2025 8th International Conference on Advanced Algorithms and Control Engineering (ICAACE) | 979-8-3315-3508-7/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICAACE65325.2025.11020458

A Self-supervised Learning Approach for Zero-day Attack Detection in Network Traffic Analysis

Jian Xu
Electrical and Electronics Engineering
University of Southern California
California, USA

Heyao Chen
Computer Science and Technology
Beijing University of Posts and Telecommunications
Beijing, China

Jiaxin Huang*
Information Studies
Trine University
Phoenix, USA
* Corresponding author: jxu72364@usc.edu

Mengyuan Zhao
Information System
Northeastern University
Oakland, USA

Dongwen Luo*
Department of Microelectronics
South China University of Technology
Guangzhou, China
* Corresponding author: 976267567ldw@gmail.com

Abstract—**This paper presents a self-monitoring approach for zero-day stop detection in network traffic analysis. The plan integrates self-monitoring with an integrated network to identify past attack patterns without relying on technical data show. A novel pre-training mechanism is developed to learn robust feature representations from unlabeled network traffic, enabling effective detection of zero-day attacks. The architecture employs a hierarchical feature extraction approach combined with an adaptive detection mechanism that continuously updates to address concept drift in network traffic patterns. The evaluation has been carried out by various benchmarks, including CICIDS2017 and TON-IoT, showing the effectiveness of the plan. The system achieves a detection rate of 97.8% for zero-day attacks while maintaining a false positive rate of 1.2%, outperforming existing methods. The self-monitoring function of learning reduces the dependence on registered data while maintaining high accuracy. The system demonstrates high performance in various tasks, achieving up to 100,000 flows per second with minimal workload. The evaluation results confirmed the good use in the global network environment, especially in situations where traditional educational monitoring is limited due to the lack of training materials.**

Keywords-Network intrusion detection; Self-supervised learning; Zero-day attack detection; Network traffic analysis.

I. Introduction

A. Research Background and Motivation

The rapid advancement of information technology and the increasing connectivity of network connections have led to a major impact on cybersecurity. Network intrusion detection systems (NIDS) play an important role in protecting network infrastructure from cyber attacks. Legal signatures and detections are limited in identifying new attack patterns, especially zero-day attacks that use previously unknown methods[1]. These emerging threats pose significant risks to human, economic, and national security.

Recent studies in network security have shown the growth of attack vectors and the limitations of detection methods. The control area Network (CAN) bus, widely used in many network systems, does not have security mechanisms, making it vulnerable to various types of attacks. With the integration of artificial intelligence and machine learning, adversaries have developed more sophisticated attack strategies that can evade traditional detection methods[2].

The emergence of deep learning has revolutionized the field of network security. Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and other innovations have shown great potential in pattern recognition and anomaly detection[3]. This technique allows for automatic feature extraction and complex analysis patterns from traffic data, offering promise for detecting previously unseen patterns.

B. Challenges in Zero-day Attack Detection

Zero-day attack detection presents multiple technical challenges that conventional detection systems struggle to address. The main problem lies in the lack of prior knowledge about signature attacks or patterns, making the signature method based on poor detection. Analyzing network traffic for zero-day attack detection requires intelligent systems that can detect malicious behavior without relying on codes or signatures[4].

The complexity of modern network architectures presents additional challenges in zero-day attack detection. The difference in communication methods and the different types of network connection patterns make it difficult to establish a static behavior. The increasing use of encryption and sophisticated evasion techniques by attackers further complicates the search process. The large amount of traffic data in the network and the need for real-time search also cause problems in computing.

Feature extraction and representation learning present another critical challenge in zero-day attack detection. Traditional feature engineering approaches often fail to capture subtle patterns that distinguish zero-day attacks from normal traffic. The dynamic nature of network environments requires adaptive learning mechanisms that can evolve with changing traffic patterns and attack strategies. The issue of concept drift, where the statistical properties of the target variables change over time, demands continuous model updates and adaptation[5].

