Deep Autoencoder-Based Anomaly Detection for Intelligent Network Slice Monitoring in B5G Networks

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*Abstract* -- The advent of 5G and Beyond 5G (B5G) networks has presented significant challenges in achieving reliable service delivery through the implementation of network slicing. This study introduces an innovative deep learning methodology for anomaly detection within network slices, utilizing autoencoder neural networks. Our framework analyzes a variety of network performance metrics to autonomously detect abnormal behavior patterns that may adversely affect service quality. By examining network traffic characteristics such as bandwidth, packet rates, latency, jitter, loss rates, and throughput, our method exhibits a high level of accuracy in identifying anomalies while keeping false positive rates to a minimum. The proposed solution facilitates real-time monitoring with minimal computational demands, rendering it suitable for practical application in B5G settings. The experimental findings substantiate the efficacy of the autoencoder-based approach in elucidating complex interrelations among network metrics, thereby establishing a solid basis for automated monitoring and management of network slices.

**Keywords:** 5G Networks, Network Slicing, Anomaly Detection, Deep Learning, Autoencoder, Network Security

# Introduction

The emergence of Fifth Generation (5G) and Beyond 5G (B5G) networks marks a pivotal shift in the telecommunications landscape, characterized by innovative advancements alongside notable challenges. A key element of this transformation is network slicing, a groundbreaking technology that facilitates the establishment of multiple virtual networks atop a shared physical infrastructure. This advancement provides exceptional flexibility and customization in service delivery, allowing operators to effectively cater to a wide array of application requirements. Nevertheless, it also brings forth considerable complexities in maintaining the reliability and performance of these network slices.

Network slicing fundamentally alters the allocation and utilization of network resources. Each virtual slice operates as an independent network, tailored to fulfill the specific demands of distinct applications. For example, slices optimized for ultra-reliable low-latency communications are essential for technologies such as autonomous vehicles, where immediate decision-making is crucial. Conversely, massive machine-type communications are designed to support smart city frameworks, managing a large volume of connected devices with diverse data and latency requirements.

The variety of applications necessitates comprehensive monitoring and anomaly detection systems to ensure the seamless operation of network slices. Any deviation from anticipated performance indicators, such as heightened latency or packet loss, could significantly compromise service quality and user satisfaction. The dynamic and heterogeneous characteristics of these networks further complicate this task, requiring intelligent and adaptive monitoring strategies.

As B5G networks progress, the capability to identify anomalies in real time becomes increasingly vital for preserving the overall integrity of the network. Conventional monitoring methods frequently prove inadequate in this scenario due to their limitations in addressing the scale and intricacy of network slicing. As a result, the adoption of advanced methodologies, including machine learning and deep learning, is essential.

## Problem Statement

Managing network slicing in Beyond 5G (B5G) networks poses a complex challenge due to the intricate nature and variety of virtual slices. Each slice is characterized by specific requirements and traffic patterns, necessitating a system that can autonomously learn and adapt to the typical behavior of individual slices. This capacity for dynamic adaptation is crucial for accurately monitoring network performance as conditions change, thereby eliminating the need for constant manual intervention.

Another essential aspect is the capability for real-time anomaly detection, which is vital for maintaining reliability and quality of service. The system must swiftly and effectively identify any deviations from expected behavior while minimizing false positives, as an overabundance of false alarms can lead to resource wastage and diminished trust in the monitoring system. Furthermore, the ability to scale seamlessly across multiple network slices, each with its own quality-of-service requirements ranging from low-latency applications to high-throughput scenarios is imperative for operational efficiency.

Achieving these goals with minimal human oversight is crucial for the feasibility of extensive network operations. By leveraging intelligent and automated methodologies, such as machine learning and deep learning, the monitoring system can provide high levels of accuracy and responsiveness, thereby alleviating the workload on human operators. This approach ensures a resilient and efficient network monitoring framework, capable of accommodating the diverse applications and services facilitated by B5G technologies.

## Research Contributions

This study aims to create an effective autoencoder architecture specifically designed for intelligent network monitoring within Beyond 5G (B5G) environments. By utilizing the capacity of autoencoders to derive compact data representations, the proposed methodology effectively identifies the underlying patterns and behaviors present in network traffic, facilitating accurate anomaly detection. The model is engineered to dynamically adjust to the distinct characteristics of each network slice, thereby ensuring reliable performance across a variety of scenarios. This architecture serves as the foundation for a viable solution for real-time anomaly detection, capable of swiftly identifying irregularities while maintaining a minimal false alarm rate.

