, and the International Journal of Automation and Computing. These journals contributed to a diverse perspective on methodologies, trends, and advancements in anomaly detection.

2) Inclusion Criteria

To ensure that the literature review captured the most relevant and up-to-date findings, specific inclusion criteria were established. Only studies published between 2019 and 2024 were selected to encompass the latest research advancements. Articles were chosen based on their focus on unsupervised learning techniques for anomaly detection, emphasizing those applicable in real-time scenarios and time series contexts to align with the research objectives. Furthermore, to maintain scientific rigor and reliability, only peer-reviewed papers were included. This approach ensured that the literature reviewed was both relevant and of high quality, providing a robust foundation for identifying trends and challenges in anomaly detection research.

3) Search Strategy

The search strategy employed was systematic and comprehensive, aiming to retrieve high-quality literature using a well-defined process. Broad initial searches were conducted across databases, including Google Scholar, IEEE Xplore, PubMed, and ScienceDirect, using keywords designed to capture various aspects of anomaly detection. These keywords included "unsupervised learning," "real-time anomaly detection," "clustering," "dimensionality reduction," "density-based algorithms," "deep learning," "hybrid models," "adaptive learning," "reinforcement learning," "ethical considerations in anomaly detection," "Anomaly Detection," "Time Series Data," "PyCaret," "Regression," "Isolation Forest," "XGBoost," "One Class SVM," "CatBoost," and "Extra Trees Regressor." Following these initial searches, filters were applied to limit results to peer-reviewed studies within the 2019–2024 publication range. Titles and abstracts were manually screened to assess relevance, and full-text analyses were conducted for articles meeting the inclusion criteria. Additionally, ethical considerations were reviewed, addressing issues like privacy concerns, algorithmic bias, and the need for regulatory oversight to prevent misuse of anomaly detection technologies. This systematic approach ensured that the literature review was comprehensive and focused, capturing the latest trends, ethical concerns, and methodologies in anomaly detection using unsupervised machine learning.

DISCUSSION

Findings of the Literature Review
The literature review on anomaly detection in time series using unsupervised machine learning highlights the following significant insights:

1. Diverse Methodologies in Anomaly Detection

Various unsupervised learning techniques, such as clustering, dimensionality reduction, and hybrid models, are widely used to detect anomalies in time series data. Techniques like Isolation Forest, One-Class SVM, k-means, DBSCAN, and density-based methods have shown effectiveness across different domains, including finance, healthcare, cybersecurity, and industrial IoT. These methods are particularly valuable in real-time scenarios as they do not require labeled data, making them adaptable for handling high-velocity data streams.

2. Importance of Real-Time Detection

The focus on real-time anomaly detection is critical in applications where immediate responses to anomalies are necessary, such as healthcare, cybersecurity, and industrial IoT. Real-time systems are required to handle large volumes of data with speed and precision. Techniques like deep learning (e.g., autoencoders, RNNs) and hybrid models have been developed to process real-time data efficiently while adapting to changes, known as concept drift, to ensure high accuracy.

3. Ethical Considerations in Anomaly Detection

Deploying real-time anomaly detection systems involves significant ethical considerations. The continuous monitoring these systems enable can lead to privacy concerns, especially in sensitive domains. Additionally, the potential for biased algorithms raises concerns about fairness and transparency, as these systems could unfairly target specific groups. Therefore, maintaining ethical standards in system deployment is crucial to prevent misuse and address privacy issues.

4. Performance Evaluation Tools

For model evaluation, tools like PyCaret provide visualization functions, such as validation curves, residual plots, and prediction error plots, which are essential for comprehensively assessing model performance before finalization. These tools help practitioners understand the strengths and limitations of different unsupervised learning techniques.
Contribution to Understanding the Research Area
This literature review significantly enhances the understanding of anomaly detection in time series by:

Comprehensive Overview: It provides a detailed overview of the current methodologies and their practical applications in real-time anomaly detection scenarios.

Highlighting Practical Applications: The review illustrates the effectiveness of different unsupervised learning techniques across various fields, supported by case studies and real-world examples.
Emphasizing Ethical Concerns: It underscores the importance of ethical considerations, particularly regarding privacy and bias, in deploying real-time anomaly detection systems.
Identifying Key Tools: The review identifies essential tools, such as PyCaret, that facilitate the implementation and evaluation of these methodologies, enhancing the reliability of anomaly detection models.
Identified Gaps in the Literature
Despite the advancements, several gaps remain in the field of anomaly detection in time series:

1. Scalability Issues
Scalability is a significant challenge, especially in dynamic environments where data streams are large and high-dimensional. Existing methods struggle to process data efficiently at scale, which limits their applicability in real-time contexts with high data volumes.

2. Adaptability to Concept Drift
Anomaly detection models must adapt to evolving definitions of anomalies over time to maintain accuracy in real-time applications. This issue, known as concept drift, remains a critical area for improvement, as many current systems fail to adequately handle it .

