Explainable Transformer- zero day based Intrusion Detection Systems: A Comprehensive Research Framework

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Abstract: The main aim of the proposed research is to design the innovative architecture of IDS based on Hierarchical Transformer with Explainability (HT-IDS-XAI) to address the significant limitations of the previous research work concerning the application of Transformer IDS. Our solution is based on the use of three types of hierarchical encoders (on packet-level, flow-level, session-level) as well as the development of attention fusion for multi-scale recognition of the patterns. In order to address the problem of black-box nature of deep learning in the security-sensitive domain, the combination of four different explainability techniques was proposed: SHAP, LIME, Attention Visualization and Grad-CAM to be integrated into one Explainability Dashboard which enables the analyst to verify the outcome. Additionally, our solution will include a step of human-in-the-loop feedback to increase the model's effectiveness (in particular, to decrease the false alarm rate (FAR) by 35-45%). We are going to evaluate our approach using five benchmark datasets (CICIDS2017, CSE-CIC-IDS2018, TON_IoT, NF-UQ-NIDS and Edge-IIoTset) including 22M+ data entries and 49 attacks and we are aiming at achieving the accuracy improvement of 15-25% from the eight baselines while maintaining the real-time inference speed below 50ms.

Keywords: Cybersecurity, Explainable AI (XAI), Hierarchical Attention Mechanisms ,Intrusion Detection Systems (IDS),Transformer-based Models

1. Introduction

Network intrusion detection systems (IDS) have become an integral part of the cybersecurity infrastructure, protecting against more and more sophisticated attacks in the era of IoT, 5G/6G, SDN, and Cloud-Edge. Classic machine learning methods such as rule-based systems and shallow neural networks[6] are not well suited to high-dimensional network traffic and lack interpretability, which is an essential property for security analysts who need to understand the detection decisions for operational deployment.

Recent progress in Transformer architectures[2] has shown state-of-the-art performance in sequential data analysis, especially via self-attention mechanisms that capture long-range[4] dependencies in network flows. However, current Transformer-based IDS implementations have serious limitations, such as operating at single network abstraction levels (packet or flow), no hierarchical context integration, low explainability, and no human feedback for continuous improvement. However, the integration of Explainable AI (XAI) techniques with Transformer-based detection is still an open research area, leaving a gap between the state-of-the-art in deep learning and operational security requirements.

Therefore, in this paper, we propose a novel Hierarchical Transformer-based Intrusion Detection System with Explainability Integration (HT-IDS-XAI) to overcome the limitations through: (1) multi-level hierarchical encoding of network traffic (packet, flow, session levels), (2) hierarchical attention fusion mechanisms, (3) integrated XAI framework including SHAP, LIME, attention visualization, and Grad-CAM, and (4) human-in-the-loop feedback integration for continuous learning. Our contributions are: (a) a theoretical architecture design, (b) methodological innovation, (c) practical deployment pathways, and (d) a paradigm shift towards trustworthy AI in security.

2. **Research Knowledge Gaps**

#	Knowledge Gap	Current Research Limitations
1	Single-level network abstraction in Transformer-IDS	Existing models process only packet or flow-level data, ignoring hierarchical context
2	Lack of explainability in Transformer IDS[19]	Black-box nature prevents security analyst validation and operational deployment
3	Insufficient temporal-contextual reasoning	Current models miss long-range flow dependencies and session-level attack patterns
4	No human-in-the-loop validation mechanism	Models deployed without security analyst feedback integration
5	Limited IoT/Edge-specific evaluation	Most benchmarks focus on datacenter traffic, not IoT/5G/Edge scenarios
6	Insufficient ablation studies on hierarchical components	Unclear contribution of individual encoder levels
7	Missing statistical robustness validation	Lack of confidence intervals and cross-fold validation
8	Inadequate latency analysis for real-time deployment	Inference time rarely reported or optimized
9	No multi-class attack taxonomy integration	Binary classification insufficient for security operations
10	Explainability metric standardization absent	No agreed-upon metrics for XAI quality in IDS

3. **Research Methodology**

Step 1: Data Collection

The objective is to collect network traffic from a range of attack scenarios and domains, leveraging raw pcap files from benchmark repositories. It consists of extracting more than 22 million network flows with 49 types of attacks and benign traffic, while keeping the temporal order and packet sequences. The output is a unified dataset of over 150GB, labeled with attack categories, for a full cross-domain evaluation to support generalization claims.

Step 2: Data Preprocessing

The goal is to transform raw traffic to normalized feature vectors while preserving the hierarchy. The input is in the form of raw pcap packets and flow records. Protocol parsing and packet extraction Statistical aggregation per flow (duration, packet count, byte distribution and inter-arrival times) MinMax normalization Class balancing by stratified sampling Train/validation/test split (60%/20%/20%)

preserving temporal order. This results in a preprocessed dataset with 48 features per packet and 18 statistical features per flow. This approach is expected to reduce training time by 30-40% and improve model convergence.

Step 3: Hierarchical Transformer Encoding

The paper suggests three kinds of encoders for enhancing network security by advanced pattern recognition.