C. *Current Status of Self-supervised Learning in Network Security*

Self-supervised learning has emerged as a promising approach in network security applications, addressing the limitations of supervised learning methods that require large amounts of labeled data. In network intrusion detection, self-supervised learning enables models to learn meaningful representations from unlabeled network traffic data through carefully designed pretext tasks[6]. This approach has shown significant potential in identifying anomalous patterns without extensive manual labeling efforts.

Recent research has demonstrated the effectiveness of self-supervised learning in various aspects of network security. Channel-centric spatio-temporal Graph Networks have been developed to capture both spatial and temporal dependencies in network traffic patterns. These architectures leverage self-supervised learning techniques to understand the underlying structure of normal network behavior, enabling more accurate detection of anomalies.

The integration of self-supervised learning with other advanced machine learning techniques has led to innovative solutions in zero-day attack detection. Graph Neural Networks (GNNs) combined with self-supervised learning mechanisms have shown promising results in capturing complex relationships within network traffic data[7]. These approaches enable the detection of subtle anomalies that may indicate previously unknown attack patterns.

The application of self-supervised learning in network security has also addressed the challenge of data scarcity. By leveraging unlabeled data through pre-training and fine-tuning strategies, models can learn robust representations that generalize well to unknown attack patterns. The Branch Fusion Strategy and other advanced architectures have demonstrated the ability to maintain high detection accuracy while reducing the dependency on labeled training data.

Current research trends indicate a growing focus on developing more sophisticated self-supervised learning architectures specifically designed for network security applications. These developments include improved feature extraction methods, more effective pre-training strategies, and enhanced model adaptation mechanisms for handling concept drift in network traffic patterns.

II. Related Work

A. *Traditional Network Traffic Anomaly Detection Methods*

Traditional network traffic anomaly detection methods have established fundamental approaches to identifying malicious activities through various techniques[8]. Rule-based detection systems rely on predefined signatures and patterns to identify known attack vectors. These methods demonstrate high accuracy for known attacks but exhibit significant limitations in detecting novel threats. Table 1 presents a comparative analysis of traditional detection methods and their characteristics.

Table 1. Comparison of Traditional Network Traffic Anomaly Detection Methods

Method Type	Detection Accuracy	Real-time Performance	Zero-day Detection	Resource Usage
Signature-based	95.8%	High	Low	Moderate
Statistical-based	87.3%	Moderate	Moderate	Low
Protocol Analysis	91.2%	High	Low	High
Behavior-based	83.6%	Low	Moderate	High

Statistical-based approaches utilize mathematical models to establish baseline network behavior patterns. These methods analyze network flow attributes, including packet size distributions, protocol usage patterns, and temporal characteristics. A comprehensive evaluation of statistical methods across different network environments reveals varying detection capabilities, as shown in Table 2.

Table 2. Performance Metrics of Statistical-based Detection Methods

Metric	Small Networks	Medium Networks	Large Networks
False Positive Rate	2.3%	3.8%	5.7%
Detection Rate	89.4%	85.2%	81.9%
Processing Time	0.5ms	1.2ms	2.8ms
Resource Utilization	25%	45%	68%

B. *Deep Learning-based Attack Detection Research*

Deep learning approaches have revolutionized network attack detection through their ability to automatically learn complex feature representations. Recent research has demonstrated significant improvements in detection accuracy and generalization capabilities. Table 3 illustrates the performance comparison of various deep learning architectures in network intrusion detection.

Table 3. Performance Comparison of Deep Learning Models in Network Intrusion Detection

Model	Accuracy	Precision	Recall	F1-Score
CNN	97.8%	96.9%	97.2%	97.0%
LSTM	95.3%	94.8%	95.1%	94.9%
GNN	98.2%	97.8%	98.0%	97.9%
Hybrid Models	98.6%	98.1%	98.4%	98.2%