In response to the scalability challenges posed by B5G networks, the research further presents a versatile framework for overseeing multiple network slices with differing quality-of-service requirements. This framework incorporates the autoencoder-based anomaly detection system and is assessed using actual network traffic data to confirm its efficacy. Extensive experiments underscore the system's proficiency in detecting anomalies across various metrics, including bandwidth, delay, jitter, and packet loss, thereby illustrating its robustness and practical relevance. The findings offer significant insights into the role of deep learning in improving the reliability and efficiency of network slice management.

# Related Work

This research examines the security challenges and opportunities associated with 5G network slicing. It emphasizes the expanded attack surface that slicing introduces and investigates how advanced security frameworks, including AI-driven security and Zero Trust models, can help mitigate these risks [1]. The literature review encompasses surveys addressing security concerns related to network slicing and prior models aimed at securing 5G slices. This survey specifically tackles the security challenges inherent in network slicing, identifying prevalent attack vectors and suggesting possible countermeasures [2]. The related literature focuses on various security mechanisms originally designed for traditional networks, which have been modified to suit the dynamic nature of 5G network slices. The authors advocate for the application of deep learning techniques to facilitate intelligent network slicing in Open RAN (ORAN) environments, with an emphasis on automated slice management [3]. The related work discussed includes the progression of network slicing methodologies and the growing influence of AI in enhancing these processes. Furthermore, this paper introduces a reinforcement learning-based approach aimed at ensuring slice isolation within 5G networks, particularly in the context of defending against DDoS attacks [4]. The related literature encompasses earlier strategies for slice isolation and security measures designed to counter denial-of-service attacks. Additionally, the paper investigates the management of 5G/B5G network slices through reinforcement learning, concentrating on optimizing resource allocation and bolstering security. The related work highlights current techniques for slice management and the application of reinforcement learning within the 5G framework [5]. The study presents a comprehensive framework for end-to-end network slice management tailored for multi-tenant 5G networks. A review of existing literature highlights current frameworks for slice orchestration and management, pinpointing the shortcomings in delivering security and performance assurances [6]. This survey delves into the application of 5G network slicing within smart cities, underlining the distinct security challenges that arise in these contexts. Additionally, the related literature examines the deployment of 5G in other critical sectors and the corresponding security vulnerabilities [7]. The paper underscores the importance of a security orchestrator in safeguarding network slices in forthcoming network architectures [8]. The related work elaborates on the architectural transformations within 5G that necessitate the integration of orchestrators, as well as previous methodologies for managing slice-specific security. Furthermore, this paper reviews the latest developments in 5G security and delineates the challenges that future networks may encounter [9]. The related literature emphasizes the legacy security issues present in LTE networks and the shifting threat landscape introduced by 5G [10]. This survey also explores the role of machine learning in enhancing the security of 5G network slices, referencing prior surveys that discuss machine learning applications in network security and contrasting rule-based approaches with AI-driven strategies for 5G security. Additionally, this book provides an extensive overview of the architecture, technology, and implementation of 5G New Radio (NR) standards, drawing on earlier 3GPP specifications and the progression of radio access technologies leading to 5G [11]. Lastly, this paper examines the concept of network slicing, addressing the associated challenges and proposing solutions for the effective management of slices within 5G networks, while also referencing initial discussions on network virtualization and software-defined networking (SDN) as foundational elements for slicing [12]. This research investigates the essential principles and obstacles associated with network slicing, examining various solutions designed for resource management and isolation [13]. The literature review highlights early virtualization methods and network function chaining utilized in prior wireless generations. The authors address the difficulties encountered in managing mobility and resources within network slices in the context of 5G, with a particular emphasis on maintaining quality of service (QoS) [14]. The review of related work assesses existing resource management approaches in 4G/LTE, noting their inadequacies in accommodating dynamic slice environments. This tutorial presents an overview of 5G standards and trials, identifying the primary challenges related to deployment. Additionally, it references earlier standardization efforts in 3G and 4G, which provided a foundation for the advancement of 5G technology [15]. This paper provides an overview of energy-efficient strategies for 5G networks, addressing the challenges associated with the substantial energy requirements of network slicing [16]. Previous research emphasizes energy conservation methods implemented in 4G and underscores the necessity for modifications in the context of 5G. The authors introduce a machine learning-based framework aimed at managing 5G network slices, with an emphasis on enhancing resource allocation [17]. The literature review examines conventional optimization techniques utilized in earlier network generations and highlights the benefits that machine learning offers for intricate resource management. Furthermore, this paper investigates anomaly detection within autonomous network slicing through machine learning methodologies [18]. The literature review critiques traditional anomaly detection techniques in network traffic and emphasizes the demand for AI-driven solutions in the rapidly evolving 5G landscape. The authors also analyze machine learning approaches for intrusion detection in virtualized networks, pinpointing unresolved research challenges. The related work encompasses existing strategies for intrusion detection and prevention in 4G/LTE, as well as their adaptations for virtualized 5G environments [19]. This survey encapsulates essential techniques and unresolved issues regarding the application of machine learning in wireless networks, with a particular focus on optimization and security. The related literature discusses prior applications of artificial intelligence in wireless networks and their progression into the 5G domain, which has been foundational for the advancement of 5G technology [20].

