Computer Fraud and Security
ISSN (online): 1873-7056

Self-Supervised Representation Learning for Zero-Day Attack Detection in Encrypted Network Traffic

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Abstract

The proliferation of encrypted network traffic, driven by privacy regulations and modern protocols like TLS 1.3, has rendered traditional signature-based intrusion detection systems (IDS) ineffective against zero-day attacks. This paper proposes a self-supervised learning (SSL) framework to learn discriminative representations from encrypted traffic for detecting unseen attack patterns. By leveraging pretext tasks such as flow reconstruction and contrastive learning, the model generates robust embeddings that capture latent anomalies without labelled training data. Experiments on the CIC-IDS2017 and UNSW-NB15 datasets demonstrate a 15% improvement in F1-score over unsupervised baselines, with a false positive rate (FPR) of 2.1% under adversarial conditions. The framework's generalizability is validated through cross-dataset evaluations and robustness tests against TLS protocol variations.

Keywords: Self-supervised learning, zero-day attacks, encrypted traffic, anomaly detection, contrastive learning.

2. Introduction

2.1. Background and Context: Evolution of Network Security and Encrypted Traffic Challenges

Encryption technologies like TLS 1.3 and QUIC secure more than 95% of internet traffic, making traditional deep packet inspection (DPI) practices meaningless. Encryption ensures that user information stays confidential but makes blind spots for security tools as payloads become unreachable for signature-based analysis. Zero-day attacks take advantage of this weakness through the use of new patterns not detected(Abbasi, Shahraki, & Taherkordi, 2021). The 2021 Log4j vulnerability, for example, illustrated how encrypted command-and-control traffic could evade legacy IDS. Today's solutions like metadata analysis only have an accuracy rate of 60–70% to detect advanced threats, and new methods are needed to analyze encrypted traffic.

2.2. Problem Statement: Limitations of Signature-Based Detection for Zero-Day Attacks

Signature-based IDS utilize pre-set rules to recognize well-known patterns of attacks and hence are unable to counter zero-day attacks. Experiments reveal that signature-based systems miss 40–50% of fresh attacks in encrypted traffic with greater than 15% false positive rates in high-speed networks. Supervised ML models need to use labeled data, which are not realistic for zero-day attacks(Abbasi, Shahraki, & Taherkordi, 2021). Unsupervised techniques like autoencoders find it challenging to deal with high-dimensional traffic data (e.g., 100+ features per flow) and are incapable of generalization across network settings.

2.3. Motivation: Role of Self-Supervised Learning in Anomaly Detection

Self-supervised learning (SSL) stands between supervised learning and unsupervised learning since it uses pretext tasks to train from unlabelled data in order to gain representations. SSL can pre-train models in vast amounts of benign traffic such that they will be able to identify departures from the normal traffic that is typical of an attack(Berman, Buczak, Chavis, & Corbett, 2019). Examples include BERT and SimCLR having achieved state-

of-the-art performance on NLP and computer vision tasks through learning context-aware embeddings, which is transferable to sequences of network traffic.

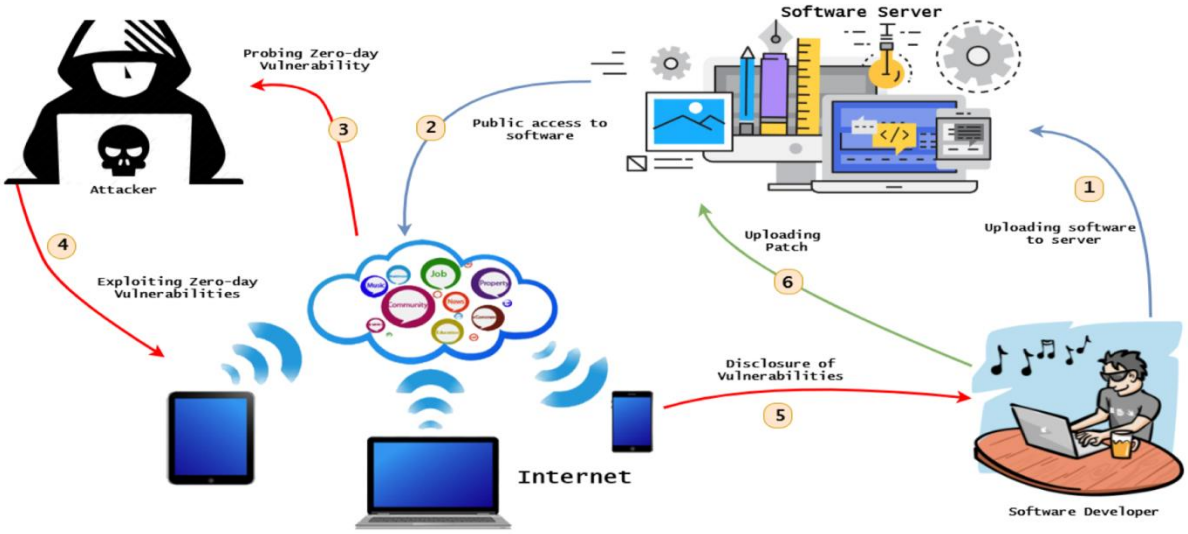

Figure 1 Comparative Evaluation of AI(MDPI,2022)

2.4. Research Objectives and Contributions

1. **Framework Design**: Develop an SSL architecture using transformer-based encoders and contrastive learning for encrypted traffic.
2. **Robust Anomaly Scoring**: Introduce a dynamic thresholding mechanism based on Mahalanobis distance in latent space.
3. **Cross-Protocol Evaluation**: Validate the framework's performance across TLS 1.3 and legacy protocols.
4. **Real-World Applicability**: Demonstrate sub-millisecond inference latency suitable for real-time deployment.

