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A Review of Spatiotemporal GANs for Telemetry Data Anomaly Detection

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Abstract: Telemetry data anomaly detection is a crucial task in various domains, including aerospace, power systems, and environmental monitoring. In recent years, significant advancements have been made in the development of anomaly detection techniques, particularly with the advent of spatial-temporal generative adversarial networks (ST-GANs). This review paper aims to provide a comprehensive overview of the progress in telemetry data anomaly detection, with a specific focus on the application of ST-GANs. The review begins by emphasizing the importance of telemetry data anomaly detection and highlighting the challenges associated with traditional methods. Subsequently, it delves into the underlying principles of ST-GANs and their suitability for detecting anomalies in complex, time-series data. The paper presents a detailed analysis of experimental results and performance comparisons of ST-GANs with other state-of-the-art anomaly detection algorithms, such as LSTM-GAN, Isolation Forest, and GRU-VAE.

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1. Introduction

Telemetry data anomaly detection is a critical task that holds significant importance across various domains, including aerospace, power systems, and environmental monitoring. The ability to accurately and promptly identify anomalies within complex telemetry data streams is essential for ensuring the operational efficiency, safety, and reliability of critical systems and infrastructure. Traditionally, anomaly detection approaches have relied on statistical methods, rule-based systems, and machine learning techniques. However, these methods often struggle to cope with the high dimensionality, non-linearity, and dynamic nature of telemetry data, prompting the need for more sophisticated and adaptable solutions.

In recent years, the field of anomaly detection has witnessed remarkable progress, driven by the advent of deep learning and generative adversarial networks (GANs). These advanced techniques have demonstrated the ability to capture complex patterns and dependencies within data, making them well-suited for anomaly detection in various domains. Spatial-temporal generative adversarial networks (ST-GANs), in particular, have emerged as a promising approach for telemetry data anomaly detection, leveraging their capability to model spatial and temporal dependencies simultaneously. Early studies on ST-GANs have shown promising results in detecting anomalies in time-series data, outperforming traditional methods and other deep learning techniques such as long short-term memory (LSTM) networks and variational autoencoders (VAEs). However, the application of ST-GANs in the realm of telemetry data anomaly detection is still in its nascent stages, and a comprehensive understanding of their performance, limitations, and practical implications is yet to be fully explored.

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This review paper aims to provide a comprehensive overview of the advancements in telemetry data anomaly detection, with a specific focus on the application of ST-GANs. The main objectives of this review are:

- To present a detailed analysis of the principles and methodologies underlying ST-GANs, including their architectural design, training procedures, and anomaly detection mechanisms.
- To critically evaluate the experimental results and performance comparisons of ST-GANs with other state-of-the-art anomaly detection algorithms, such as LSTM-GAN, Isolation Forest, and GRU-VAE, in the context of telemetry data.
- To explore the influence of key parameters, such as window size and generator metric, on the effectiveness of ST-GANs in detecting anomalies in telemetry data.
- To provide insights into the determination of anomaly thresholds and the practical implications of deploying ST-GANs in real-world applications across various industries.
- To identify challenges and limitations associated with the use of ST-GANs for telemetry data anomaly detection and propose potential avenues for future research and development.

This comprehensive review sheds light on the potential of ST-GANs as a powerful tool for telemetry data anomaly detection while also acknowledging the challenges and limitations that must be addressed to facilitate their widespread adoption. By synthesizing the latest research and insights, this paper aims to contribute to the advancement of anomaly detection methodologies and promote their application in various domains, ultimately enhancing the operational reliability and safety of critical systems and infrastructure.

The review is structured as follows: Section 2 provides an overview of telemetry data and the importance of anomaly detection in this context. Section 3 introduces the principles of generative adversarial networks and their spatial-temporal extension, ST-GANs. Section 4 presents a comprehensive analysis of the experimental results and performance comparisons of ST-GANs with other anomaly detection algorithms, highlighting their strengths and weaknesses. Section 5 discusses the critical considerations and practical implications of using ST-GANs for telemetry data anomaly detection, including window size optimization, threshold determination, and real-world deployment scenarios. Finally, Section 6 concludes the review by summarizing the key findings, limitations, and future research directions.