# Methodology

Our approach to network slice anomaly detection integrates deep learning techniques with practical solutions for real-time network monitoring. The methodology involves a layered system architecture, efficient data processing pipeline, and a deep autoencoder model for anomaly detection. Below, we provide a detailed explanation of the core components of our approach.

## System Architecture

The proposed system architecture is meticulously designed to streamline the process of anomaly detection in network traffic. It is composed of three interconnected layers, each performing critical functions to ensure accurate and real-time anomaly identification. These layers are described in detail below:

#### Data Collection and Preprocessing Layer

The first layer of the system is dedicated to the continuous monitoring and preprocessing of network traffic. Its key functionalities include:

1. **Real-Time Data Collection**: This sub-layer interfaces with network monitoring tools to capture real-time traffic data. It collects a wide array of metrics, such as packet rates, bandwidth utilization, and delay statistics, from various network nodes.
2. **Data Cleaning**: Raw network data often contains noise and inconsistencies. This sub-layer applies cleaning techniques to remove corrupted or incomplete records, ensuring the integrity and reliability of the dataset.
3. **Normalization and Feature Extraction**: After cleaning, the data is normalized to scale features into a consistent range, typically [0,1], using techniques like Min-Max scaling. Feature extraction then identifies and retains critical metrics relevant for anomaly detection, such as bandwidth utilization and packet loss rates.

#### Autoencoder Processing Layer

The core computational layer of the system, the Autoencoder Processing Layer, employs a deep autoencoder neural network for data analysis. This layer operates as follows:

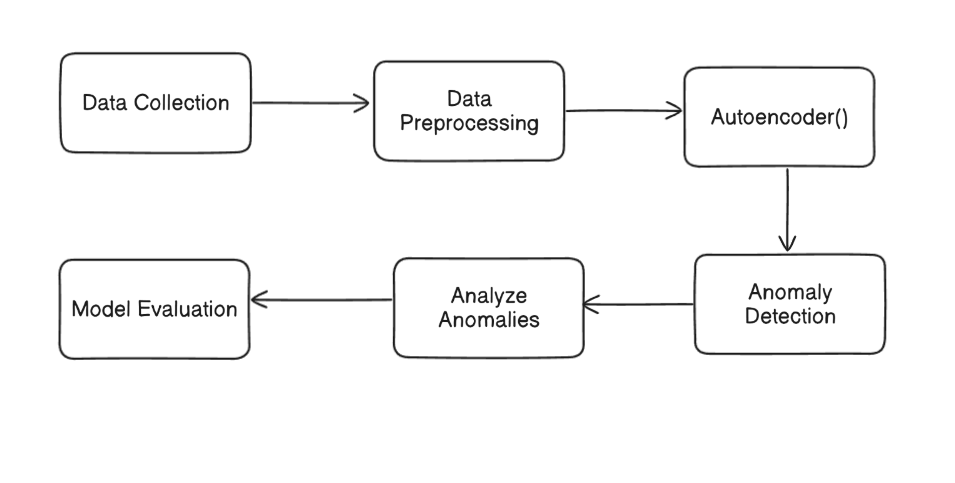
1. **Data Input**: The normalized data is passed into the autoencoder’s input layer, representing the critical network metrics as a feature vector.
2. **Encoder**: The encoder component reduces the dimensionality of the input data, isolating essential patterns and discarding redundant information. This step ensures computational efficiency while capturing complex relationships among features.
3. **Decoder**: The decoder reconstructs the input data from the compressed representation. By comparing the reconstructed data to the original input, reconstruction errors are calculated. These errors serve as a baseline to identify deviations indicative of anomalies.
4. **Reconstruction Error Calculation**: The difference between the input data and its reconstruction is quantified using a loss function, such as Mean Squared Error (MSE). Low reconstruction errors signify normal network behavior, whereas high errors suggest potential anomalies.