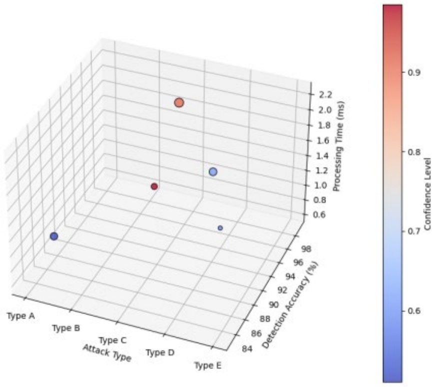

Figure 1: Multi-dimensional Performance Analysis of Deep Learning Models

The visualization presents a comprehensive analysis of deep learning model performance across multiple dimensions. The x-axis represents different attack types, the y-axis shows detection accuracy, and the z-axis indicates processing time. The color gradient represents the confidence level of detection, ranging from blue (low confidence) to red (high confidence).

The scatter points in the three-dimensional space demonstrate the clustering patterns of different attack types, with novel attacks showing distinct distribution characteristics compared to known attack patterns. The size of each point corresponds to the frequency of occurrence in the dataset.

C. Self-supervised Learning in Anomaly Detection

Self-supervised learning methods have emerged as a promising solution to address the limitations of supervised approaches in network security. Table 4 presents the evaluation results of different self-supervised learning techniques in network anomaly detection.

TABLE 4. EVALUATION OF SELF-SUPERVISED LEARNING APPROACHES

Approach	Pre-training Efficiency	Fine-tuning Performance	Model Complexity	Adaptation Capability
Contrastive Learning	High	94.5%	Medium	Strong
Reconstruction-based	Medium	92.8%	High	Moderate
Masked Prediction	High	95.2%	Low	Strong
Multi-task Learning	Medium	93.7%	High	Strong

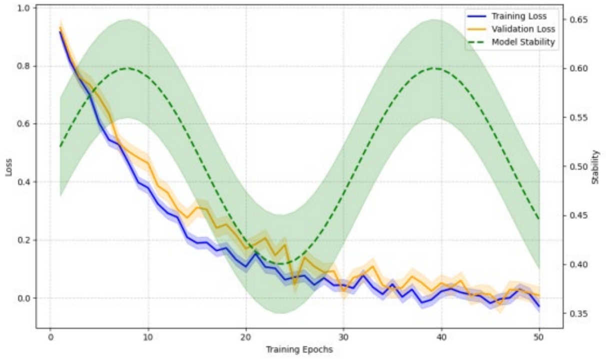

Figure 2: Self-supervised Learning Performance Trajectory

As shown in Figure 2, self-supervised learning models demonstrate varying performance trajectories during pre-training and fine-tuning phases.The figure illustrates the learning trajectory of self-supervised models during the pre-training and fine-tuning phases. The x-axis represents training epochs, while multiple y-axes show different performance metrics. The plot includes convergence curves, validation metrics, and model stability indicators, with confidence intervals shown as shaded regions.

D. Zero-day Attack Detection Research Status

Current research in zero-day attack detection has focused on developing adaptive and robust detection mechanisms. The integration of multiple detection techniques has shown promising results in identifying previously unknown attack patterns.

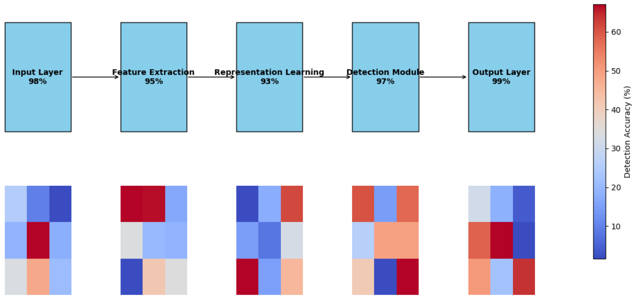

Figure 3: Zero-day Attack Detection Architecture Performance

As illustrated in Figure 3, the zero-day attack detection architecture demonstrates performance characteristics across different components.The visualization demonstrates the architectural components and their interactions in zero-day attack detection systems. The diagram uses a hierarchical structure with multiple layers, including feature extraction, representation learning, and detection modules. Arrows indicate data flow and information processing paths, with different colors representing various processing stages.