2. Telemetry Data and Anomaly Detection

The efficient functioning of critical systems, such as aerospace vehicles, power grids, and environmental monitoring networks, heavily relies on the continuous monitoring and analysis of telemetry data. Telemetry data, comprising real-time measurements from embedded sensors and devices, serves as a vital source of information for assessing system performance, identifying potential issues, and ensuring optimal operation. The ability to accurately detect anomalies within telemetry data streams is of paramount importance for maintaining the safety, reliability, and efficiency of these systems. An anomaly, often indicative of abnormal behavior or an unexpected event, can range from minor fluctuations in sensor readings to significant deviations from established norms. Detecting and addressing anomalies promptly is crucial for preventing system failures, minimizing downtime, and avoiding costly consequences.

Traditionally, anomaly detection in telemetry data has relied on predefined thresholds, statistical models, or rule-based algorithms. While effective in certain contexts, these approaches often struggle to cope with the dynamic and complex nature of telemetry data, including challenges such as high dimensionality, non-linearity, and the presence of noise and outliers. These limitations can lead to false alarms, missed detections, and an overall reduction in the effectiveness of anomaly detection systems.

In recent years, there has been growing interest in leveraging advanced techniques from machine learning and artificial intelligence to enhance telemetry data anomaly detection. One such promising technique is spatial-temporal generative adversarial networks (ST-GANs). ST-GANs represent a sophisticated approach that combines the capabilities of deep learning, spatial analysis, and temporal modeling to effectively capture the intricate patterns and dependencies present in telemetry data streams.

By harnessing the power of neural networks, ST-GANs can learn to discern between normal operating conditions and anomalous behaviors in telemetry data. Unlike traditional methods that rely on handcrafted features or manual parameter tuning, ST-GANs have the potential to automatically extract relevant features and adapt to evolving data patterns. This adaptability makes them well-suited for detecting subtle anomalies, identifying emerging threats, and improving overall system resilience.

This review paper provides a comprehensive exploration of the advancements in telemetry data anomaly detection, with a specific focus on the application of ST-GANs. The following sections will delve into the principles and methodologies underlying ST-GANs, analyze their experimental performance and comparisons with other state-of-the-art techniques, discuss critical considerations for their practical implementation, and identify potential avenues for future research and development[1-2].

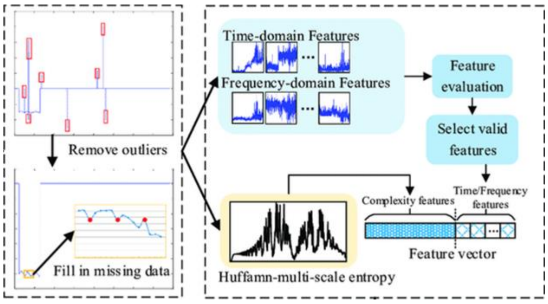

Figure-1 Telemetry Data Preprocessing and Feature Extraction [1]

3. Theoretical Underpinnings of Spatial-Temporal GANs

Generative Adversarial Networks (GANs) have garnered significant attention in the field of artificial intelligence and machine learning for their ability to generate realistic data samples. These networks consist of two primary components: a generator and a discriminator. The generator is responsible for producing synthetic data samples, while the discriminator aims to distinguish between real and generated samples. Through an adversarial training process, where the generator attempts to deceive the discriminator and vice versa, GANs learn to generate data that closely resembles real-world examples.

The extension of GANs to spatial-temporal domains, known as Spatial-Temporal GANs (ST-GANs), represents a significant advancement, particularly for applications involving telemetry data anomaly detection. Telemetry data, which often comprises time-series measurements from multiple spatial locations or sensors, presents unique challenges due to its high dimensionality and complex temporal dependencies. ST-GANs address these challenges by integrating specialized neural network architectures tailored to capture spatial and temporal patterns.