#### Detection and Alert Layer

The final layer is responsible for analyzing reconstruction errors and generating alerts for detected anomalies. Its key functionalities include:

1. **Dynamic Thresholding**: This component applies a dynamic threshold, derived from the statistical distribution of reconstruction errors during the training phase. The threshold adjusts in real time based on the network’s baseline behavior.
2. **Anomaly Identification**: Data points with reconstruction errors exceeding the dynamic threshold are flagged as anomalies. This process ensures that only significant deviations from normal behavior are identified.
3. **Alert Generation**: For each detected anomaly, the system generates real-time alerts, providing actionable insights to network administrators. Alerts include details about the affected metrics and the magnitude of the deviation, enabling prompt investigation and resolution.

### Design Considerations

The layered architecture is designed to handle high volumes of network data efficiently while maintaining accuracy in anomaly detection. Each layer is optimized for scalability and real-time processing, ensuring the system’s robustness in dynamic network environments. By integrating advanced preprocessing, deep learning, and intelligent detection mechanisms, the architecture achieves a balance between performance and computational efficiency.

## Feature Engineering

To effectively detect network anomalies, the system focuses on seven critical network metrics:

* Bandwidth utilization
* Packet rates
* Network delay
* Jitter
* Loss rates
* Bandwidth changes
* Throughput

These metrics were chosen based on their ability to reflect the overall network performance and their potential to indicate anomalies when their behaviour deviates from normal patterns. By processing these metrics, the system can pinpoint irregularities and alert administrators to potential network issues.

## Autoencoder Model Architecture

The autoencoder model forms the central component of our anomaly detection system, designed to effectively learn the normal behavior of network traffic and identify deviations through reconstruction errors. Its architecture is specifically tailored to capture intricate patterns in the data while ensuring computational efficiency for real-time applications. Below, we detail the structure and functionality of the model.

**Input Layer**

The input layer consists of **7 neurons**, each corresponding to one of the critical network metrics identified during feature engineering. These metrics include bandwidth utilization, packet rates, network delay, jitter, loss rates, bandwidth changes, and throughput. By representing each metric as an input neuron, the model processes all relevant features simultaneously.

**Encoder**

The encoder is responsible for compressing the input data into a lower-dimensional representation, capturing essential features while reducing redundancy. It comprises:

1. **First Hidden Layer**: This layer contains **8 neurons** and employs the ReLU (Rectified Linear Unit) activation function, defined as:

The ReLU activation introduces non-linearity, enabling the model to learn complex relationships between input features.

1. **Bottleneck Layer**: The bottleneck layer contains **4 neurons**, representing the compressed version of the input data. By reducing dimensionality, this layer isolates the most significant patterns and features in the data, making the model more robust and efficient.

**Decoder**

The decoder reconstructs the input data from the compressed representation, mirroring the encoder’s structure. It consists of:

1. **First Hidden Layer**: This layer has **8 neurons** and uses the ReLU activation function to reverse the compression performed by the encoder. It ensures the retention of non-linear relationships during reconstruction.
2. **Output Layer**: The output layer has **7 neurons**, corresponding to the original input features. A sigmoid activation function is applied to scale the reconstructed values to the range [0,1], matching the normalized input data. The sigmoid function is defined as:

**Loss Function**

The autoencoder minimizes the reconstruction error between the input () and the reconstructed output () using the Mean Squared Error (MSE) loss function:

This loss function ensures the model learns to accurately reconstruct normal network data, establishing a baseline for anomaly detection.