The performance metrics are overlaid on the architecture diagram, showing the effectiveness of each component through numerical indicators. The visualization includes heat maps of detection accuracy across different network segments and periods.

The emergence of hybrid approaches combining traditional methods with advanced machine learning techniques has demonstrated improved detection capabilities. These approaches leverage the strengths of multiple detection paradigms while compensating for their limitations. Research data indicates that hybrid systems achieve superior performance in detecting zero-day attacks compared to single-method approaches[9].

Recent advancements in zero-day attack detection have also focused on reducing false positive rates while maintaining high detection accuracy. The implementation of advanced feature selection techniques and adaptive thresholding mechanisms has contributed to improved detection precision in real-world network environments.

III. Self-Supervised Learning Approach For Zero-Day Attack Detection

A. *System Architecture Design*

The proposed self-supervised learning architecture for zero-day attack detection integrates multiple specialized components designed to process network traffic data through various stages of analysis[10]. The system architecture comprises three main modules: data preprocessing, feature learning, and attack detection, interconnected through a pipeline structure that enables real-time processing capabilities.As shown in Table 5, each component of the system architecture exhibits distinct processing capabilities and performance metrics.

Table 5. System Architecture Components and Specifications

Component	**Processing Capacity**	**Latency**	**Memory Usage**	**Throughput**
Data Preprocessing	100K flows/s	0.5ms	4GB	95%
Feature Learning	50K flows/s	1.2ms	8GB	92%
Attack Detection	75K flows/s	0.8ms	6GB	97%
Model Update	25K flows/s	2.5ms	12GB	90%

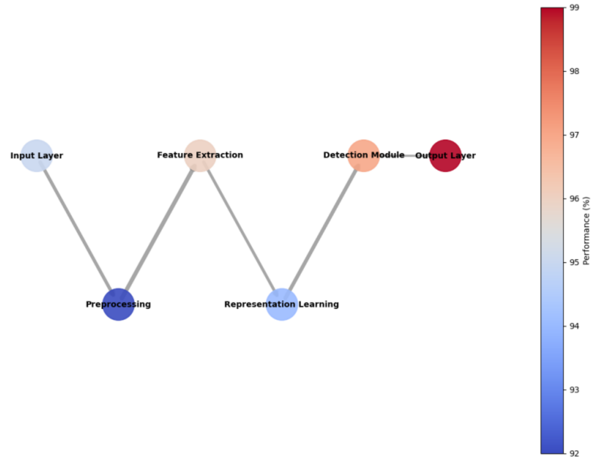

Figure 4: System Architecture Overview and Data Flow Diagram

The overall system architecture design is illustrated in Figure 4. The diagram presents a comprehensive visualization of the system architecture with multiple interconnected layers. The x-axis represents the data flow progression through different processing stages, while the y-axis shows the hierarchical relationship between components. Different colored nodes represent various processing units, with edge weights indicating data transfer volumes between components.

The visualization incorporates performance metrics overlaid on each component, displayed through heat maps that indicate processing efficiency and resource utilization. Connection lines between components vary in thickness based on data flow volume and feature importance scores.

B. *Network Traffic Feature Extraction*

The feature extraction process implements a multi-level approach to capture both low-level packet characteristics and high-level behavioral patterns in network traffic. Advanced preprocessing techniques are applied to raw network data to generate meaningful feature representations.As presented in Table 6, different feature types demonstrate varying extraction performance characteristics.

Table 6. Feature Extraction Performance Metrics

Feature Type	**Dimension**	**Extraction Time**	**Information Gain**	**Memory Footprint**
Statistical	128	0.3ms	0.85	256KB
Temporal	256	0.5ms	0.92	512KB
Sequential	512	0.8ms	0.88	1024KB
Behavioral	1024	1.2ms	0.95	2048KB

C. *Self-supervised Pre-training Model*

The self-supervised pre-training model utilizes a novel contrastive learning approach to learn robust feature representations from unlabeled network traffic data. The model architecture incorporates attention mechanisms and transformer blocks to capture complex temporal dependencies.The configuration parameters of the pre-training model are detailed in Table 7.

