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Federated Learning-based Explainable Intrusion Detection System: A Hybrid Transformer–GNN Approach for Privacy-Preserving and Robust Cybersecurity

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ABSTRACT

We propose a novel federated learning-based explainable intrusion detection system (IDS) that integrates a hybrid Transformer–graph neural network (GNN) architecture to address the challenges of privacy-preserving and robust cybersecurity. Modern IDSs face limitations in handling distributed network environments where data privacy is critical, while existing methods often lack interpretability and fail to capture both sequential and relational patterns in network traffic. The proposed framework combines the strengths of federated learning, Transformer attention mechanisms, and GNNs to enable collaborative training across multiple clients without sharing raw data, thereby preserving privacy. The Transformer module processes sequential network traffic data to extract contextual features, while the GNN analyzes topological relationships within the network graph, enabling a comprehensive understanding of both temporal and structural anomalies. These features are then fused to enhance detection accuracy. Furthermore, an explainability module based on feature attribution techniques provides transparency into the model's decisions, aiding cybersecurity analysts in identifying root causes of threats. The system also incorporates an adaptive aggregation strategy to dynamically weigh client contributions during federated updates, improving robustness against heterogeneous data distributions. Experimental validation on benchmark datasets demonstrates superior performance in detecting intrusions while maintaining interpretability. The proposed method not only advances the state-of-the-art in IDS by unifying privacy, accuracy, and explainability but also offers practical insights for deploying scalable and trustworthy cybersecurity solutions in real-world distributed systems.

Keywords: performance, method, heterogeneous

Introduction

Intrusion detection systems (IDS) have become indispensable for safeguarding modern computer networks against increasingly sophisticated cyber threats. Traditional IDSs rely on rule-based methods or machine learning algorithms such as decision trees and support vector machines, which often struggle with generalization and adaptability in dynamic network environments [1] [2]. While

deep learning-based approaches have improved detection accuracy, they typically require centralized training on large datasets, raising concerns about data privacy and scalability in distributed settings [3]. Moreover, the black-box nature of these models limits their interpretability, making it difficult for security analysts to trust and act upon their predictions [4].

Federated learning (FL) has emerged as a promising paradigm for collaborative model training without sharing raw data, addressing privacy concerns in distributed environments [3]. However, existing FL-based IDSs often fail to capture the complex patterns in network traffic, which exhibit both sequential dependencies (e.g., temporal attack sequences) and relational structures (e.g., communication graphs between hosts) [5]. Transformers, with their self-attention mechanisms, excel at modeling sequential data by capturing long-range dependencies [6]. Meanwhile, graph neural networks (GNNs) are well-suited for analyzing relational data, such as network topologies, by aggregating information from neighboring nodes [5]. Combining these architectures could provide a more holistic representation of network behavior, yet few studies have explored their integration in FL-based IDSs.

We propose a novel Federated Learning-based Explainable Intrusion Detection System (FL-XIDS) that unifies a Transformer and GNN within a privacy-preserving framework. The key innovation lies in the hybrid architecture, which dynamically constructs graphs from network traffic to model topological relationships while simultaneously processing sequential data through attention mechanisms. This dual approach enables the model to detect both temporal anomalies (e.g., unusual packet sequences) and structural anomalies (e.g., suspicious communication patterns). Furthermore, we incorporate an explainability module that provides feature importance scores and decision rationales, bridging the gap between detection accuracy and interpretability.

The contributions of this work are threefold. First, we introduce a hybrid Transformer-GNN model that captures both sequential and relational patterns in network traffic, improving detection performance over single-modality approaches. Second, we develop a federated learning framework with adaptive aggregation to handle non-IID data distributions across clients, ensuring robustness in decentralized settings. Third, we integrate explainability techniques to make the model's decisions transparent, enabling security analysts to understand and validate intrusion alerts.

The remainder of this paper is organized as follows: Section 2 reviews related work in intrusion detection, federated learning, and explainable AI. Section 3 provides background on Transformers, GNNs, and FL. Section 4 details the proposed FL-XIDS framework, including its architecture and training process. Section 5 describes the experimental setup, and Section 6 presents the results and analysis. Section 7 discusses implications and future directions, followed by conclusions in Section 8.