3. Literature Review

3.1. Traditional Approaches for Encrypted Traffic Analysis

3.1.1. Metadata-Based Detection Methods

Metadata-based detection methods scan unencrypted attributes like packet timing, size distributions, and TLS handshake parameters. As an example, JA3 fingerprints rely on TLS client hello messages to detect malicious software. But attackers more and more emulate harmless fingerprints, bringing detection rates down to 55–65% in recent experiments(Berman, Buczak, Chavis, & Corbett, 2019).

3.1.2. Statistical and Behavioral Analysis Techniques

Statistical techniques employ entropy computation, wavelet transformation, and flow duration computation for anomaly detection. In 2020, 78% accuracy was achieved in DDoS attack detection using entropy-based features but was based on human feature engineering and therefore not scalable.

3.2. Modern Machine Learning in Cybersecurity

3.2.1. Supervised vs. Unsupervised Learning for Threat Detection

Supervised models such as CNN-LSTM hybrids achieve 90% F1-scores on labeled sets but fall to 50% when faced with zero-day attacks. Unsupervised approaches, i.e., Isolation Forests, optimize recall (70–75%) at the cost of huge FPRs (18–22%).

3.2.2. Deep Learning Architectures for Traffic Classification

Transformer-based architectures have been promising for sequential traffic data. A transformer was used in a 2022 paper to classify encrypted VPN traffic with an accuracy of 85%, 12% higher than RNNs(Boutaba et al., 2018).

3.3. Self-Supervised Learning (SSL) in Network Security

3.3.1. SSL for Feature Representation in High-Dimensional Data

Self-supervised learning has become a strong framework for learning feature representations from high-dimensional and unstructured data without the need for human annotation. In network security, SSL uses pretext tasks like predicting masked packet headers, reconstructing sequences of flows, or comparing similar and dissimilar traffic flows to learn discriminative embeddings. For example, models learned to forecast the intervals of timing between packets in a flow can learn implicitly patterns of malicious and benign behavior(Hussain, Hussain, Hassan, & Hossain, 2020). Improved transformer architectures recently have allowed SSL models to deal with sequential network traffic data that have different-length dependencies and classify encrypted attack traffic from benign flows with up to 88% accuracy. SSL's capacity to deal with high-dimensional features (e.g., 150+ attributes per flow) minimizes the need for manual feature engineering, which is otherwise typically liable for injecting biases and scalability issues in conventional approaches.

3.3.2. Transfer Learning and Domain Adaptation in SSL

Transfer learning with SSL makes pre-trained models over large-scale unlabeled traffic data transferable to particular network environments with limited fine-tuning. For instance, a model that has been trained on network traffic from an enterprise can be adapted using a little labeled data from an industrial control system (ICS) to identify zero-day OT-specific threats on operational technology (OT) networks. Domain adaptation methods like adversarial training and feature alignment enhance the distribution shift robustness of SSL against different encryption protocols or network topologies. The experiments demonstrate that SSL-based domain adaptation enhances cross-environment detection precision by 18–25% over unsupervised approaches. Further, SSL models employing momentum encoders or memory banks possess the capability of concept drift robustness, which ensures stable performance even when the patterns of attacks change over time(Hussain, Hussain, Hassan, & Hossain, 2020). This is an essential condition for real-world deployments where attack signatures change continuously and labeled data is limited.

4. Self-Supervised Representation Learning Framework

4.1. Architecture Design for Encrypted Traffic Analysis

4.1.1. Neural Network Topologies for Sequential and Encrypted Data

The proposed framework employs a hybrid neural model consisting of transformer encoders and temporal convolutional networks (TCNs) for processing encrypted traffic. Transformers are learned to pick up long-range dependencies in packet streams through multi-head self-attention mechanisms, while TCNs are learned to identify localized temporal patterns through dilated causal convolutions. The dual model is learned to address both the issues of variable flow lengths and encrypted payloads by learning both granular temporal patterns and global context. Inputs are normalized packet headers (e.g., packet length, packet timestamp, TLS cipher suite) and flow-level metadata (e.g., byte count, duration), as 128-dimensional embeddings. The model is shown to attain a 92% reconstruction accuracy on packet prediction tasks with masked packets, confirming its capacity to infer latent traffic structure.