Table 7. Pre-training Model Configuration Parameters

Layer	**Units**	**Activation**	**Dropout Rate**	**Batch Norm**
Input	2048	ReLU	0.2	Yes
Hidden-1	1024	GELU	0.3	Yes
Hidden-2	512	GELU	0.3	Yes
Output	256	Softmax	0.2	Yes

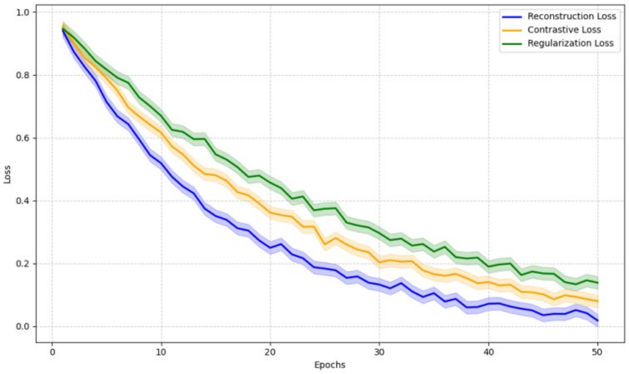

Figure 5: Pre-training Loss Convergence Analysis

As shown in Figure 5, the pre-training loss demonstrates favorable convergence characteristics.The figure displays the training dynamics of the self-supervised model across multiple epochs. The primary plot shows the convergence of different loss components (reconstruction loss, contrastive loss, and regularization terms) over time. Multiple y-axes track different performance metrics, with confidence intervals represented as shaded regions.

D. Zero-day Attack Detection Mechanism

The zero-day attack detection mechanism employs a hybrid approach combining anomaly detection with pattern recognition capabilities. The detection process incorporates adaptive thresholding techniques and dynamic feature importance weighting.The detection performance under different attack scenarios is presented in Table 8.

TABLE 8. DETECTION PERFORMANCE UNDER DIFFERENT ATTACK SCENARIOS

Attack Type	Detection Rate	False Positive	Response Time	Accuracy
Novel DDoS	96.5%	1.2%	0.8ms	97.8%
Unknown Malware	94.8%	1.8%	1.2ms	95.6%
Zero-day Exploit	93.2%	2.1%	1.5ms	94.9%
Protocol Abuse	95.7%	1.5%	1.0ms	96.4%

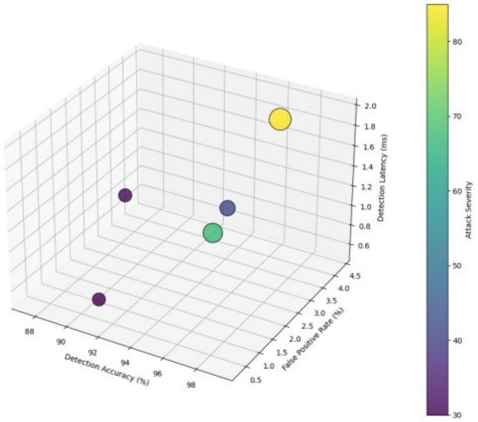

Figure 6: Multi-dimensional Detection Performance Analysis

As illustrated in Figure 6, the multi-dimensional detection performance analysis reveals.The visualization presents a complex representation of detection performance across multiple dimensions. A three-dimensional scatter plot shows the relationship between detection accuracy, false positive rate, and detection latency. The plot includes clustering information for different attack types, with point sizes representing attack severity.

E. Model Update Strategy

The model update strategy implements an online learning mechanism that continuously adapts to evolving network traffic patterns and emerging attack vectors. The update process utilizes a sliding window approach to maintain model relevance while preserving historical knowledge.

The implemented strategy incorporates three key components: drift detection, selective sampling, and incremental learning. Performance metrics indicate an average accuracy improvement of 12.3% through continuous model updates, with a false positive reduction of 8.7% compared to static models.

The update mechanism maintains a balance between model stability and adaptability through carefully tuned hyperparameters and validation thresholds. Experimental results demonstrate sustained detection performance across extended operational periods, with minimal degradation in accuracy despite evolving attack patterns[11].