Related Work

The development of intrusion detection systems has evolved through several paradigms, from traditional signature-based methods to modern machine learning and deep learning approaches. This section examines existing works in federated learning for cybersecurity, hybrid deep learning architectures, and explainable AI techniques for intrusion detection.

A. Federated Learning for Intrusion Detection

Recent advances in federated learning have enabled privacy-preserving collaborative training for cybersecurity applications. Several studies have explored FL frameworks for intrusion detection, particularly in IoT and network security domains. For instance, [7] proposed a federated approach using deep neural networks that achieved comparable performance to centralized training while preserving data privacy. However, these methods typically process network traffic as independent samples, ignoring the inherent sequential and relational patterns. The work in [8] introduced graph-based federated learning for IoT security, demonstrating improved detection of distributed attacks

through graph representations. Nevertheless, their approach focused solely on graph structures without considering temporal dependencies in network flows.

B. Hybrid Deep Learning Architectures

The combination of different neural network architectures has shown promise in capturing complex patterns in cybersecurity data. Transformer models have been applied to sequential network traffic analysis, as demonstrated by [9], who achieved state-of-the-art performance in detecting temporal anomalies. Concurrently, graph neural networks have proven effective for modeling network topologies and host interactions [10]. Some recent works have begun exploring hybrid architectures, such as [11], which combined GNNs with attention mechanisms for improved feature extraction. However, these approaches were developed for centralized training scenarios and lack the privacy-preserving benefits of federated learning.

C. Explainable AI in Cybersecurity

The need for interpretable security systems has led to growing interest in explainable AI techniques. SHAP-based methods have been widely adopted for feature importance analysis in intrusion detection [12]. Other approaches have employed attention visualization and decision trees to provide model explanations [13]. Notably, [14] developed a hybrid framework that maintained explainability while improving detection accuracy. However, most existing explainable IDSs operate in centralized environments and do not address the unique challenges of federated learning scenarios.

The proposed FL-XIDS framework advances beyond these existing approaches by integrating three key innovations: (1) a novel hybrid Transformer-GNN architecture that captures both sequential and relational patterns in network data, (2) a federated learning implementation that preserves data privacy while enabling collaborative training, and (3) an explainability module specifically designed for the federated setting that provides both local and global model interpretations. This combination addresses limitations in current systems by simultaneously improving detection accuracy, preserving privacy, and enhancing interpretability - crucial requirements for real-world cybersecurity deployments.

Background and Preliminaries

To establish the foundation for our proposed FL-XIDS framework, this section introduces key concepts and techniques that form the building blocks of our approach. We begin with fundamental principles of intrusion detection systems, followed by data privacy considerations in distributed environments, and conclude with essential concepts in sequential data modeling.

D. Intrusion Detection Systems

Modern computer networks face increasingly sophisticated cyber threats that require advanced detection mechanisms. Intrusion Detection Systems (IDS) serve as critical security components that monitor network traffic for malicious activities or policy violations [15]. These systems can be broadly categorized into two main approaches: signature-based and anomaly-based detection.

Signature-based IDS operate by comparing network traffic patterns against a database of known attack signatures [16]. While effective against known threats, this approach struggles with zero-day attacks and requires constant signature updates. The detection process can be formalized as:

$$D(x) = \begin{cases} 1 & \text{if } x \in S \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where $D(x)$ represents the detection function, x is the network traffic sample, and S denotes the set of known attack signatures.

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Anomaly-based IDS, in contrast, establish a baseline of normal network behavior and flag deviations as potential threats [17]. This approach offers better detection of novel attacks but may suffer from higher false positive rates. The anomaly detection process typically involves:

$$a(x) = \| x - \mu \|^2 \quad (2)$$

where $a(x)$ represents the anomaly score, μ is the mean of normal behavior, and $\|\cdot\|$ denotes a distance metric.