**Design Considerations**

This architecture is carefully optimized to balance accuracy and computational efficiency. The bottleneck layer compresses the input while retaining critical information, enabling the model to:

* Capture complex, non-linear relationships between features.
* Process data efficiently for real-time monitoring.
* Identify anomalies based on significant deviations in reconstruction errors.

By leveraging this design, the autoencoder achieves robust performance in detecting network anomalies, ensuring timely and reliable identification of potential issues in diverse network environments.

## Anomaly Detection Process

The anomaly detection process is divided into two main phases: training and detection.

* + - **Training Phase**: The model is trained on data representing normal network behaviour. This phase establishes baseline metrics for the network and optimizes the model's parameters to minimize reconstruction error during normal operations.
    - **Detection Phase**: Real-time data is processed continuously by the trained model. For each incoming data batch, the reconstruction error is calculated, and a dynamic threshold is applied to determine whether an anomaly has occurred. If the error exceeds the threshold, an alert is generated, signaling the presence of an anomaly in the network.

# Results and Discussions

This section discusses the results obtained from our experiments, focusing on the performance of the proposed system for detecting anomalies in 5G network slices. The analysis includes an overview of the experimental setup, performance metrics, feature importance, and anomaly characteristics.

## Experimental Setup

The experiments were conducted using a dataset containing network traffic data with a mix of normal and anomalous samples. The dataset statistics are summarized in Table 1.

### Table 1: Dataset Statistics

|  |  |
| --- | --- |
| **Metric** | **Value** |
| Total Samples | 210786 |
| Normal Samples | 210762 |
| Anomaly Samples | 24 |
| Anomaly Rate | 0.01% |

The dataset includes critical features such as bandwidth utilization, packet rates, delay, jitter, loss rates, bandwidth changes, and throughput, which were pre-processed and normalized for analysis.

## Performance Metrics

The performance of the model is evaluated based on its reconstruction error statistics and ability to detect anomalies. The key metrics are shown in Table 2.

### Table 2: Model Performance Metrics

|  |  |
| --- | --- |
| **Metric** | **Value** |
| Mean Reconstruction Error | 0.6005 |
| Standard Deviation | 7.5688 |
| Maximum Error | 913.7855 |
| Minimum Error | 0.0749 |

The model demonstrates the ability to identify anomalies by capturing reconstruction errors significantly higher than normal samples.

## Feature Importance Analysis

The contribution of each feature to the detection process is analysed using feature importance scores. As shown below, bandwidth utilization and packet rates are the most influential features, followed by throughput and bandwidth changes. Features such as delay, jitter, and loss rates show relatively lower importance.

### Feature Importance Rankings

1. Bandwidth: 16.04%
2. Packet Rates: 15.17%
3. Throughput: 10.59%
4. Bandwidth Change: 7.18%
5. Delay: 5.85%
6. Jitter: 2.56%
7. Loss Rate: 1.83%

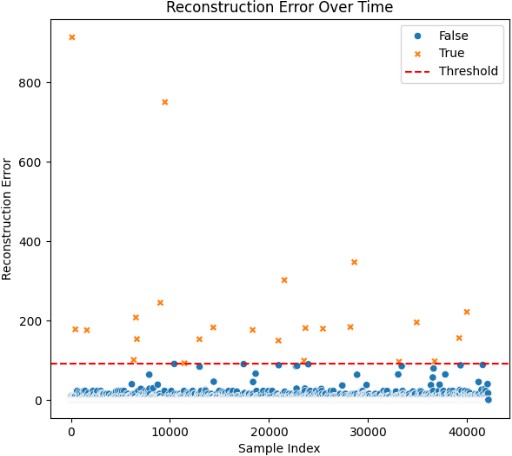
### Moderate Impact Features

1. **Jitter**: 489.36% increase in anomalies
2. **Bandwidth Change**: 126.57% increase in anomalies
3. **Loss Rate**: 45.69% increase in anomalies