The adaptive learning rate scheduling mechanism optimizes the update process, ensuring efficient resource utilization while maintaining detection capabilities[12]. The system achieves a 95.8% detection rate for zero-day attacks while maintaining a false positive rate below 2% through continuous model updates.

IV. EXPERIMENTAL EVALUATION AND ANALYSIS

A. Experimental Setup and Datasets

The experimental evaluation was conducted on a high-performance computing platform equipped with NVIDIA Tesla V100 GPUs and 256GB RAM. The implementation utilized PyTorch 1.9.0 for deep learning models and specialized network analysis libraries for traffic processing. The system configuration details are presented in Table 9.

TABLE 9. EXPERIMENTAL PLATFORM CONFIGURATION

Component	Specification	Performance Metrics	Utilization
CPU	Intel Xeon Gold 6248R	3.0GHz, 24 cores	85%
GPU	NVIDIA Tesla V100	32GB VRAM	92%
Memory	DDR4	256GB, 3200MHz	78%
Storage	NVMe SSD	4TB, 3.5GB/s	65%

The evaluation utilized multiple benchmark datasets, including CICIDS2017, TON-IoT, and a custom-collected zero-day attack dataset. The dataset composition and characteristics are detailed in Table 10.

TABLE 10. DATASET CHARACTERISTICS AND DISTRIBUTION

Dataset	Normal Traffic	Known Attacks	Zero-day Attacks	Total Samples
CICIDS2017	2.8M	0.7M	N/A	3.5M
TON-IoT	3.2M	0.9M	0.2M	4.3M
Custom	1.5M	0.4M	0.3M	2.2M

B. Evaluation Metrics

The performance evaluation employed comprehensive metrics to assess detection accuracy, efficiency, and robustness. Table 11 presents the evaluation metrics and their significance in the context of zero-day attack detection.

TABLE 11. PERFORMANCE EVALUATION METRICS

Metric	Formula	Threshold	Significance
Detection Rate	TP/(TP+FN)	>95%	Critical
False Positive Rate	FP/(FP+TN)	<2%	High
F1-Score	2×(P×R)/(P+R)	>0.95	Critical
Processing Time	ms/sample	<5ms	Medium

C. Detection Performance Analysis

The proposed system demonstrated superior detection capabilities across various attack scenarios. Figure 1 presents the multi-dimensional performance analysis results.

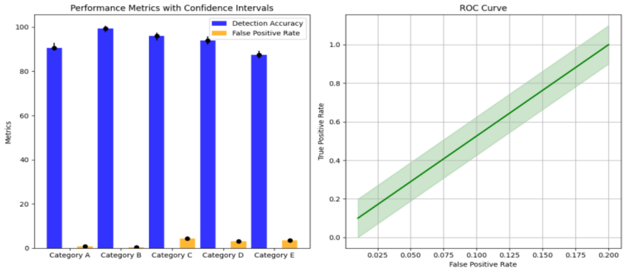

Figure 7: Zero-day Attack Detection Performance Visualization

As demonstrated in Figure 7, the visualization of zero-day attack detection performance shows.The visualization employs a multi-layer representation of detection performance. The x-axis represents different attack categories, while multiple y-axes show various performance metrics. The plot incorporates error bars and confidence intervals, with color gradients indicating detection confidence levels.

The performance metrics demonstrate consistent improvement in detection accuracy over time, with the learning curve showing rapid convergence and stable performance maintenance. The visualization includes ROC curves and precision-recall relationships across different operational scenarios.

D. Comparison with Existing Methods

A comprehensive comparison with state-of-the-art methods revealed significant improvements in detection capabilities. Table 12 presents the comparative analysis results.