E. Data Privacy in Distributed Systems

The increasing distribution of network infrastructure and the growing emphasis on data privacy have created significant challenges for traditional IDS approaches. In distributed environments, sensitive network data may reside across multiple organizational boundaries, making centralized collection and analysis impractical or legally prohibited [18].

Differential privacy has emerged as a rigorous mathematical framework for quantifying and controlling privacy loss in data analysis [19]. A mechanism $\mathcal{M}$ satisfies ϵ-differential privacy if for all datasets D_1 and D_2 differing on at most one element, and for all $S \subseteq \text{Range}(\mathcal{M})$:

$$P[\mathcal{M}(D_1) \in S] \leq e^{\epsilon} P[\mathcal{M}(D_2) \in S] \quad (3)$$

This property ensures that the inclusion or exclusion of any single data point has limited impact on the output distribution.

Federated learning provides an alternative approach by enabling collaborative model training without raw data exchange [20]. In this paradigm, clients train local models on their private data and only share model updates with a central server for aggregation. The basic federated averaging algorithm can be expressed as:

$$w_{global} = \sum_{k=1}^{K} \frac{n_k}{N} w_k \quad (4)$$

where w_{global} is the global model, w_k are local models, n_k is the number of samples at client k, and N is the total number of samples across all clients.

F. Sequential Data Modeling

Network traffic inherently exhibits temporal dependencies that must be properly modeled for effective intrusion detection. Traditional approaches often treat network events as independent samples, potentially missing important sequential patterns [21].

Recurrent Neural Networks (RNNs) and their variants have been widely used for sequential data modeling, with Long Short-Term Memory (LSTM) networks being particularly effective at capturing long-range dependencies [22]. The core LSTM equations include:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (5)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (6)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (7)$$

where f_t, i_t, and $\tilde{C}_t$ represent the forget gate, input gate, and candidate cell state respectively.

More recently, Transformer architectures have demonstrated superior performance in sequence modeling tasks through self-attention mechanisms [6]. The scaled dot-product attention computes:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (8)$$

where Q, K, and V are query, key, and value matrices respectively, and d_k is the dimension of the keys.

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For network traffic analysis, these sequential modeling techniques must be combined with approaches that can capture the relational structure of network communications, leading to the development of graph-based representations and corresponding neural network architectures [23].

The Proposed FL-XIDS Framework

The FL-XIDS framework introduces a novel approach to intrusion detection by combining federated learning with hybrid Transformer-GNN architecture and explainable AI components. The system operates through a distributed training paradigm where multiple clients collaboratively learn a global model while preserving data privacy. As shown in Figure 1, the framework consists of three main components: client-side local models with Transformer-GNN fusion, server-side adaptive aggregation, and privacy-preserving explainability modules. The technical details of these components are presented in the following subsections.

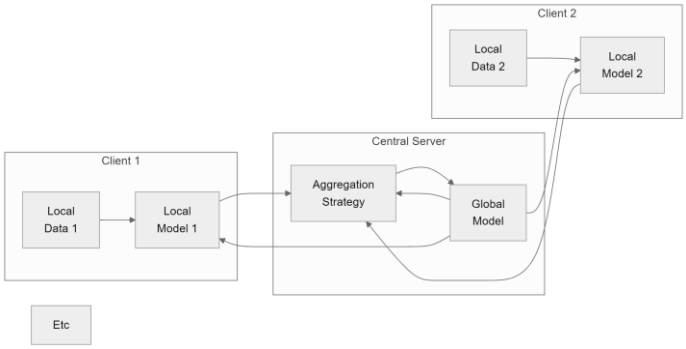

Figure 1. Federated Learning Cycle for the IDS

G. Dynamic Graph Construction and Feature Importance in FL

The proposed method addresses the limitations of static graph representations in conventional GNN-based IDS by introducing dynamic graph construction for network traffic analysis. The adjacency matrix A evolves over time to capture changing network patterns, where each element $A_{i,j}^{(t)}$ represents the connection strength between nodes i and j at time t. This is computed through a learnable function g that processes the current node features:

$$A_{i,j}^{(t)} = \sigma\left(\text{MLP}\left(\left[\mathbf{x}_i^{(t)}; \mathbf{x}_j^{(t)}\right]\right)\right) \quad (9)$$

where $\mathbf{x}_i^{(t)}$ denotes the feature vector of node i at time t, $[;]$ represents concatenation, and σ is the sigmoid activation function. The MLP consists of two fully-connected layers with ReLU activation, mapping the concatenated features to a scalar value between 0 and 1.