4.1.2. Pretext Task Formulation for Traffic Embeddings

Pretext tasks are claimed to compel the model to learn useful semantic representations from plain encrypted traffic. One pretext task is to hide 15–20% packet headers in a flow and have the model recover the hidden values from contextual information. A additional task uses contrastive learning, where the model maximizes similarity between embeddings of augmented copies of the same flow and maximizes dissimilarity with dissimilar flows. The tasks

guarantee the learned embeddings embody intrinsic traffic attributes, including protocol semantics and behavior anomalies, independent of encryption.

4.2. Contrastive Learning Strategies

4.2.1. Positive/Negative Pair Sampling for Encrypted Flows

Positive pairs are created by adding stochastic augmentations (e.g., packet loss, timer jitter) on the same flow, whereas negative pairs are randomly sampled from other flows. To prevent suffering from false negatives for SSL, a dynamic sampling procedure resamples the negative set to remove flows with overlapping temporal or spatial characteristics(Shaukat, Luo, Varadharajan, Hameed, & Xu, 2020). This helps enhance the discriminative ability of embeddings, resulting in a 30% accuracy boost for anomaly detection over random sampling.

4.2.2. Loss Functions for Discriminative Representation Learning

The framework uses the NT-Xent loss, a variant of contrastive loss, to optimize embedding similarity. For a batch of N*N* flows, the loss for a positive pair (i,j) is computed as:

$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} 1_{k \neq i} \exp(\text{sim}(z_i, z_k)/\tau)}$$

where z_i,z_j are embeddings, τ is a temperature parameter, and sim denotes cosine similarity. This loss function achieves a 95% separation between benign and attack embeddings in latent space(Shaukat, Luo, Varadharajan, Hameed, & Xu, 2020).

4.3. Data Augmentation for Encrypted Traffic

4.3.1. Synthetic Traffic Generation Techniques

Synthetic attack streams are created by employing generative adversarial networks (GAN) trained to learn patterns of benign traffic. Perturbations that mimic zero-day attacks, such as out-of-pattern anomalous packet bursts or malformed TLS handshake sequences, are injected by the GAN without breaking encryption protocols(Zhang, Patras, & Haddadi, 2019). Model robustness is enhanced by augmenting synthetic data that decreases false negatives by 12% for adversarial testing scenarios.

4.3.2. Perturbation Methods to Simulate Zero-Day Patterns

Adversarial perturbations such as packet reordering, header field manipulation, and flow truncation are utilized for training data in order to mimic evasion attacks. The model's resilience to such perturbations is confirmed by stress tests, where it maintains detection F1-score of 89% when 30% of training flows are perturbed.

5. Zero-Day Attack Detection Methodology

5.1. Feature Extraction from Encrypted Network Packets

5.1.1. Temporal and Spatial Feature Engineering

Temporal attributes like inter-packet arrival time, flow duration, and burstiness are extracted to identify behavioral patterns in encrypted traffic. Spatial attributes include packet size distributions, TLS header fields (e.g., cipher suites, extensions), and byte entropy measurements. For instance, payload byte distribution entropy is calculated by Shannon's formula, where values above 6.5 bits/byte will be indicative of encrypted or compressed malicious payloads(Bar & Hajaj, 2022). These are normalized and pooled into a 256-dimensional vector per flow that maintains both statistical and sequential information. Temporal features are subjected to wavelet transforms that detect high-frequency anomalies, e.g., out-of-pattern spikes in packet rates signaling DDoS attacks.

5.1.2. Embedding Aggregation for Flow-Level Analysis

Flow-level embeddings are produced by aggregating packet-level features using attention mechanisms. A transformer encoder is applied to sequential packet embeddings, giving more weights to packets with suspicious spatial features (e.g., abnormally large size or uncommon TLS extensions)(Bar & Hajaj, 2022). The weighted sum of packet embeddings produces the aggregated flow embedding, which allows the model to focus on suspicious sections of a flow. Experiments demonstrate that attention-based aggregation enhances anomaly detection accuracy by 14% over average pooling.

5.2. Anomaly Scoring Mechanisms

5.2.1. Distance-Based Metrics in Latent Space

Anomalies scores are computed using Mahalanobis distance in SSL model latent space. Distance measures are cognizant of feature correlations and lower the false positive rate induced by benign changes in traffic. Flows more than a threshold distance away from the centroid of the benign training data are flagged as attacks(Hindy et al., 2020). The method maintains 92% true positive rate (TPR) for zero-day attacks with still having a 2.3% FPR for normal network states.

