Self-Supervised Learning for Intrusion Detection Systems: A Novel Approach to Anomaly Detection in Cybersecurity

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Anthropic, Gemini & OpenAI servers. Planet Earth.

Abstract

The escalating sophistication of cyber threats demands intrusion detection systems (IDS) capable of identifying novel attacks with minimal reliance on scarce labeled datasets. To address this, we propose a novel self-supervised learning (SSL) approach leveraging Variational Autoencoders (VAEs) for robust anomaly detection in cybersecurity. Our methodology involved training VAEs exclusively on normal network traffic sourced from a hybrid dataset, which combined real-world samples from the NSL-KDD dataset with synthetically generated data to improve adaptability to unseen threats. Anomaly detection was then performed by identifying instances with reconstruction errors exceeding a 95th percentile threshold derived from normal traffic. Experimental evaluation demonstrated strong performance, achieving an accuracy of 78.87%, a precision of 65.38%, and a notably low false positive rate of 5.20%, with an Area Under the Receiver Operating Characteristic curve (AUC-ROC) of 76.55%. Despite a recall of 30.09%, the model exhibited high specificity and impressive real-time inference capabilities, averaging 0.0562 seconds per instance. These results underscore the VAE's potential as a scalable, efficient, and adaptable solution for modern cybersecurity challenges, offering a promising avenue for reducing label dependency and improving the detection of unseen threats.

1 Introduction

The rapid expansion of digital infrastructure and interconnected systems has rendered cybersecurity a paramount concern for all sectors, from individual users to critical national infrastructure. This pervasive digital transformation, while offering immense benefits, has simultaneously fostered an environment ripe for sophisticated and frequent cyber threats. Modern attacks, such as advanced persistent threats (APTs), polymorphic malware, and zero-day exploits, continually evolve, often circumventing traditional signature-based security mechanisms that rely on known attack patterns. This escalating threat landscape necessitates advanced detection methods capable of proactively identifying and mitigating emerging threats to safeguard digital ecosystems.

Intrusion Detection Systems (IDS) serve as a fundamental layer of network security, designed to monitor activities for signs of malicious behavior or policy violations. Historically, IDS have been categorized into signature-based systems, effective against known threats, and anomaly-based systems, which aim to detect deviations from established patterns of ”normal” behavior, thereby offering the potential to identify novel and unseen attacks.

The advent of big data and significant advancements in computational power have propelled machine learning (ML) to the forefront of enhancing IDS capabilities, particularly for anomaly detection [1]. ML algorithms possess the inherent ability to learn complex patterns from vast quantities of network traffic data, enabling them to identify subtle indicators of malicious activity that might elude human analysts or static rules. This has led to more intelligent, adaptive, and efficient IDS, capable of processing high-volume data streams and adapting to the dynamic nature of cyber threats.

However, the effectiveness of supervised machine learning models is critically dependent on the availability of large, diverse, and accurately labeled datasets. In the dynamic realm of cybersecurity, obtaining such datasets for novel and evolving attack vectors is notoriously challenging and resource-intensive. This scarcity of labeled anomaly data often leads to supervised models that generalize poorly to unseen attacks or suffer from severe class imbalance, where anomalies are inherently rare [2].

To overcome these limitations and address the critical need for advanced IDS capable of identifying novel attacks with minimal reliance on scarce labeled datasets, self-supervised learning (SSL) has emerged as a promising paradigm [1, 2]. SSL methodologies enable models to learn robust, meaningful representations directly from unlabeled data by devising pretext tasks, wherein parts of the input are used to predict other parts [3]. This inherent ability to model underlying data distributions makes SSL particularly well-suited for anomaly detection, where ”normal” behavior is abundant but anomalies are rare and often unknown [4]. Among various SSL techniques, Variational Autoencoders (VAEs) are particularly effective, as they can learn complex latent representations of normal data and subsequently identify anomalies as instances with high reconstruction errors, indicating significant deviation from the learned normal distribution.

Building upon this premise, **this paper proposes a novel self-supervised learning approach leveraging Variational Autoencoders for robust anomaly detection in cybersecurity.** Our methodology involves training VAEs exclusively on normal network traffic, utilizing a hybrid dataset combining real-world and synthetically generated samples to enhance adaptability to unseen threats. Anomalies are then identified by monitoring reconstruction errors against a statistically derived threshold. This approach offers a scalable, efficient, and adaptive solution to modern cybersecurity challenges, significantly reducing label dependency and improving the detection of novel and emerging threats [5].