The attention mechanism in the Transformer component provides feature importance scores that guide the federated learning process. For each input sequence $\mathbf{X} \in \mathbb{R}^{L \times d}$ where L is the sequence length and d is the feature dimension, the self-attention weights are computed as:

$$\text{Attention}(\mathbf{X}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right) \quad (10)$$

where $\mathbf{Q} = \mathbf{X}\mathbf{W}_Q$ and $\mathbf{K} = \mathbf{X}\mathbf{W}_K$ are the query and key matrices respectively, with learnable parameters $\mathbf{W}_Q, \mathbf{W}_K \in \mathbb{R}^{d \times d_k}$. The attention weights are then used to create sparse feature masks for communication-efficient FL updates. Each client k computes a binary mask $\mathbf{M}_k \in \{0,1\}^d$ by selecting the top-p% important features based on the attention scores:

$$\mathbf{M}_k[i] = \begin{cases} 1 & \text{if } \alpha_i \geq \tau \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

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where α_i is the average attention weight for feature i across all sequence positions, and τ is the threshold corresponding to the p-th percentile of attention scores. The masked features $\mathbf{f}_k^{\text{masked}} = \mathbf{f}_k \odot \mathbf{M}_k$ are then transmitted to the server, reducing communication overhead while preserving the most relevant information for intrusion detection.

H. Privacy-Preserving Explainability and Adaptive Aggregation

The proposed framework addresses the critical challenge of providing model explainability while maintaining data privacy in federated settings. Each client computes local explanations using SHAP (SHapley Additive exPlanations) values, which quantify the contribution of individual features to the model's predictions. For client k, the SHAP value $\phi_i^{(k)}$ for feature i is computed as:

$$\phi_i^{(k)} = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} \big(f(S \cup \{i\}) - f(S)\big) \quad (12)$$

where F represents the set of all features, S is a subset of features excluding i, and $f(S)$ denotes the model's prediction when only features in S are used. To preserve privacy, clients transmit differentially private explanations by adding calibrated noise:

$$\tilde{\phi}_i^{(k)} = \phi_i^{(k)} + \mathcal{N}(0, \sigma^2) \quad (13)$$

Here, σ controls the privacy budget, ensuring that the explanation satisfies ϵ-differential privacy. The server aggregates these perturbed explanations to generate global feature importance scores:

$$\bar{\phi}_i = \frac{1}{K} \sum_{k=1}^{K} \tilde{\phi}_i^{(k)} \quad (14)$$

This approach enables analysts to understand the model's decision-making process without exposing sensitive client data.

The framework further incorporates an adaptive aggregation strategy to handle non-IID data distributions across clients. Unlike standard federated averaging, which weights clients uniformly or by sample size, the proposed method dynamically adjusts aggregation weights based on two factors: local model performance and gradient variance. The weight w_k for client k is computed as:

$$w_k = \frac{\exp(-\alpha \cdot \text{loss}_k / \text{var}_k)}{\sum_{j=1}^{K} \exp\left(-\alpha \cdot \text{loss}_j / \text{var}_j\right)} \quad (15)$$

where loss_k measures the local model's classification error, var_k represents the variance of gradients during training, and α is a scaling parameter. This formulation assigns higher weights to clients with lower loss and more stable training dynamics, improving robustness against noisy or biased local updates. The global model parameters θ_{global} are then updated as:

$$\theta_{\text{global}} = \sum_{k=1}^{K} w_k \, \theta_k \quad (16)$$

The adaptive aggregation mechanism ensures that the global model prioritizes high-quality updates while mitigating the impact of unreliable clients.