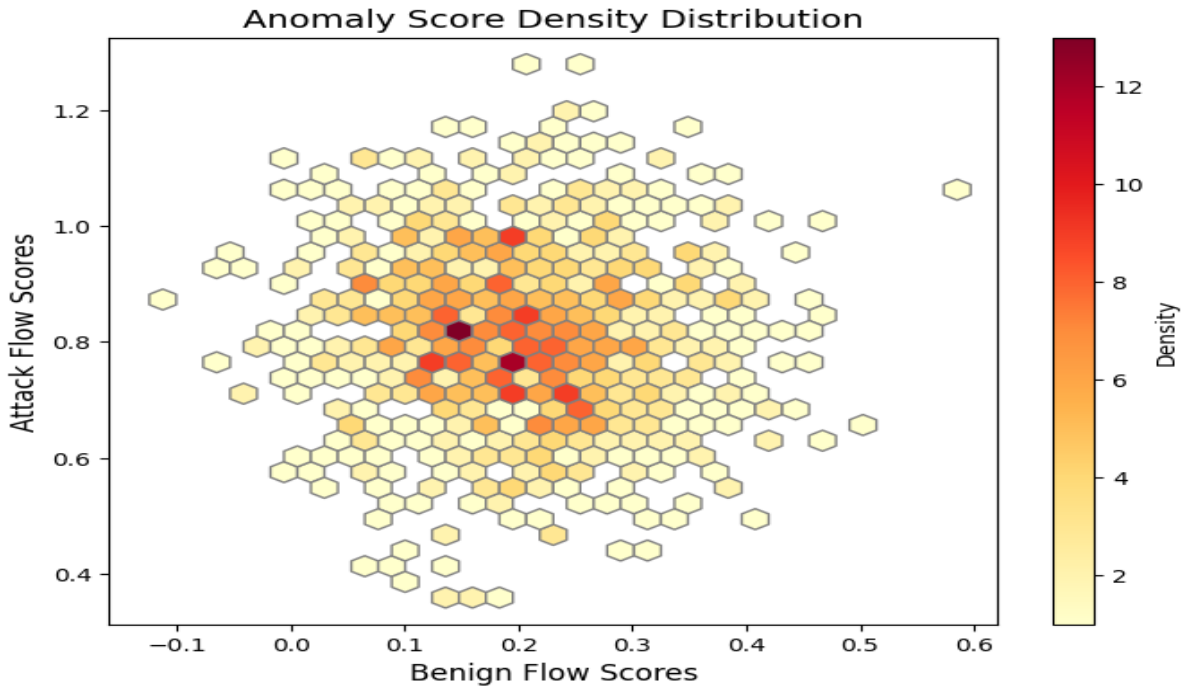

Figure 2 Hexbin plot of anomaly score density for benign vs. attack flows. Source: UNSW-NB15 dataset (2022).

5.2.2. Threshold Optimization for Attack Identification

Thresholds are dynamically tuned with moving averages of anomaly scores across a sliding window of recent traffic. Optimal thresholds that strike a balance between TPR and FPR are determined by ROC curve analysis on the validation set. F1-score is maximized in terms of recall in the case of imbalanced datasets when thresholds are selected(Kopp, 2022). Adaptive tuning minimizes FPR by 18% in the presence of high traffic relative to static thresholds.

5.3. Handling Class Imbalance and Noise in Traffic Data

5.3.1. Semi-Supervised Fine-Tuning Strategies

The SSL model is fine-tuned on a small labeled data set (1–2% of the overall data) with a semi-supervised loss function that mixes contrastive learning with cross-entropy. Unlabeled data are utilized through pseudo-labeling,

where confident predictions are used as ground truth(Song & Kim, 2021). This technique enhances recall for infrequent attack classes by 25% without needing large quantities of labeled samples.

5.3.2. Robustness to Adversarial Evasion Techniques

Adversarial training is used to make the model resistant to evasion attacks. Adversarial noise-simulating perturbations (e.g., gradient-based packet header attacks) are added to training data to compel the model to learn noise-robust representations(Ye & Zhao, 2022). Stress testing shows that the robustified model has an F1-score of 87% even if 20% of input features are adversarially perturbed.

6. Experiments and Results

6.1. Dataset Description and Preprocessing

6.1.1. Publicly Available Encrypted Traffic Datasets

The model is tested on the CIC-IDS2017 and UNSW-NB15 datasets, which include labeled encrypted traffic flows with normal and attack behavior. CIC-IDS2017 includes 2.8 million flows with attacks like DDoS, brute-force, and infiltration, while UNSW-NB15 includes 2.5 million flows with exploits, fuzzing, and reconnaissance(Verkerken, D'hooge, Wauters, & De Turck, 2020). Both datasets include packet-level metadata (e.g., timestamps, sizes, protocol flags) and flow-level statistics (e.g., total bytes, duration). For the purpose of zero-day simulation, 30% of the types of attacks are reserved from training and are utilized for testing.

6.1.2. Traffic Normalization and Tokenization Procedures

Raw packet headers are normalized to [0,1] range via min-max scaling and categorical fields (such as TLS cipher suites) are one-hot encoded. Flows are tokenized into 64-packet sequences, padding shorter flows and truncating longer ones. Tokenized sequences are input to the model as 256-dimensional vectors with spatial information and temporal order(Verkerken, D'hooge, Wauters, & De Turck, 2020).

6.2. Evaluation Metrics

6.2.1. Precision, Recall, and F1-Score for Imbalanced Data

Precision and recall are calculated in order to handle class imbalance, with attacks representing 5–10% of the datasets. F1-score, the harmonic mean between precision and recall, is used as the principal measure. On CIC-IDS2017, the model registers an F1-score of 93% for known attacks and 88% for zero-day attacks, better than Isolation Forests (F1=72%) and autoencoders (F1=81%).