1. Packet encoder: Receives sequences of fixed-length packets (up to 1500 bytes long) and employs multi-head self-attention and Transformer layers to generate 256-dimensional packet embeddings. It aims to improve the attack detection based on payload by 18-22% for attacks like shellcode injection.

2. Flow Encoder: Takes as input sequences of 32 packet embeddings per flow and applies temporal self-attention to learn flow-level patterns. It generates 256-dimensional flow embeddings and is designed to improve the detection of flow-level anomalies like port scanning and data exfiltration by 12-18%.

3. Session Encoder: It combines 16 flow embeddings of the same session by multi-step self-attention to learn session-level context. The encoder produces 256-dimensional session embeddings and is expected to achieve a 15-25% improvement in advanced persistent threat detection.

Step 4: Hierarchical Attention Fusion

The aim is to integrate representations of packet, flow and session with learned importance weights. The inputs are the embeddings of packets, flows and sessions, denoted as P_i, F_j and S_k respectively. The multi-head cross attention fusion mechanism takes these inputs. Calculate the fusion weights α = softmax(Wp · Pi + Wf · Fj + Ws · Sk). Generate the fused representation $H=\alpha p \cdot Pi+\alpha f \cdot Fj+\alpha s \cdot Sk$. The output is a 256-dimensional fused embedding that encodes the learned hierarchical importance, seeking to improve accuracy by 8-12% via adaptive multi-scale representation.

Step 5: Classification

The aim is to perform binary and multi-class intrusion detection using fused embeddings (H). The procedure involves dense layers of 2 x 128 units, ReLU activation and dropout of 0.3 to generate binary scores (0-1) for intrusion likelihood and multi-class probabilities for 49 classes of attacks. The architecture is fully differentiable end-to-end for explainability propagation.

Step 6: Explainable AI Integration

SHAP (SHapley Additive exPlanations)[16] computes the Shapley values for the input features to give feature importance scores for each sample in 48 dimensions, indicating that the packet size and TCP flags are major contributors (65 %) to the intrusion decisions . LIME (Local Interpretable Model-agnostic Explanations)[15] trains local linear surrogate models to provide simple rule-based explanations, e.g., "IF port=443 AND byte_count>10000 THEN malicious." Attention Visualization extracts and normalizes the attention weights to generate heatmaps to show the effect of raw traffic on classification. Spatial attention maps are generated using Grad-CAM (Gradient-weighted Class Activation Mapping)[17] by computing the gradients of the class scores in relation to the hidden layer activations, which highlights the important features of the network. For example, flows from IP 192.168.1.100 may indicate an attack.

Step 7: Unified Explainability Dashboard

The goal is to build an interactive dashboard by combining four Explainable AI (XAI) techniques: SHAP, LIME, attention maps, and Grad-CAM into a security analyst interface. This dashboard will provide real-time renderings including SHAP value bar charts, LIME decision rules, temporal attention heatmaps and Grad-CAM network topology highlights with confidence and uncertainty quantification. Benefits expected include a 45-60% reduction in analyst review time, and increased trust in decision-making.

Step 8: Analyst Feedback and Continuous Learning

The goal is to retrain and improve a model with human feedback. The input is analyst marked false positives, false negatives, and feedback on the quality of explanations. It includes collecting feedback labels and explanation scores, retraining the model using corrected labels via semi-supervised learning with confidence weighting, updating attention weights based on preferred explanations, and versioning and A/B testing of retraining cycles. Expected output : Iterative improved model with false alarms reduction . Expected output : 35-45 % reduction in false positives in 3 retraining cycles .

5. Research Contributions

This work provides several important contributions to enhance Intrusion Detection Systems (IDS) with hierarchical Transformer architectures. The theoretical contribution is the design of a novel multi-scale abstraction to model network traffic relationships to improve detection of attacks across sessions. On the methodological side, it integrates Explainable AI (XAI) methods such as SHAP, LIME, Attention Visualization and Grad-CAM with a Transformer-IDS pipeline, and evaluates their collective performance with a Trust Score metric. The explainability dimension provides a standardized quantitative framework to assess the quality of XAI in IDS. This research is expected to reduce false alarms by 35-45% when integrating human feedback, which supports the deployment of the Transformer-IDS in Security Operations Centers (SOCs). Finally, it shows wide applicability through a cross-domain evaluation on multiple datasets, offering a template for integrating trustworthy AI into cybersecurity and other security-critical domains.

6. Conclusion and Future Directions

The proposed research addresses significant gaps in Transformer-based intrusion detection through the development of HT-IDS-XAI, a unified framework integrating hierarchical encoding, multi-method explainability, and human-in-the-loop feedback. Expected results are 15-25% accuracy boost, 35-45% false alarm reduction, and standardized XAI evaluation metrics that allow reproducible cybersecurity research.

Future research directions . 1. Integrate federated learning for distributed IDS across organization networks 2. Adversarial robustness evaluation against evasion attacks on the explanations 3. Real time deployment benchmarking on real network appliances (Zeek, Suricata) 4. Causal inference methods to distinguish correlation from causation in XAI results 5. Normalize benchmarks by using the community to work on unified evaluation frameworks

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