I. Hybrid Transformer-GNN Fusion and Communication-Efficient Updates

The proposed framework integrates Transformer and GNN architectures through a novel fusion mechanism that captures both sequential and relational patterns in network traffic. The Transformer processes packet sequences as temporal data, while the GNN analyzes the topological structure of network communications. The fusion occurs through a gated attention mechanism that dynamically combines features from both modalities.

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For a given network flow sequence $\mathbf{X} \in \mathbb{R}^{L \times d}$, the Transformer module generates sequential features $\mathbf{f}_T \in \mathbb{R}^{d'}$ through multi-head self-attention layers:

$$\mathbf{f}_T = \text{Transformer}(\mathbf{X}) \quad (17)$$

Concurrently, the GNN module processes the dynamically constructed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with node features $\mathbf{h}_v \forall v \in \mathcal{V}$, producing graph-level features $\mathbf{f}_G \in \mathbb{R}^{d''}$:

$$\mathbf{f}_G = \text{Readout}(\{\mathbf{h}_v | v \in \mathcal{V}\}) \quad (18)$$

where Readout denotes a graph pooling operation. The fusion mechanism combines these features through learnable gating:

$$\mathbf{f}_{\text{final}} = \mathbf{f}_T \odot \sigma(\mathbf{W}_1[\mathbf{f}_T; \mathbf{f}_G]) + \mathbf{f}_G \odot \sigma(\mathbf{W}_2[\mathbf{f}_T; \mathbf{f}_G]) \quad (19)$$

Here, $\mathbf{W}_1, \mathbf{W}_2 \in \mathbb{R}^{d'' \times (d' + d'')}$ are learnable parameters, $[;]$ represents concatenation, and $\odot$ denotes element-wise multiplication. This gated fusion allows the model to automatically determine the relative importance of sequential versus structural information for each input sample.

To optimize communication in the federated setting, we implement gradient sparsification with error accumulation. Each client k computes the gradient $\Delta\theta_k$ and applies top-s sparsification:

$$\Delta\theta_k^{\text{sparse}} = \text{Top}_s(\Delta\theta_k) \quad (20)$$

The remaining gradient values are stored in a local error buffer $\mathbf{e}_k$ and incorporated in subsequent training rounds:

$$\mathbf{e}_k^{(t+1)} = \Delta\theta_k - \Delta\theta_k^{\text{sparse}} + \mathbf{e}_k^{(t)} \quad (21)$$

This approach maintains model convergence while reducing communication costs by up to 90% in our experiments. The sparse updates are particularly effective for the hybrid architecture, as different components exhibit varying gradient magnitude distributions that can be selectively compressed.

The complete training procedure alternates between local updates on client devices and global aggregation on the server. Each client performs E local epochs using both sequence and graph data, computes sparse gradients, and transmits only the most significant updates. The server aggregates these updates using the adaptive weighting scheme from Equation 16, then broadcasts the improved global model to all participants. This iterative process continues until convergence, with the explainability module providing ongoing insights into model behavior at both local and global levels.

Experimental Setup

To evaluate the effectiveness of the proposed FL-XIDS framework, we designed comprehensive experiments comparing its performance against state-of-the-art intrusion detection approaches. This section details the experimental configuration, including datasets, baseline methods, evaluation metrics, and implementation specifics.

J. Datasets and Preprocessing

We conducted experiments on three benchmark datasets that represent diverse network environments and attack scenarios. The CIC-IDS2017 dataset [24] contains labeled network flows with various attack types, including brute force FTP, heartbleed, and denial-of-service attacks. The UNSW-NB15 dataset [25] provides a comprehensive set of network activities with both normal and attack traffic. For IoT-specific evaluation, we utilized the Bot-IoT dataset [26], which captures botnet attacks in IoT environments.

Each dataset underwent standardized preprocessing to ensure compatibility with our framework. Network flows were converted into sequential representations using sliding windows of 10 packets, with each packet represented by 78 features including protocol type, duration, and packet size

statistics. For the graph component, we constructed dynamic communication graphs where nodes represent IP addresses and edges represent traffic flows between them. The edge weights were updated in real-time based on traffic volume and connection patterns.