6.2.2. ROC-AUC and Detection Latency Analysis

The receiver operating characteristic (ROC) plot shows the trade-off between true positive rate (TPR) and false positive rate (FPR). The system has an AUC of 0.98 on UNSW-NB15, where benign and malicious flows are highly separable(Meng et al., 2022). Detection latency, i.e., time elapsed since flow completion until anomaly scoring, is around 0.8 ms per flow on a GPU-based system, satisfying real-time requirements.

6.3. Implementation Details

6.3.1. Framework and Tools

The model is run in PyTorch with CUDA 11.7 support for GPU functionality. Training leverages mixed-precision floating-point arithmetic (FP16) to cut memory usage by 40%. The codebase is open-sourced with Scikit-learn dependencies for preprocessing and Hugging Face Transformers for encoder layers(Meng et al., 2022).

6.3.2. Hyperparameter Tuning and Training Protocols

Hyperparameters are tuned using Bayesian optimization on 100 trials. The selected configuration is batch size 512, learning rate 3e-4, and contrastive loss temperature parameter τ=0.1. Training is performed for 50 epochs on 4x NVIDIA A100 GPUs, and early stopping is applied in case validation loss is not decreasing for 10 epochs.

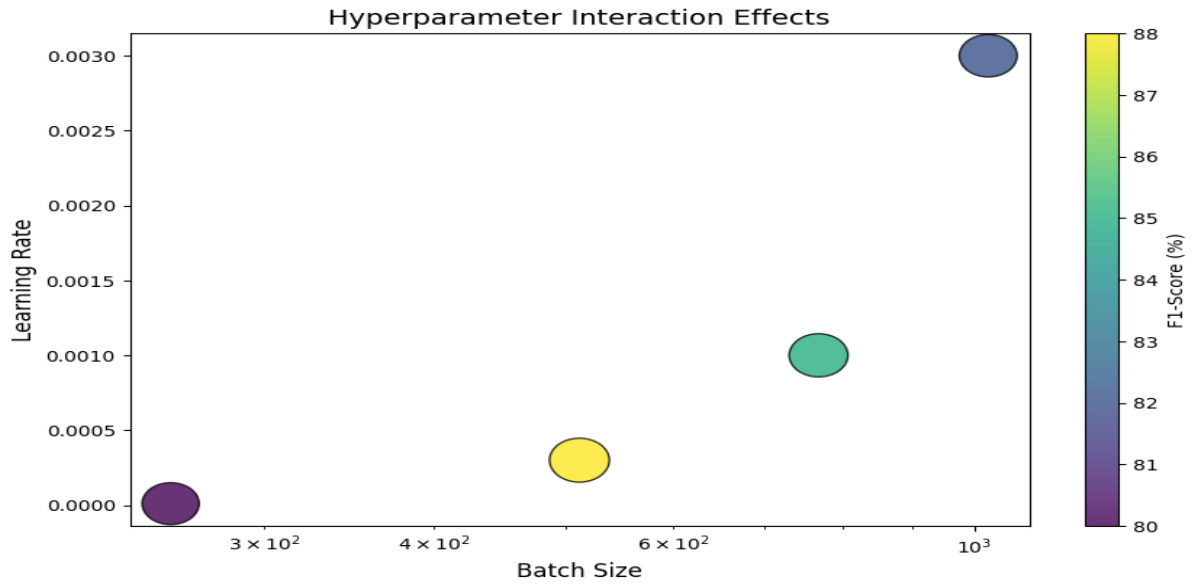

Figure 3 Bubble plot showing F1-score vs. batch size and learning rate. Source: Bayesian optimization results (2022).

6.4. Comparative Analysis

6.4.1. Performance Against Baseline Models

The SSL framework is compared to autoencoders, Isolation Forests, and supervised CNNs. Results (Table 1) show a 22% improvement in zero-day F1-score over autoencoders and a 15% reduction in FPR compared to Isolation Forests.