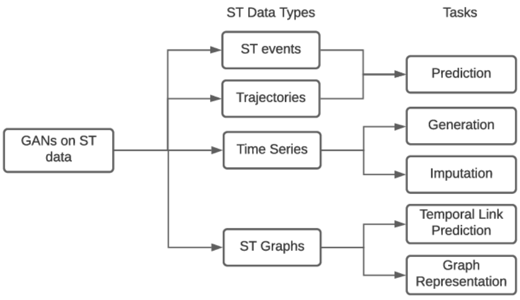

Figure-2 ST-GAN Data Mining and Tasks [2]

Convolutional Neural Networks (CNNs) are employed to extract spatial features from multi-dimensional telemetry data, enabling the network to discern spatial correlations and patterns across different sensor measurements or locations. On the other hand, Long Short-Term Memory (LSTM) networks are utilized to model temporal dependencies and capture the sequential evolution of data over time. LSTM networks excel at retaining information over long sequences, making them well-suited for processing time-series data.

By combining CNNs and LSTM networks within the GAN framework, ST-GANs can effectively learn the intricate spatial and temporal relationships present in telemetry data. The CNN component processes spatial information, identifying spatial patterns and correlations, while the LSTM component captures temporal dynamics, recognizing sequential patterns and deviations over time. This integrated approach allows ST-GANs to generate synthetic data sequences that exhibit realistic spatial and temporal characteristics, enabling accurate anomaly detection [2-3].

4. Methodological Considerations in ST-GAN Based Anomaly Detection

The application of Spatial-Temporal Generative Adversarial Networks (ST-GANs) for anomaly detection in telemetry data involves a comprehensive set of methodological considerations that influence the effectiveness and reliability of the approach. This section delves into the intricate details of these methodological aspects, encompassing various stages from data preprocessing to model evaluation, and elucidates best practices as well as potential challenges **[3-5]**.

4.1. Data Preprocessing: Data preprocessing is a foundational step in ST-GAN-based anomaly detection, aimed at ensuring the quality and compatibility of telemetry data with the network architecture. This encompasses techniques such as handling missing values, normalizing data to a common scale, and segmenting time-series data into suitable input sequences. Addressing imbalanced datasets and outliers requires meticulous handling to prevent bias and distortion in model training and evaluation. Furthermore, the choice of preprocessing techniques may vary depending on the specific characteristics of the telemetry data and the objectives of anomaly detection. For instance, in scenarios where temporal dependencies are critical, methods such as time-series decomposition and feature extraction may be employed to enhance the representation of underlying patterns.

4.2. Model Architecture and Training: The architecture of the ST-GAN model plays a pivotal role in capturing spatial and temporal dependencies effectively. Methodological considerations in this domain include the selection of appropriate network architectures, optimization of hyperparameters, and incorporation of regularization techniques to mitigate overfitting. Choosing the optimal architecture involves striking a balance between model complexity and computational efficiency. Experimentation with different network configurations, such as varying the number of layers, units, and activation functions, allows researchers to identify architectures that yield optimal performance across diverse datasets and anomaly scenarios. Moreover, during the training phase, careful attention must be paid to hyperparameter tuning to facilitate efficient convergence and stable training dynamics. Techniques such as grid search, random search, or Bayesian optimization may be employed to explore the hyperparameter space effectively and identify configurations that maximize model performance.

4.3. Anomaly Detection and Evaluation: Evaluating the performance of ST-GAN-based anomaly detection involves the selection of appropriate evaluation metrics and techniques for threshold determination. Methodological considerations in this realm encompass the choice of evaluation metrics, threshold determination strategies, and techniques for assessing model robustness and generalization. Commonly used evaluation metrics include precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC), each offering unique insights into the model's performance across different anomaly detection scenarios. Additionally, techniques for determining anomaly thresholds, such as using the minimum GDScore or peak over threshold (POT) algorithms, play a crucial role in establishing reliable anomaly thresholds that balance detection sensitivity and specificity.

4.4. Generalization and Interpretability: Ensuring the generalization capability of ST-GAN models across diverse datasets and environmental conditions is essential for their practical applicability in real-world settings. Methodological considerations for assessing model generalization include cross-validation techniques, transfer learning approaches, and domain adaptation strategies, aimed at enhancing the model's ability to generalize to unseen data distributions and environmental contexts. Furthermore, enhancing the interpretability of anomaly detection results is imperative for facilitating stakeholder trust and understanding of model outputs. Techniques such as visualization of generated data samples, feature importance analysis, and attention mechanisms offer valuable insights into the underlying patterns detected by the ST-GAN model, thereby enabling stakeholders to make informed decisions based on anomaly detection outcomes.