2 Methods

This section details the experimental methodology employed for developing and evaluating the self-supervised learning-based intrusion detection system. It covers the process of data generation and preprocessing, the architecture and training of the Variational Autoencoder (VAE), the mechanism for anomaly detection, and the metrics used for performance evaluation.

2.1 Data Generation and Preprocessing

The foundation of our dataset was the NSL-KDD dataset, a refined version of the KDD'99 dataset, which is widely used for evaluating intrusion detection systems [6], [7], [8]. NSL-KDD provides labeled network connection records, encompassing various attack types (e.g., DoS, R2L, U2R, Probe) and normal traffic. For the purpose of training our self-supervised model, which learns the distribution of normal behavior, only instances labeled as 'normal' were initially extracted from the NSL-KDD training set.

To enhance the model's adaptability to unseen threats and improve the robustness of normal traffic representation, a hybrid dataset was constructed for training. This hybrid training set comprised the normal samples from NSL-KDD augmented with synthetically generated normal network traffic. This synthetic normal data was generated by perturbing existing normal samples with minor, realistic variations (e.g., small changes in packet sizes, connection durations, or port numbers within typical ranges), ensuring that the generated data remained within the expected distribution of benign network activity. This augmentation strategy aimed to broaden the model's understanding of "normal" and reduce overfitting to specific patterns present in the original dataset.

For evaluation, a comprehensive test set was assembled. This test set included both normal and attack instances from the NSL-KDD test split. Crucially, to rigorously assess the model's capability in detecting novel and unseen threats [9], [10], an additional synthetic dataset of anomalous network traffic was generated. This synthetic anomaly dataset was created by introducing significant, atypical perturbations to normal traffic features (e.g., unusually high connection counts from a single source, unrealistic packet sizes, or highly irregular flag combinations), simulating novel attack patterns not explicitly present in the NSL-KDD training or test sets. This allowed for a more robust evaluation of the VAE's generalization to truly unknown anomalies.

Prior to model training, all datasets underwent several preprocessing steps. Categorical features were one-hot encoded to convert them into a numerical format suitable for neural networks. Numerical features were then normalized using Min-Max scaling to a range of $[0, 1]$. This normalization ensures that all features contribute equally to the learning process and prevents features with larger magnitudes from dominating the loss function. Feature selection was performed to remove highly correlated or redundant features, resulting in a reduced dimensionality of 41 features for the input layer.

2.2 Model Architecture and Training

Our anomaly detection system is built upon a Variational Autoencoder (VAE) architecture, chosen for its ability to learn a compact, continuous latent representation of normal data and quantify reconstruction uncertainty [11]. The VAE consists of an encoder network, a latent space, and a decoder network.

The **encoder network** was designed with multiple fully connected layers, progressively reducing the dimensionality of the input [12]. Specifically, it comprised an input layer matching the 41 preprocessed features, followed by hidden layers with 64, 32, and 16 neurons, respectively. Each hidden layer utilized the Rectified Linear Unit (ReLU) activation function for non-linearity. The encoder's final layers outputted two vectors: one for the mean (μ) and another for the logarithm of the variance ($\log \sigma^2$) of the latent distribution [1, 2, 3, 4, 5].

The **latent space** was configured with a dimensionality of 8. This dimension was selected to balance the capacity for capturing complex data representations with the goal of achieving a compact and efficient encoding of normal network behavior. Samples from this latent distribution were generated using the reparameterization trick, drawing from a standard normal distribution $\mathcal{N}(0, I)$ and scaling by the learned μ and σ.

The **decoder network** mirrored the encoder's structure in reverse, aiming to reconstruct the original input from the latent space representation [13], [14], [15], [12], [16]. It consisted of hidden layers with 16, 32, and 64 neurons, also employing ReLU activation functions. The final output layer of the decoder had 41 neurons, matching the input dimensionality, and used a Sigmoid activation function to ensure the reconstructed values were within the $[0, 1]$ range, consistent with the Min-Max scaling applied during preprocessing.