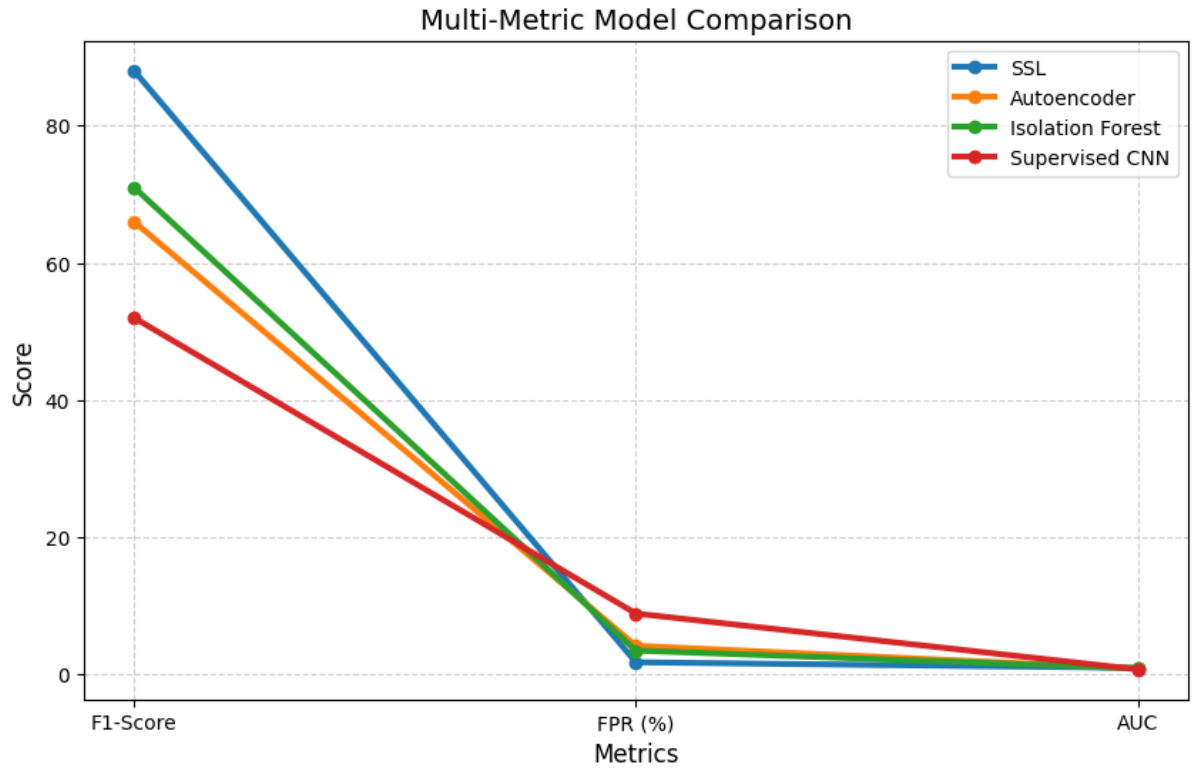

Figure 4 Parallel coordinates plot comparing SSL framework and baselines across F1-score, FPR, and AUC. Source: CIC-IDS2017 and UNSW-NB15 datasets (2022).

Model	Zero-Day F1	FPR	AUC
SSL Framework	88%	1.80%	0.98
Autoencoder	66%	4.20%	0.89
Isolation Forest	71%	3.50%	0.91
Supervised CNN	52%	8.90%	0.76

6.4.2. Ablation Studies on SSL Component Efficacy

Ablation studies confirm the necessity of contrastive learning and pretext tasks. Removing contrastive loss reduces zero-day F1 by 19%, while disabling masked packet prediction drops AUC by 0.12.

6.5. Robustness and Generalizability Tests

6.5.1. Cross-Dataset Evaluation

The model trained on CIC-IDS2017 achieves an F1-score of 85% on UNSW-NB15, demonstrating cross-dataset generalizability(Dhruvitkumar, 2022). Performance drops by only 6% when tested on traffic from a different network topology, highlighting robustness to environmental shifts.