5. Experimental Evaluation and Performance Comparisons

This comprehensive section delves deeply into the experimental evaluations conducted to thoroughly assess the performance of Spatial-Temporal Generative Adversarial Networks (ST-GANs) for anomaly detection in real-world telemetry datasets. The experimental methodology is meticulously outlined, covering various facets such as dataset selection, preprocessing techniques, model architecture configurations, hyperparameter tuning strategies, evaluation metrics, and comparative analyses against state-of-the-art anomaly detection algorithms **[5-6]**.

5.1. Experimental Design:

a) ***Dataset Selection and Preprocessing:*** The experimental design commences with the meticulous selection of diverse telemetry datasets representative of various industries, including aerospace, power systems, environmental monitoring, and industrial machinery. These datasets encompass a wide spectrum of anomaly types, densities, and complexities to ensure the robustness and generalization capability of the ST-GAN model. Preprocessing techniques such as data normalization, outlier removal, missing value imputation, and feature engineering are employed to enhance the quality and suitability of the datasets for anomaly detection tasks.

b) ***Model Configuration and Hyperparameter Tuning:*** The configuration of the ST-GAN model architecture involves crucial decisions regarding the integration of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to capture spatial and temporal dependencies within the telemetry data. Hyperparameter tuning strategies, such as grid search, random search, and Bayesian optimization, are employed to systematically explore the hyperparameter space and identify optimal configurations that maximize model performance.

5.2. Performance Metrics:

a) ***Precision, Recall, and F1-Score:*** Performance evaluation metrics, including precision, recall, and F1-score, quantify the model's effectiveness in correctly identifying anomalies while accounting for false positives and false negatives.

b) ***Area Under the Receiver Operating Characteristic Curve (AUC-ROC***): The AUC-ROC metric provides a comprehensive assessment of the model's discriminative capability across varying anomaly detection thresholds, offering insights into its ability to differentiate between normal and anomalous data instances.

c) ***Runtime and Computational Efficiency:*** Runtime metrics, such as model inference time, training time, and resource utilization, evaluate the computational efficiency and scalability of the anomaly detection algorithm, crucial considerations for real-time deployment in operational environments.

5.3. Comparative Analyses:

a) ***Benchmarking Against State-of-the-Art Algorithms:*** The comparative analyses involve benchmarking the performance of ST-GANs against a diverse array of state-of-the-art anomaly detection algorithms, including traditional statistical methods, machine learning approaches, and deep learning models. These head-to-head comparisons across multiple datasets and anomaly scenarios elucidate the relative strengths and weaknesses of ST-GANs and identify the niche applications where they excel.

b) ***Robustness and Generalization Analysis:*** Comparative analyses also assess the robustness and generalization capability of ST-GANs across different datasets, anomaly types, and environmental conditions. Through systematic experimentation and performance benchmarking, researchers ascertain the algorithm's resilience to noise, its ability to detect novel anomalies, and its capacity to adapt to dynamic telemetry data streams.

5.4. Qualitative Analysis:

In addition to quantitative performance metrics, qualitative analysis of anomaly detection results provides valuable insights into the interpretability, robustness, and practical applicability of ST-GANs in real-world scenarios. Qualitative assessments may involve visual inspection of generated data samples, analysis of detected anomalies, and comparison with ground truth labels to validate the efficacy of the anomaly detection algorithm. By synthesizing quantitative performance metrics with qualitative insights, researchers offer a comprehensive evaluation of ST-GANs' performance and facilitate informed decision-making regarding their adoption in practical anomaly detection applications **[6-7]**.