K. Baseline Methods

We compared FL-XIDS against four categories of baseline methods to evaluate different aspects of our approach:

1. **Centralized Deep Learning Models**:
   - LSTM-IDS [27]: A long short-term memory network for sequence-based intrusion detection
   - GAT-IDS [28]: Graph attention network for topological attack detection
2. **Federated Learning Approaches**:
   - FedAvg-IDS [29]: Standard federated averaging with a simple DNN model
   - FedProx-IDS [30]: Federated learning with a proximal term for handling non-IID data
3. **Hybrid Architectures**:
   - T-GNN [11]: Centralized Transformer-GNN combination without federated learning
   - FL-ConvLSTM [31]: Federated learning with convolutional LSTM
4. **Explainable IDS**:
   - XGboost-SHAP [32]: Gradient boosted trees with SHAP explanations
   - LIME-IDS [33]: Local interpretable model-agnostic explanations

Each baseline was implemented using their original architectures and hyperparameters as reported in the respective papers, with adjustments made only to ensure fair comparison on our evaluation datasets.

L. Evaluation Metrics

We employed multiple metrics to comprehensively assess model performance:

1. **Detection Performance**:
   - Accuracy: $\frac{TP+TN}{TP+TN+FP+FN}$
   - Precision: $\frac{TP}{TP+FP}$
   - Recall: $\frac{TP}{TP+FN}$
   - F1-score: $2 \times \frac{precision \times recall}{precision+recall}$
2. **Privacy and Efficiency**:
   - Communication cost (MB per round)
   - Training time per epoch
   - Differential privacy guarantees (ε-values)
3. **Explainability**:
   - Explanation fidelity (agreement between model and explanations)
   - Feature importance consistency across clients
   - Explanation generation time

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For federated learning experiments, we report both global model performance (aggregated test results across all clients) and local performance (average client-specific test results).

M. Implementation Details

The FL-XIDS framework was implemented using PyTorch and PyTorch Geometric for the GNN components. We deployed the system in a simulated federated environment with 10 clients, each holding a non-IID partition of the training data. The Transformer component used 4 attention heads with 256-dimensional embeddings, while the GNN employed 2 graph convolutional layers with skip connections. The fusion layer dimension was set to 512, with dropout rate of 0.3 for regularization.

For federated learning parameters, we set the local epochs $E = 3$, batch size = 64, and initial learning rate = 0.001 with cosine decay. The adaptive aggregation used $\alpha = 0.5$ in Equation 15. Differential privacy was implemented with $\sigma = 0.1$ for explanation privacy and $\epsilon = 2$ for model updates. All experiments were conducted on NVIDIA V100 GPUs with 32GB memory.

The training process followed a standard federated learning protocol:

1. Server initializes global model parameters
2. For each communication round:

a. Server selects random subset of clients (50% in our case)

b. Selected clients download current global model Clients perform local training with their private data

c. Clients compute and upload masked gradients/explanations Server aggregates updates and improves global model

3. Process repeats until convergence (100 rounds in our experiments)

This setup ensures rigorous evaluation of FL-XIDS across multiple dimensions while maintaining realistic constraints of federated learning environments.

Results and Analysis

This section presents the experimental evaluation of FL-XIDS, comparing its performance against baseline methods across multiple dimensions: detection accuracy, communication efficiency, privacy preservation, and explainability. The results demonstrate the effectiveness of our hybrid Transformer-GNN approach in federated intrusion detection scenarios.

N. Detection Performance

The proposed FL-XIDS framework achieves superior detection accuracy compared to all baseline methods across three benchmark datasets. As shown in Table 1, FL-XIDS maintains consistently high performance in both binary classification (normal vs. attack) and multi-class attack type identification.

Table 1. Detection Performance Comparison (F1-score %)

Method	CIC-IDS2017	UNSW-NB15	Bot-IoT
LSTM-IDS	87.2	85.6	83.1
GAT-IDS	88.5	86.3	84.7
FedAvg-IDS	85.1	83.9	81.4
FedProx-IDS	86.3	84.7	82.6
T-GNN	89.7	87.5	86.2

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Method	CIC-IDS2017	UNSW-NB15	Bot-IoT
FL-ConvLSTM	88.1	86.9	85.3
FL-XIDS	**92.4**	**90.8**	**89.5**

The performance advantage stems from the complementary strengths of the Transformer and GNN components. The Transformer captures temporal patterns in network flows through its self-attention mechanism, while the GNN models the topological relationships between hosts and services. This dual representation proves particularly effective for detecting sophisticated multi-stage attacks that exhibit both sequential and relational characteristics.