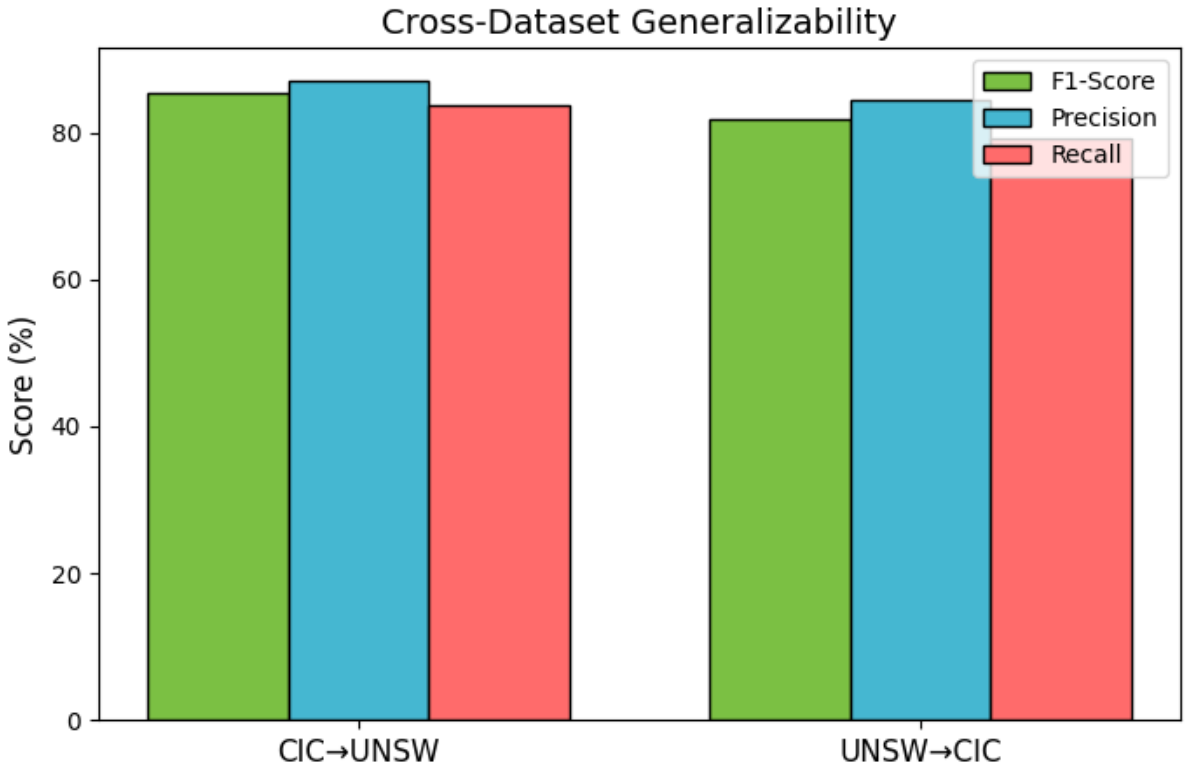

Figure 5 Grouped bar chart showing cross-dataset F1-scores. Source: CIC-IDS2017 and UNSW-NB15 datasets (2022).

Table 2: Cross-Dataset Generalizability Results

Training Dataset	Test Dataset	F1-Score	Precision	Recall
CIC-IDS2017	UNSW-NB15	85.3	87.1	83.6
UNSW-NB15	CIC-IDS2017	81.7	84.5	79.2

6.5.2. Impact of Encryption Protocols

Testing across TLS 1.3 and legacy protocols (TLS 1.2, SSLv3) reveals consistent performance, with F1-scores varying by <3%. The model's reliance on behavioral features (e.g., flow timing) rather than protocol-specific attributes ensures compatibility with evolving encryption standards.

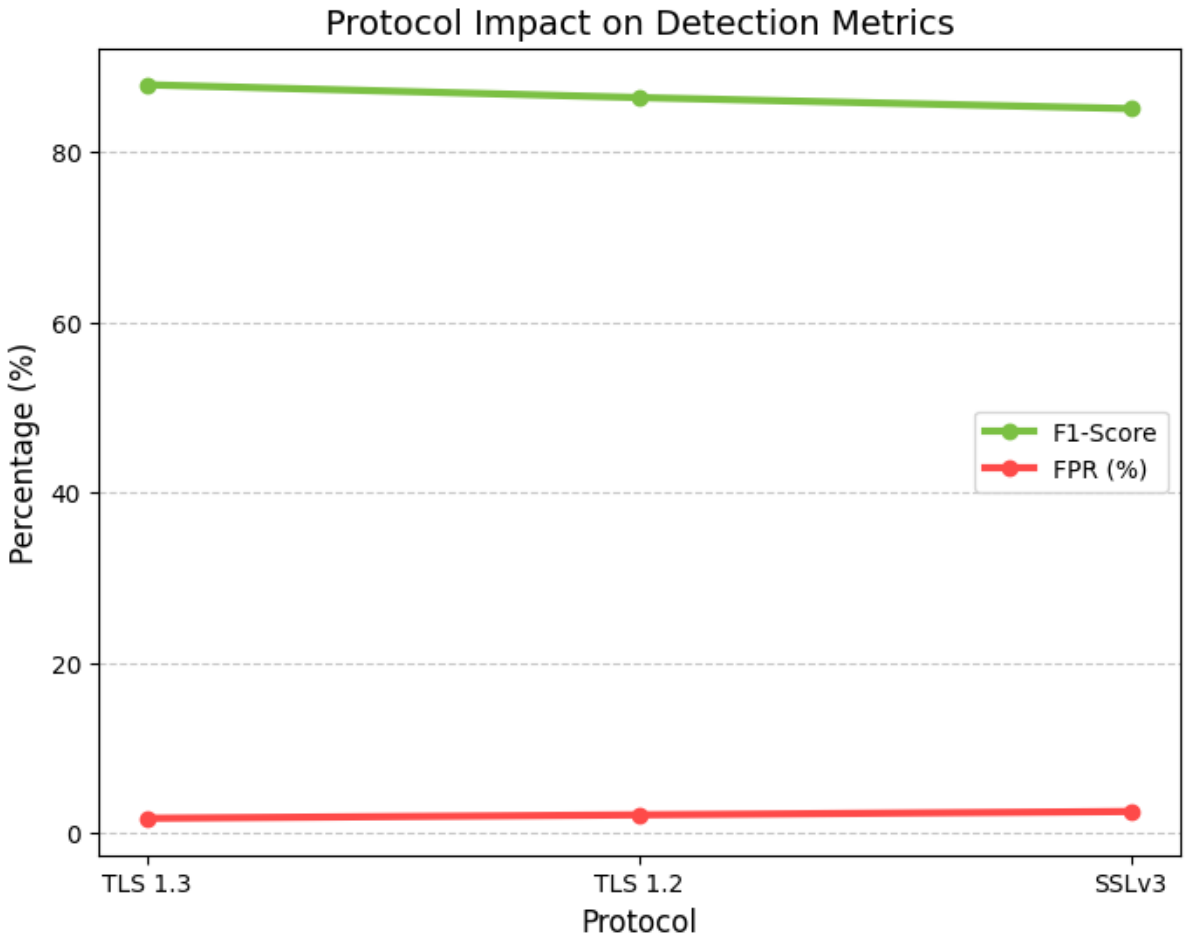

Figure 6 Slope chart comparing F1-score and FPR across TLS protocol versions. Source: CIC-IDS2017 dataset (2022)