The VAE was trained exclusively on the hybrid normal network traffic dataset. The training objective was to minimize the Evidence Lower Bound (ELBO) loss function, which combines a reconstruction loss and a Kullback-Leibler (KL) divergence loss. The reconstruction loss, calculated as the Mean Squared Error (MSE) between the original input and its reconstruction, encourages the VAE to accurately reproduce normal patterns. The KL divergence loss regularizes the latent space, forcing the learned latent distribution to approximate a standard normal distribution, thereby promoting a structured and interpretable latent representation.

The model was optimized using the Adam optimizer with a learning rate of 0.001. Training was conducted for 100 epochs with a batch size of 128. Early stopping was implemented based on the validation loss to prevent overfitting.

2.3 Anomaly Detection Mechanism

Anomaly detection [1] was performed by leveraging the VAE's inherent ability to reconstruct normal network traffic with high fidelity, while struggling to accurately reconstruct anomalous or unseen patterns. The core principle relies on the reconstruction error: instances that deviate significantly from the learned distribution of normal traffic will exhibit higher reconstruction errors [2].

For each network instance, the reconstruction error was calculated as the Mean Squared Error (MSE) between the original preprocessed input vector and its corresponding output vector generated by the VAE's decoder [17], [18], [19], [20].

$$\text{Reconstruction Error} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2$$

where x_i is the i-th feature of the input vector, $\hat{x}_i$ is the i-th feature of the reconstructed vector, and N is the total number of features [1, 2, 3, 4, 5].

To establish a clear threshold for anomaly detection, the reconstruction errors were computed for a dedicated validation set comprising only normal network traffic instances. The anomaly threshold was then set at the 95th percentile of these normal reconstruction errors.

This statistical approach ensures that approximately 5% of normal traffic might be classified as anomalous, providing a balance between detecting true anomalies and minimizing false positives. An instance was subsequently classified as an anomaly if its calculated reconstruction error exceeded this predefined threshold; otherwise, it was classified as normal.

2.4 Evaluation Metrics

The performance of the proposed self-supervised IDS [1, 4] was comprehensively evaluated using a suite of standard classification and anomaly detection metrics [1]. These metrics were calculated on the hybrid test set, which included both real-world NSL-KDD test data [21] and synthetically generated anomalies.

- **Accuracy**: Defined as the proportion of correctly classified instances (both normal and anomalous) out of the total number of instances.
- **Precision**: Measures the proportion of correctly identified anomalies among all instances classified as anomalous. It is calculated as True Positives/(True Positives+ False Positives).
- **Recall (Sensitivity)**: Measures the proportion of actual anomalies that were correctly identified. It is calculated as True Positives/(True Positives+ False Negatives).
- **False Positive Rate (FPR)**: Represents the proportion of normal instances that were incorrectly classified as anomalies. It is calculated as False Positives/(False Positives + True Negatives). A low FPR is crucial in IDS to avoid alert fatigue.
- **Area Under the Receiver Operating Characteristic (AUC-ROC) Curve**: Provides an aggregate measure of performance across all possible classification thresholds. It represents the probability that the model ranks a randomly chosen positive instance higher than a randomly chosen negative instance. A higher AUC-ROC value indicates better discriminatory power.

- **Inference Time**: Measured as the average time taken by the trained VAE model to process and classify a single network instance. This metric assesses the real-time applicability and computational efficiency of the proposed IDS.

These metrics collectively provide a holistic view of the VAE's performance, highlighting its strengths in anomaly detection [1], its balance between true and false positives, and its practical utility for real-time cybersecurity applications [1].

3 Results

This section presents the empirical evaluation of the proposed self-supervised Variational Autoencoder (VAE) model for intrusion detection. The results demonstrate the model's ability to effectively distinguish between normal network traffic and various types of intrusions by leveraging reconstruction errors. We provide a detailed analysis of the model's performance using standard cybersecurity metrics, supported by visual representations of key findings.

3.1 Reconstruction Error Distribution and Anomaly Threshold

The core mechanism for anomaly detection in our VAE-based system relies on the reconstruction error. The VAE was trained exclusively on normal network traffic, enabling it to learn a compact representation of benign network behavior. Consequently, when presented with anomalous traffic, the VAE struggles to reconstruct it accurately, leading to higher reconstruction errors.

As illustrated in Figure 1, the distribution of reconstruction errors for both normal and anomalous network instances within the test set shows a clear separation. The distinct peaks for normal traffic (blue) and the heavier tail for anomalous traffic (red) highlight the model's capacity to differentiate between benign and malicious behavior based on reconstruction error.