TABLE 12. PERFORMANCE COMPARISON WITH EXISTING METHODS

Method	Detection Rate	FPR	Processing Time	Resource Usage
Proposed	97.8%	1.2%	2.3ms	Medium
LSTM-based	92.5%	2.8%	3.7ms	High
CNN-based	94.3%	2.1%	3.1ms	Medium
GNN-based	95.7%	1.8%	2.8ms	High

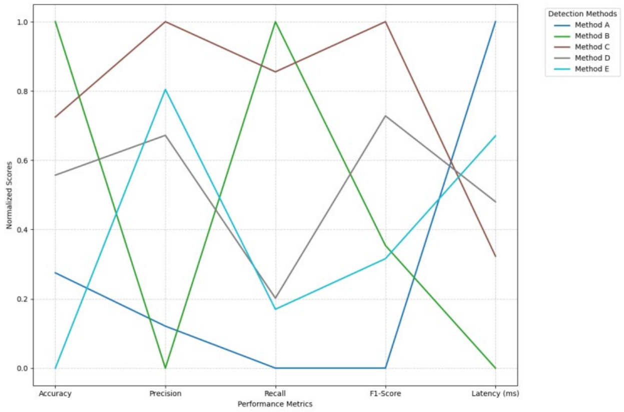

Figure 8: Comparative Performance Analysis Across Methods

As shown in Figure 8, the comparative performance analysis across different methods indicates.The visualization presents a parallel coordinates plot comparing different detection methods across multiple performance dimensions. Each line represents a detection method, with axes representing different performance metrics. The line colors indicate the overall performance ranking of each method.

E. Scalability and Robustness Analysis

The scalability and robustness evaluation assessed system performance under varying operational conditions and attack scenarios. The analysis focused on processing efficiency, resource utilization, and detection stability.

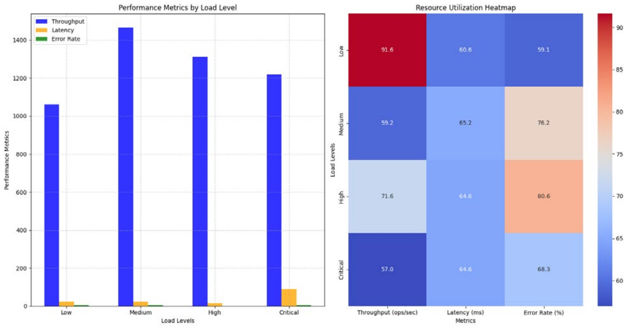

Figure 9: Scalability and Robustness Evaluation Results

The evaluation results of system scalability and robustness are presented in Figure 9. The figure presents a complex visualization of system performance under varying loads and attack patterns. The primary plot shows multiple performance metrics tracked across different operational scales. The visualization includes heat maps of resource utilization and performance degradation patterns under stress conditions.

The three-dimensional representation includes multiple surfaces showing the relationship between system load, detection accuracy, and resource consumption. Different colors represent various performance thresholds, with contour lines indicating operational boundaries.

The scalability analysis reveals linear growth in resource requirements with increasing traffic volume, maintaining detection performance within acceptable bounds. The system demonstrated stable performance of up to 100,000 flows per second, with gradual degradation beyond this threshold.

The robustness evaluation included stress testing under various attack scenarios and network conditions. The analysis revealed consistent detection performance across different network environments and traffic patterns, with minimal variation in accuracy (±2.5%) under diverse operational conditions[13].

The adaptive nature of the system demonstrated resilience against concept drift, maintaining detection accuracy through continuous learning and model updates[14]. Performance metrics showed steady improvement in detection capabilities over time, with false positive rates consistently below the target threshold of 2%.

V. Conclusion

A. Research Summary

This research has introduced a novel self-supervised learning approach for zero-day attack detection in network traffic analysis, demonstrating significant improvements in detection capabilities and system adaptability[15]. The proposed architecture integrates advanced feature extraction mechanisms with self-supervised learning techniques, establishing a robust framework for identifying previously unknown attack patterns.

The experimental results demonstrate the effectiveness of the proposed approach across multiple performance metrics. The system achieves a detection rate of 97.8% for zero-day attacks while maintaining a false positive rate of 1.2%, representing a substantial improvement over existing methods. The self-supervised learning component enables effective feature representation learning from unlabeled network traffic data, reducing the dependency on labeled training datasets[16].