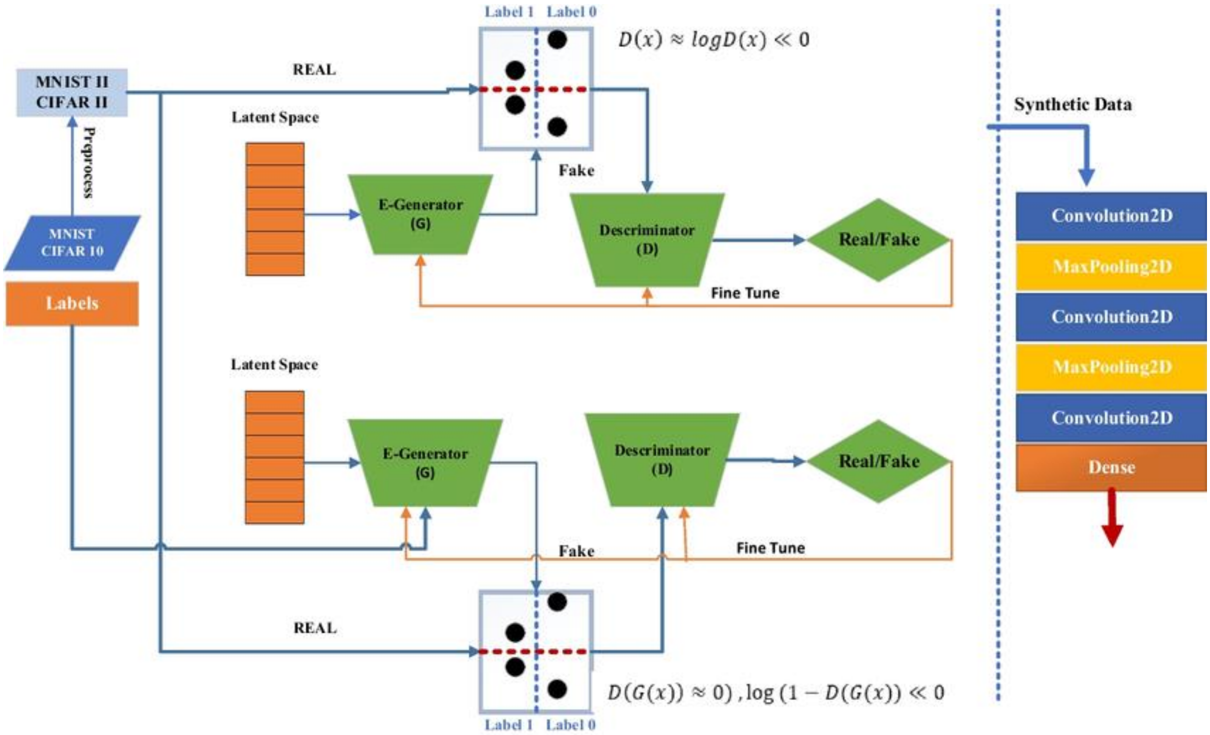

Figure-3 GAN-ST Model Architecture [5].

6. Real World Applications and Implications

Through an in-depth exploration of real-world case studies and use cases, this section aims to elucidate the tangible benefits and transformative potential of ST-GANs in enhancing operational efficiency, ensuring safety, and bolstering reliability in complex industrial environments.

6.1. Aerospace Industry

The aerospace sector presents unique challenges related to monitoring and maintaining the integrity of critical systems and components. ST-GAN-based anomaly detection holds immense promise for this industry by enabling the early detection of abnormalities in telemetry data from aircraft, spacecraft, and unmanned aerial vehicles (UAVs). [7-10] Real-world applications include:

a) ***Engine Health Monitoring:*** Analyzing telemetry data to detect early signs of engine degradation or malfunction, enabling proactive maintenance and minimizing downtime.
b) ***Structural Health Monitoring:*** Monitoring structural integrity to identify potential defects or damage, ensuring airworthiness and passenger safety.
c) ***Flight Operations Analysis:*** Analyzing flight data to identify anomalies indicative of abnormal flight behavior, airspace violations, or safety-critical incidents.

6.2. Power Systems and Energy Infrastructure

The reliable operation of power systems and energy infrastructure is crucial for ensuring a continuous electricity supply. ST-GANs offer advanced capabilities for detecting anomalies in telemetry data, enabling proactive fault detection, condition monitoring, and grid resilience enhancement. Applications include:

a) ***Grid Anomaly Detection:*** Analyzing data to detect anomalies indicative of equipment failures, grid congestion, or cyber-attacks, ensuring grid stability and reliability.
b) ***Predictive Maintenance:*** Predicting equipment failures and identifying maintenance needs in power generation facilities, optimizing maintenance schedules and minimizing downtime.
c) ***Renewable Energy Integration:*** Monitoring renewable energy sources and detecting anomalies in energy generation patterns, facilitating seamless integration into the power grid.