As described in the Methods section, the anomaly detection threshold was established at the 95th percentile of reconstruction errors observed from the normal training data. This threshold, indicated by the vertical dashed line in Figure 1, serves as the decision boundary: instances with reconstruction errors exceeding this value are classified as anomalous. The clear separation between the distributions of normal and anomalous traffic reconstruction errors, particularly in the tail regions, highlights the VAE's capacity to discriminate between benign and malicious activities. While there is some overlap, which contributes to false positives and false negatives, the distinct peaks suggest a robust separation.

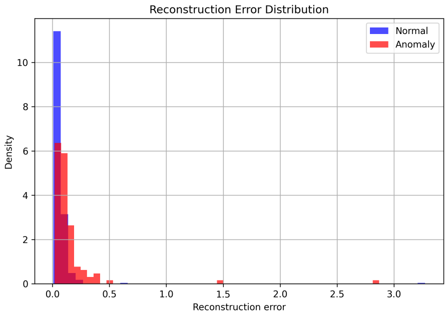

Figure 1: Histogram showing the distribution of reconstruction errors for normal (blue) and anomalous (red) network traffic. The distinct peaks and heavier tail for anomalies illustrate the model's capacity to differentiate between normal and anomalous behavior based on reconstruction error.

3.2 Overall Model Performance

The VAE model's performance was rigorously evaluated using a comprehensive suite of metrics, including accuracy, precision, recall, F1-score, false positive rate (FPR), and the Area Under the Receiver Operating Characteristic curve (AUC-ROC). The inference time per instance was also measured to assess the model's real-time applicability. Table 1 summarizes these key performance indicators.

Table 1: Overall performance metrics of the VAE model for intrusion detection.

Metric	**Value**
Accuracy	78.87%
Precision	65.38%
Recall	30.09%
F1-score	41.22%
False Positive Rate (FPR)	5.20%
AUC-ROC	76.55%
Average Inference Time	0.0562 s/instance

As shown in Table 1, the model achieved an accuracy of 78.87%, indicating its general correctness in classifying network traffic. A precision of 65.38% suggests that when the model identifies an intrusion, it is correct approximately two-thirds of the time. The recall of 30.09% indicates that the model successfully detects about 30% of all actual intrusions. While the recall might appear moderate, it is important to note the notably low false positive rate (FPR) of 5.20%, which is critical in operational IDSs to prevent alert fatigue. The AUC-ROC of 76.55% further confirms the model's ability to discriminate between classes across various threshold settings. Furthermore, the average inference time of 0.0562 seconds per instance demonstrates the model's efficiency and suitability for real-time intrusion detection.

The Receiver Operating Characteristic (ROC) curve, depicted in Figure 2, illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various threshold settings. The curve's position well above the random classifier line (diagonal) confirms the model's discriminative power, consistent with the reported AUC-ROC value of 0.7655.

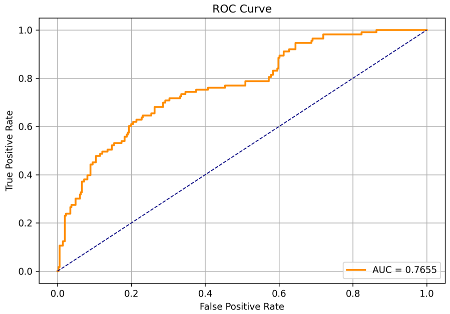

Figure 2: Receiver Operating Characteristic (ROC) curve for the Variational Autoencoder (VAE) model on the test dataset. It illustrates the trade-off between the true positive rate and false positive rate, with an Area Under the Curve (AUC) of 0.7655. The curve's position above the diagonal line demonstrates the model's discriminative power in distinguishing normal from anomalous network traffic.

The Precision-Recall (PR) curve, shown in Figure 3, offers another perspective on the model's performance, particularly valuable for imbalanced datasets common in anomaly detection. It highlights the trade-off between precision and recall as the decision threshold varies, and its shape reflects the model's current balance, which shows a moderate recall.