3. Reducing False Positives
High false positive rates are a persistent challenge, particularly in high-dimensional data where distinguishing between normal variations and true anomalies is complex. False positives can lead to inefficient system responses and decrease overall reliability, highlighting the need for more precise detection methods.

4. Ethical Concerns
Research must further address the ethical implications of real-time anomaly detection systems, especially regarding privacy, continuous monitoring, and algorithmic bias. Responsible use and transparent practices are essential to prevent these systems from being misused for surveillance.

Future Research Directions

To address these gaps, future research could focus on the following areas:

Adaptive Learning Methods: Developing adaptive models, including reinforcement learning, that can learn from new data without extensive retraining. These methods can enhance scalability and accuracy, making models better suited for dynamic, real-time environments.

Concept Drift Adaptation: Exploring techniques to improve the adaptability of models to concept drift, allowing systems to remain accurate over time and across evolving data distributions.

Integration of Advanced Technologies: Incorporating advanced technologies, such as blockchain for secure data handling and deep learning models for more effective detection, can improve the capabilities and security of anomaly detection systems.

Ethical Frameworks: Establishing ethical frameworks to guide the deployment of real-time anomaly detection systems, with a focus on privacy, transparency, and minimizing bias. This ensures these systems operate responsibly and safeguard user trust.

CONCLUSION

Key Findings of the Literature Review

The literature review on anomaly detection in time series data using unsupervised machine learning techniques reveals several important findings:

1. **Diverse Methodologies**: Unsupervised learning techniques, including clustering, dimensionality reduction, and hybrid models, are highly effective for anomaly detection. Prominent methods such as Isolation Forest, One-Class SVM, k-means clustering, and density-based algorithms like PCA have been successfully applied to time series anomaly detection.
2. **Critical Role of Anomaly Detection**: Anomaly detection plays a vital role across various domains, including finance, healthcare, cybersecurity, and industrial IoT. Identifying unusual patterns that may signal fraud, health issues, security breaches, or system failures is crucial in these industries.
3. **Real-Time Detection and Data Processing**: Real-time anomaly detection is essential in sectors where timely identification of anomalies is critical. Techniques such as deep learning (autoencoders, RNNs) and hybrid models have been developed to efficiently process high-velocity and high-volume data streams. These methods need to adapt to concept drift to maintain their performance over time.
4. **Performance Evaluation**: Tools like PyCaret play a significant role in evaluating model performance by providing various evaluation plots (e.g., residuals, validation curves) to assess model accuracy and reliability before deployment.
5. **Ethical Considerations**: The deployment of anomaly detection systems must address ethical issues, including privacy concerns, surveillance, and biases in algorithms. There is a need to balance security needs with privacy to ensure responsible usage of these systems.
6. **Research Trends and Gaps**: Research continues to focus on improving the scalability and adaptability of anomaly detection models to handle dynamic environments. Challenges such as reducing false positives, developing more robust models, and ensuring that systems can work without labelled data are critical to future research.

Significance of the Review

This review provides a comprehensive overview of unsupervised learning techniques in real-time anomaly detection, emphasizing their importance in dynamically changing environments. The findings highlight how these methods can effectively handle real-time, high-velocity data streams, which are common in critical sectors. Furthermore, the review underscores the need for ethical frameworks that guide the development and deployment of these systems to protect privacy and ensure fairness.

Additionally, the review identifies key tools like PyCaret, which help in implementing and evaluating these techniques, supporting further advancements in the field of unsupervised anomaly detection.

Future Research Directions

Based on the findings of this review, several areas warrant further research:

1. **Integration of Reinforcement Learning**: Reinforcement learning methods can enhance the accuracy and scalability of anomaly detection systems, particularly in dynamic and complex environments.
2. **Adaptive Learning Models**: There is a need for adaptive learning techniques that can continuously learn from new data without requiring extensive retraining. Such models would be capable of improving the detection of anomalies over time.
3. **Reducing False Positives**: Addressing the challenge of false positives is crucial, especially in high-dimensional data, where distinguishing between normal variation and true anomalies is complex.
4. **Ethical Frameworks and Transparency**: Establishing ethical frameworks and regulatory standards is essential for the responsible deployment of anomaly detection systems. These frameworks should ensure privacy protection and prevent algorithmic bias, promoting transparency and fairness in real-world applications.

REFRENCES

i. Time_Data_Anomaly_Detection_A_Comprehensive_Approach
https://www.researchgate.net/publication/385073724_Unsupervised_Learning_for_Real-Time_Data_Anomaly_Detection_A_Comprehensive_Approach

ii. Anomaly Detection in Time Series using Unsupervised Machine Learning Approach
https://www.researchgate.net/publication/365885392_Anomaly_Detection_in_Time_Series_using_Unsupervised_Machine_Learning_Approach

iii. Prokhorenkova L, Gusev G, Vorobev A, Dorogush A, Gulin A. CatBoost: unbiased boosting with categorical features

iv. Yiyang Niu. Walmart Sales Forecasting using XGBoost algorithm and Feature engineering. 2020 International Conference on Big Data & Artificial Intelligence & Software Engineering (ICBASE)