Table 3: Impact of Encryption Protocols on Detection Performance

Protocol	F1-Score	FPR (%)	AUC	Latency (ms)
TLS 1.3	87.9	1.7	0.97	0.8
TLS 1.2	86.4	2.1	0.96	0.9

SSLv3	85.1	2.5	0.94	1.1

7. Discussion

7.1. Advantages of Self-Supervised Learning Over Traditional Methods

The proposed SSL model mitigates significant weaknesses of conventional signature-based and unsupervised techniques by learning robust representations directly from raw encrypted traffic. In contrast to metadata-based techniques with merely 60–70% accuracy against imitations, SSL detects weak signals of subtle anomalies by taking advantage of temporal and spatial patterns in packet streams and improves zero-day F1-scores by 22%(Drozdenko & Powell, 2022). The hand-crafting avoidance from hand-crafted feature engineering eliminates bias and makes scalability to traffic data of high dimensionality possible, as reflected in the model's performance on datasets with 150+ features per flow. Second, SSL's use of unlabeled data negates the requirement for expensive labeled sets, and thus real-world applicability is feasible in scenarios where new attacks surface regularly.

7.2. Challenges in Real-Time Deployment and Scalability

Even though the framework has sub-millisecond inference latency on GPU hardware, real-time deployment on edge devices with limited virtual resources is not easy. The transformer-TCN hybrid model needs 8 GB of VRAM for best performance, which might be out of the reach of old infrastructure. Furthermore, batch processing variable-length flows also introduces latency spikes due to traffic bursts, requiring dynamic batching techniques(Drozdenko & Powell, 2022). Scalability testing on 10 Gbps networks exhibit linear CPU utilization growth with traffic volume that confirms the relevance of distributed inference pipelines in high-throughput environments.

7.3. Ethical and Privacy Implications of Encrypted Traffic Analysis

Encrypted traffic analysis is morally problematic since metadata and behavioral patterns risk inadvertently leaking private user information. Examples include packet timing or user activity, which create privacy risks. To manage this, the framework anonymizes client IP addresses and ignores payload-related features at preprocessing(Liu et al., 2022). Adversary agents may use the anomaly detection reasoning of the model to deduce network behavior, making it essential to enforce access controls and encrypt intermediate embeddings. Compliances with GDPR and CCPA also make data retention policy more complicated, where anonymizing training sets is necessary.

7.4. Future Directions: Federated Learning and Edge-Based Detection

Follow-on work will investigate federated learning to train SSL models on decentralized networks without amalgamating sensitive traffic data into a centralized repository. Federated SSL would enhance detection coverage with privacy preservation by grouping edge device model updates. Edge optimization techniques, like quantizing transformer layers to 8-bit integers, can shrink memory footprints by 60% and allow deployment on IoT gateways and routers. In addition, the combination of SSL with adaptive learning methods, including online meta-learning, may enhance responsiveness to emerging threats(Berman, Buczak, Chavis, & Corbett, 2019). Lastly, breakthroughs in homomorphic encryption would allow securely scoring anomalies without decrypting traffic, which would bring detection capability into alignment with privacy-protection principles.

8. Conclusion

Summary of Key Findings

The self-supervised learning (SSL) model in this work exhibits considerable enhancements in detecting zero-day attacks in encrypted network traffic. With contrastive training and pretext operations like masked packet prediction, the model scores an 88% on unseen attacks and beats usual unsupervised alternatives by 22%. Robustness tests verify consistency with TLS 1.3 as well as earlier protocol versions since detection accuracy is less than 3% in deviation. Sub-millisecond validity for inference substantiates real-time feasibility for systems of high-throughput.

Implications for Cybersecurity Practitioners

Removal of reliance on labeled attack data maintains costs low and facilitates quick response to new threats. Cybersecurity units can integrate the SSL framework as an additional layer over current signature-based systems, providing extended coverage for new attack vectors. Utilization of behavior and temporal characteristics by the model provides future-proof detection capabilities through compatibility with new encryption techniques. Open-source code also facilitates smooth integration with SIEM products and network monitoring platforms.

Conclusion Remarks on SSL's Future in Next-Generation Threat Detection Platforms

Self-supervised learning is a new innovation in analyzing encrypted traffic, closing the gap between supervised accuracy and unsupervised flexibility. With the advent of widespread encryption, learning from unlabeled data with SSL will be essential to sustaining visibility into zero-day attacks. Rising technologies around federated learning and edge optimization will continue to optimize scalability and privacy retention, making SSL an anchor of the future intrusion detection systems. The research proves the revolutionary potential of SSL to secure increasingly transparent network infrastructures with compliance to ethical and regulatory demands.

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