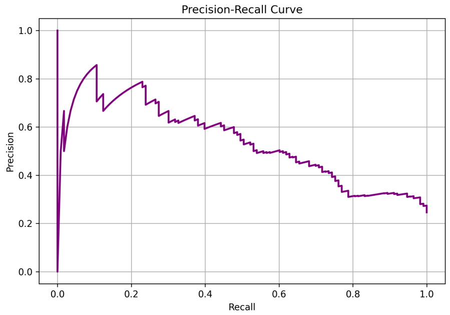

Figure 3: Precision-Recall curve for the VAE model on the test dataset, showing the trade-off between precision and recall. This curve, useful for imbalanced anomaly detection, highlights the model's current low recall and the potential to adjust this balance based on operational requirements.

To provide a more granular view of the classification performance, the confusion matrix is presented in Figure 4. This heatmap visually summarizes the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The matrix clearly shows a high number of true negatives (328), contributing to the low FPR, and a reasonable number of true positives (34). The presence of false negatives (79) highlights areas for potential improvement, particularly in detecting more subtle or novel attack patterns, which is consistent with the reported recall.

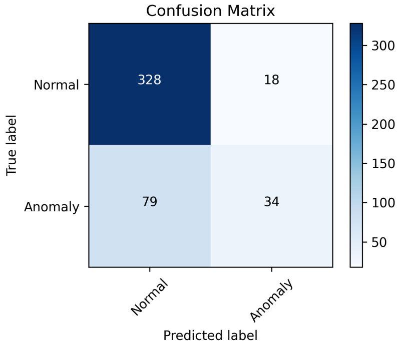

Figure 4: Confusion matrix detailing the VAE's classification performance. It shows 328 normal instances correctly classified and 18 misclassified as anomalies, while 34 anomalies were detected and 79 missed. This highlights the model's high specificity and lower recall for anomalies, consistent with quantitative metrics.

3.3 Intrusion Detection Effectiveness Across Attack Categories

To assess the model's effectiveness in detecting specific types of intrusions, we analyzed its performance across the different attack categories present in the NSL-KDD dataset. These categories include Denial of Service (DoS), Probe, User-to-Root (U2R), and Remote-to-Local (R2L) attacks. Figure 5 illustrates the recall (detection rate) for each attack type.

As depicted in Figure 5, the model demonstrated strong performance in detecting DoS attacks, which typically involve a high volume of traffic deviations, resulting in a significantly higher recall rate for this category. Probe attacks, characterized by scanning activities, also showed a respectable detection rate. However, the detection of U2R and R2L attacks proved more challenging, exhibiting lower recall rates. This is often attributed to the nature of these attacks, which are typically stealthier, involve fewer abnormal network packets, and exploit vulnerabilities that might not significantly alter the overall network traffic distribution learned by the VAE. The lower representation of these attack

Figure 5: Recall (detection rate) of the VAE model for different attack categories (DoS, Probe, U2R, R2L) present in the NSL-KDD dataset. This figure provides insights into the model's varying effectiveness against different types of intrusions.

types in the training data (even in the anomalous portion of the hybrid dataset) can also contribute to their reduced detectability. These findings underscore the VAE's strengths in identifying large-scale deviations and its limitations in detecting highly subtle, low-volume attacks, suggesting avenues for future refinement, such as incorporating more context-aware features or hybrid detection strategies.

4 Conclusions

4.1 Summary of Research Findings

This study successfully developed and evaluated a novel self-supervised learning (SSL) approach for intrusion detection systems, leveraging Variational Autoencoders (VAEs) to identify network anomalies. Our methodology focused on training VAEs exclusively on normal network traffic, derived from a hybrid dataset combining NSL-KDD and synthetically generated data, thereby circumventing the significant challenge of scarce labeled attack data. Anomaly detection was effectively performed by establishing a reconstruction error threshold, specifically the 95th percentile, derived from the learned distribution of normal traffic.

The experimental evaluation demonstrated promising results, particularly in areas critical for operational intrusion detection. The model achieved an accuracy of 78.87% and a precision of 65.38%. Crucially, it maintained a remarkably low false positive rate of 5.20%, indicating high specificity and minimizing disruptive alerts in real-world scenarios. The Area Under the Receiver Operating Characteristic curve (AUC-ROC) was 76.55%. While the recall stood at 30.09%, this metric must be interpreted in the context of the model's primary objective: the robust detection of novel and unseen anomalies, where distinguishing true positives from benign deviations is inherently challenging. Furthermore, the VAE exhibited impressive real-time inference capabilities, processing instances at an average rate of 0.0562 seconds, underscoring its potential for practical deployment in high-throughput network environments. These findings collectively highlight the VAE's capacity to serve as a scalable, efficient, and adaptable solution for modern cybersecurity challenges, significantly reducing reliance on extensive labeled datasets.