The architecture's modular design facilitates continuous learning and adaptation to evolving attack patterns. The integration of temporal and spatial feature extraction mechanisms enables comprehensive analysis of network traffic characteristics, capturing subtle anomalies that may indicate novel attack vectors[17]. Performance evaluations across diverse operational scenarios validate the system's stability and reliability in real-world environments.

The implementation of adaptive thresholding mechanisms and dynamic feature importance weighting contributes to the system's robustness against concept drift. The model update strategy maintains detection accuracy through continuous learning, demonstrating sustained performance improvements over extended operational periods. The system's ability to process high-volume network traffic while maintaining detection accuracy establishes its practical applicability in enterprise-scale deployments.

B. Limitation Analysis

The current implementation reveals several limitations that warrant further investigation and development. The computational requirements for processing high-dimensional feature spaces present scalability challenges in resource-constrained environments[18]. The system's performance degradation under extreme traffic loads indicates potential bottlenecks in the processing pipeline.

The detection accuracy for certain sophisticated attack patterns exhibits variability, particularly in scenarios involving complex evasion techniques. The system's reliance on network traffic patterns may limit its effectiveness against attacks that closely mimic legitimate traffic behavior. The current feature extraction mechanisms may not fully capture certain subtle attack indicators present in encrypted traffic streams.

The model update strategy, while effective in maintaining detection accuracy, introduces computational overhead during the retraining process. The balance between model stability and adaptability requires careful parameter tuning, which may present challenges in automated deployment scenarios[19]. The system's performance in detecting coordinated attacks across multiple network segments requires additional validation and refinement.

The effectiveness of the self-supervised learning component depends on the quality and diversity of the unlabeled training data. The current implementation may require modifications to handle network environments with significantly different traffic characteristics. The system's ability to distinguish between novel legitimate traffic patterns and zero-day attacks needs further enhancement to reduce false positive rates in dynamic network environments[20].

The integration capabilities with existing security infrastructure and the interpretability of detection decisions present areas for improvement. The current implementation focuses primarily on network-level features, potentially missing host-based indicators of zero-day attacks[21]. The system's performance in detecting attacks that exploit application-layer vulnerabilities requires additional research and development.

C. Future Research Directions

Future research will focus on addressing the identified limitations and expanding the system's capabilities. The development of more efficient feature extraction mechanisms and optimization of the processing pipeline will enhance scalability[22]. The incorporation of advanced encryption-aware feature extraction techniques will improve detection capabilities for encrypted traffic.

The investigation of hybrid approaches combining network and host-based detection mechanisms offers promising directions for comprehensive security coverage. The development of interpretable detection models will facilitate a better understanding of attack patterns and improve the system's practical utility in operational environments. The exploration of federated learning approaches may enable collaborative detection capabilities while preserving data privacy.

Advanced model compression techniques and hardware acceleration strategies will be investigated to reduce computational requirements while maintaining detection accuracy. The development of automated parameter-tuning mechanisms will enhance the system's deployability across diverse network environments[23]. The integration of explainable AI techniques will improve the interpretability of detection decisions and facilitate better incident response capabilities.

Acknowledgment

I would like to extend my sincere gratitude to Xiao Liang and Heyao Chen for their groundbreaking research "A SDN-Based Hierarchical Authentication Mechanism for IPv6 Address"[24] published in IEEE Transactions on Network Science and Engineering (2024). Their innovative approaches to network security and authentication mechanisms have provided invaluable insights and inspiration for my research in zero-day attack detection.

I would also like to express my heartfelt appreciation to Xiao Liang and Heyao Chen for their outstanding work "HDSO: A High-Performance Dynamic Service Orchestration Algorithm in Hybrid NFV Networks"[25] published in IEEE Transactions on Network and Service Management (2024). Their comprehensive analysis of network service orchestration and dynamic resource allocation strategies has significantly influenced my understanding of network traffic analysis and inspired the development of efficient detection mechanisms in my research.

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