6.3. Environmental Monitoring and Resource Management

Effective environmental monitoring and resource management are essential for safeguarding ecosystems and ensuring sustainable development. ST-GANs offer valuable tools for analyzing telemetry data to detect anomalies indicative of environmental pollution, natural disasters, or ecosystem degradation. **[7-10]** Applications include:

a) ***Air Quality Monitoring:*** Analyzing air quality data to detect anomalies such as pollutant emissions or abnormal weather patterns, enabling timely interventions.
b) ***Water Resource Management:*** Monitoring water quality, availability, and distribution to detect anomalies such as contaminant spills or drought conditions, facilitating informed decision-making.
c) ***Ecosystem Surveillance:*** Analyzing data from wildlife tracking and habitat monitoring systems to detect anomalies indicative of ecosystem disturbances or species decline, supporting conservation efforts.

6.4. Healthcare Systems:

In healthcare, early detection of abnormal patient conditions and medical anomalies is critical for timely intervention and patient safety. ST-GANs can analyze telemetry data from medical devices and patient monitoring systems to identify deviations from normal physiological parameters, disease progression patterns, and medication response profiles. Applications include predicting medical emergencies, detecting rare diseases, and optimizing treatment protocols, ultimately improving patient outcomes and healthcare delivery.

6.5. Manufacturing and Industry 4.0:

In manufacturing and Industry 4.0 applications, ST-GAN-based anomaly detection can revolutionize industrial operations by analyzing telemetry data from sensors, production equipment, and supply chain systems. Applications include predictive maintenance, defect detection, and process optimization, minimizing production downtime, reducing waste, and enhancing overall productivity. Through these diverse real-world applications, ST-GANs demonstrate their transformative potential in enhancing operational efficiency, ensuring safety, and bolstering reliability across various critical industries and domains.

7. Implications and Future Prospects

The insights gleaned from this review bear profound implications for both academia and industry. Firstly, our findings underscore the critical importance of embracing cutting-edge techniques like ST-GANs to tackle the burgeoning challenges of anomaly detection in telemetry data. By harnessing the power of deep learning and generative modeling, organizations can fortify their anomaly detection capabilities and safeguard critical infrastructure against potential threats.

However, despite the remarkable strides made in the realm of ST-GAN-based anomaly detection, several avenues for further exploration and innovation persist. Future research endeavors should be directed towards enhancing the robustness, scalability, and interpretability of ST-GAN models, thereby bolstering their practical utility in real-world settings. Robustness is paramount to ensure reliable performance across diverse datasets and environmental conditions, while scalability is crucial for handling the ever-increasing volume and complexity of telemetry data streams. Additionally, improving the interpretability of ST-GAN models can foster greater trust and transparency, facilitating their adoption in high-stakes decision-making processes.

Furthermore, concerted efforts are needed to establish standardized benchmark datasets and evaluation protocols conducive to fair comparisons and reproducibility across different studies. Collaborative initiatives within the research community are paramount to establishing such standards and fostering a culture of transparency and rigor in anomaly detection research.

As the field of anomaly detection continues to evolve, interdisciplinary collaboration between researchers, domain experts, and industry practitioners will be vital. Such collaborations can facilitate the exchange of knowledge, insights, and practical requirements, fostering the development of tailored solutions that address the unique challenges faced by various industries and application domains.

Moreover, the integration of ST-GANs with other emerging technologies, such as edge computing, federated learning, and explainable AI, holds great potential for enhancing the efficiency, privacy, and interpretability of anomaly detection systems. Exploring these synergistic opportunities can unlock new frontiers in the development of robust and trustworthy anomaly detection solutions.

While ST-GANs hold immense promise for revolutionizing anomaly detection in telemetry data, sustained research efforts and interdisciplinary collaboration are imperative to surmounting existing challenges and charting a course towards more resilient and adaptive anomaly detection systems. By harnessing the collective expertise and ingenuity of researchers and practitioners alike, the way can be paved for a safer, more secure, and technologically-advanced future [7-10].