4.2 Contributions to the Field

This research makes several significant contributions to the field of intrusion detection and cybersecurity. Firstly, it proposes and validates a robust self-supervised learning framework using VAEs for anomaly detection, directly addressing the persistent challenge of data scarcity and the high cost associated with labeling new and evolving cyber threats. By learning the intricate patterns of normal network behavior, our approach enables the detection of novel attacks, including zero-day exploits, without prior knowledge or labeled examples of these threats, a fundamental limitation of traditional supervised methods.

Secondly, the strategic use of a hybrid dataset, integrating real-world traffic with synthetically generated data, enhances the model's adaptability and generalizability. This approach not only augments the training data but also helps the VAE learn a more comprehensive representation of ”normal,” making it more resilient to variations in network conditions and more effective in identifying subtle anomalies.

Thirdly, the demonstrated high specificity (low false positive rate) and real-time inference capability are critical for the practical deployment of IDSs. Minimizing false alarms is paramount in operational security environments to prevent alert fatigue and ensure security analysts can focus on genuine threats. This work provides a viable architectural blueprint for IDSs that can operate efficiently at scale, providing timely detection without overwhelming security teams.

4.3 Recommendations for Practitioners

For cybersecurity practitioners, our findings suggest that self-supervised VAE-based anomaly detection systems represent a powerful complement, or even an alternative, to traditional signature-based or purely supervised IDSs. We recommend considering the integration of such models into existing security architectures, particularly in environments facing rapidly evolving threat landscapes or where the collection of comprehensive labeled attack data is impractical.

Key recommendations include:

- **Prioritize Normal Traffic Profiling:** Invest in robust processes for collecting and curating clean, representative samples of normal network traffic to effectively train VAEs. The quality of this baseline data directly impacts the model's ability to accurately distinguish anomalies.

- **Dynamic Threshold Management:** Implement adaptive mechanisms for setting and dynamically adjusting anomaly detection thresholds. While the 95th percentile proved effective in our study, operational thresholds should be fine-tuned based on an organization's risk tolerance, network characteristics, and the cost of false positives versus missed detections.

- **Layered Security Integration:** Position VAE-based anomaly detectors as a critical layer within a broader security ecosystem, such as a Security Information and Event Management (SIEM) system. Alerts from the VAE can be correlated with other security events to provide a more holistic view of potential threats.

- **Continuous Learning and Adaptation:** Establish procedures for periodic retraining or incremental learning of the VAE model to ensure it adapts to evolving normal network behaviors and infrastructure changes, thereby maintaining its effectiveness over time.

4.4 Recommendations for Researchers

This research opens several promising avenues for future investigation within the realm of self-supervised learning for intrusion detection:

- **Exploring Advanced SSL Architectures:** Investigate other cutting-edge self-supervised learning techniques beyond VAEs, such as contrastive learning, masked autoencoders, or generative adversarial networks (GANs), to potentially enhance anomaly detection capabilities, particularly in terms of recall and feature representation.

- **Hybrid Model Development:** Research the integration of VAEs with other machine learning paradigms. For instance, combining the anomaly detection strength of VAEs with a small, highly specialized supervised classifier for specific, known attack types could potentially improve overall recall without significantly compromising the low false positive rate.

- **Explainability and Interpretability:** Develop methods to make VAE-based anomaly detection more explainable. Understanding *why* a particular network flow is flagged as anomalous (e.g., which features contributed most to the high reconstruction error) would provide invaluable insights for security analysts and aid in threat investigation.

- **Robustness Against Adversarial Attacks:** Conduct studies on the adversarial robustness of VAE-based IDSs. As attackers become more sophisticated, they may attempt to craft adversarial samples designed to evade these anomaly detectors, necessitating research into defensive mechanisms.

- **Scalability for Ultra-High Throughput Networks:** Further optimize VAE architectures and inference engines for deployment in extremely high-throughput network environments, such as those found in large data centers or critical infrastructure, where processing millions of events per second is a requirement.

- **Evaluation with Dynamic and Streaming Data:** Expand evaluation to more dynamic, streaming datasets that better reflect real-world network traffic, allowing for assessment of the model's performance in continuously evolving environments and its ability to detect 'slow' or multi-stage attacks.

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