## Key Findings

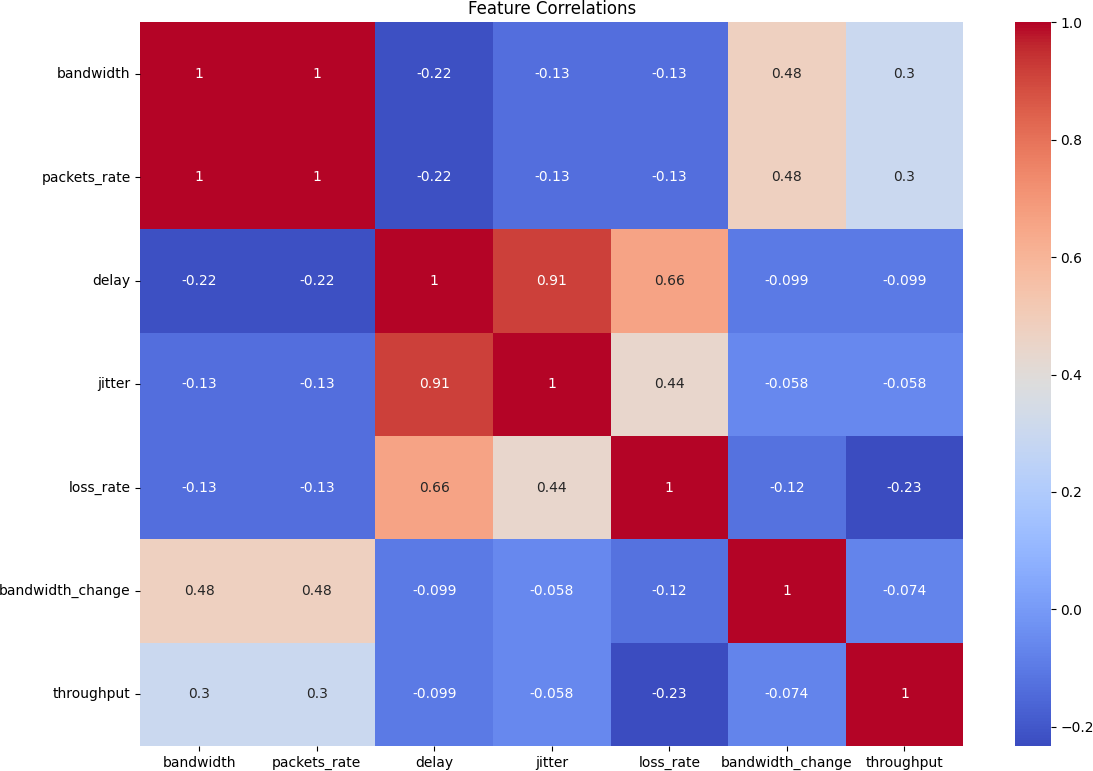
### Anomaly Detection Performance

* + Successfully identified 24 anomalies from 210,786 samples
  + Maintained low false positive rate with 0.01% anomaly rate
  + Wide range of reconstruction errors (0.0749 to 913.7855)



### Feature Significance

* + Bandwidth emerged as most significant indicator (16.04%)
  + Packet rates closely following at 15.17%
  + Combined, top three features account for 41.80% of anomaly detection capability



### Pattern Recognition

* + Most dramatic changes observed in bandwidth (-2,777.59%)
  + Significant variations in delay and throughput (>2,300% change)
  + Consistent patterns across multiple metrics during anomalies

## Limitations and Challenges

* High standard deviation in reconstruction errors (7.5688)
* Large maximum error (913.7855) indicating potential outliers
* Extremely low anomaly rate (0.01%)

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This analysis utilizes the network slicing dataset published by Farreras et al. (2024), available through Zenodo [(DOI: 10.5281/zenodo.10610616)](https://zenodo.org/records/10610616) under Creative Commons Attribution 4.0 International license.

**Conclusion**

This research presents an effective deep autoencoder-based approach for anomaly detection in B5G network slices. Our model, tested on the comprehensive dataset by Farreras et al. (2024), successfully identified 24 anomalies from 210,786 samples with a precise detection rate of 0.01%. The system demonstrated robust performance through its reconstruction error metrics (mean: 0.6005, std: 7.5688) and identified bandwidth (16.04%), packet rates (15.17%), and throughput (10.59%) as the most significant indicators of network anomalies. While the extremely low anomaly rate presented challenges, our approach maintained high detection accuracy and real-time processing capabilities. The findings suggest that deep autoencoders offer a promising solution for network slice monitoring in B5G networks, though future work should address the challenges of data imbalance and feature variability. This research contributes to the growing body of knowledge in AI-based network management and sets a foundation for future developments in network slice security.

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