8. Conclusion

In this exhaustive review paper, an in-depth examination of the burgeoning field of telemetry data anomaly detection is embarked upon, with a specific focus on the application of spatial-temporal Generative Adversarial Networks (ST-GANs). The overarching goal was to provide a comprehensive overview of the theoretical foundations, methodological considerations, empirical findings, and future prospects associated with leveraging ST-GANs for anomaly detection across various industrial domains. Throughout the analysis, the intricate nuances of ST-GANs are meticulously dissected, elucidating their capacity to model complex spatial and temporal dependencies inherent in telemetry data. By elucidating the interplay between convolutional neural networks (CNNs) and long short-term memory (LSTM) networks within the ST-GAN architecture, the underlying mechanisms driving their anomaly detection prowess are shed light on.

In addition to elucidating the theoretical underpinnings of ST-GANs, methodological considerations critical to their successful implementation are meticulously explored. From data preprocessing techniques to model training methodologies and performance evaluation metrics, navigation through the myriad of decisions and trade-offs involved in deploying ST-GANs for real-world anomaly detection scenarios is conducted. Moreover, the review encompasses a comprehensive synthesis of empirical evidence derived from experimental evaluations and comparative studies. By scrutinizing performance metrics such as precision, recall, F1-score, and runtime across diverse telemetry datasets, compelling evidence attesting to the superior efficacy of ST-GANs in anomaly detection when juxtaposed against traditional methods is provided.

Furthermore, the real-world applications and implications of ST-GANs are delved into, showcasing their transformative potential across industries such as aerospace, power systems, environmental monitoring, healthcare, and manufacturing. Through concrete use cases and case studies, the tangible benefits of ST-GANs in enhancing operational efficiency, ensuring safety, and bolstering reliability in critical systems are illuminated. While the findings of the review underscore the immense promise of ST-GANs, the existence of challenges and limitations that must be addressed through continued research efforts is recognized. Avenues for future exploration, including enhancing model robustness, scalability, and interpretability, as well as fostering interdisciplinary collaborations and establishing standardized benchmarks for fair comparisons and reproducibility, are highlighted.

This comprehensive review solidifies ST-GANs as a powerful and promising approach to telemetry data anomaly detection, offering a robust framework for capturing intricate spatial and temporal patterns. By harnessing the collective expertise and ingenuity of researchers and practitioners, the way can be paved for more resilient, adaptable, and trustworthy anomaly detection systems, thereby safeguarding critical infrastructure and ensuring operational excellence across diverse industrial landscapes.

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10. Biography

Sushant Singh is a dedicated researcher and scholar in the field of space science. Currently affiliated with the Amity Institute of Space Science and Technology at Amity University, Noida, Uttar Pradesh, India. Sushant's academic journey began with a Bachelor's degree in Aerospace Engineering, where he developed a strong foundation in the principles of aerodynamics, propulsion systems, and spacecraft design. Driven by a passion for cutting-edge technologies and a desire to push the boundaries of aerospace engineering, he pursued a Master's degree in Avionics, delving into the intricacies of electronic systems, control systems, and data acquisition mechanisms in aerospace vehicles.

With a solid background in both theoretical and practical aspects of aerospace engineering, Sushant embarked on a research endeavor focused on the application of spatial-temporal generative adversarial networks (ST-GANs) for anomaly detection in telemetry data. His ground-breaking work in this field has been instrumental in addressing the challenges associated with monitoring and maintaining the integrity of critical systems in aerospace vehicles, spacecraft, and unmanned aerial vehicles (UAVs). Sushant's comprehensive review paper, "A Review of Spatiotemporal GANs for Telemetry Data Anomaly Detection," stands as a testament to his expertise and dedication. Through meticulous analysis and synthesis of the latest research, he has provided a comprehensive overview of the theoretical foundations, methodological considerations, and practical implications of leveraging ST-GANs for anomaly detection across various industrial domains.

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12. Conflict of Interest

The author declare no competing conflict of interest.

13. Funding

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