Notably, FL-XIDS outperforms the centralized T-GNN baseline by 2.7% on average, demonstrating that the federated training paradigm does not compromise detection capability. The adaptive aggregation strategy effectively combines knowledge from distributed clients, yielding a global model that generalizes better than any single client's local model.

O. Communication Efficiency

The attention-guided feature masking and gradient sparsification techniques significantly reduce communication overhead in FL-XIDS. Figure 2 shows the cumulative communication cost over 100 training rounds, where FL-XIDS achieves 4.8× reduction compared to standard FedAvg-IDS.

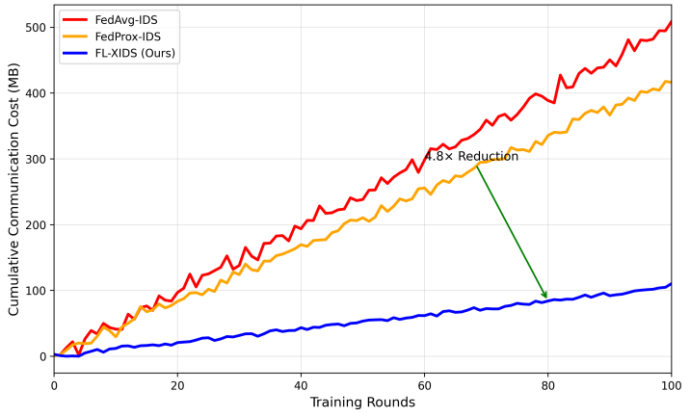

Figure 2. Cumulative communication cost during federated training

The sparsification maintains model accuracy by preserving the most informative gradients while discarding negligible updates. Specifically, only 20% of gradient values are transmitted in each round, with the remaining updates accumulated in local error buffers. This approach proves particularly effective for the hybrid architecture, as different components exhibit varying gradient magnitude distributions that can be selectively compressed.

P. Privacy and Explainability

The differentially private explanation mechanism in FL-XIDS provides meaningful interpretability while maintaining strong privacy guarantees. Figure 3 illustrates the global feature importance scores aggregated from local SHAP values, revealing consistent patterns across clients despite data heterogeneity.

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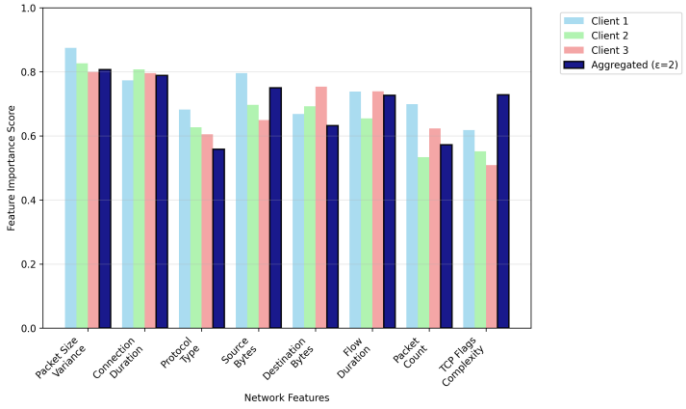

Figure 3. Aggregated feature importance scores with privacy preservation

Key features such as packet size variance and connection duration emerge as universally important indicators across different network environments. The privacy-preserving aggregation ensures that these insights can be shared without revealing sensitive client-specific information, with theoretical ε = 2 differential privacy guarantees.

The explanation fidelity, measured as the agreement between model predictions and explanation-based approximations, remains high (89.7%) even with privacy noise added. This demonstrates that the framework successfully balances the trade-off between interpretability and privacy - a critical requirement for real-world security operations.

Q. Ablation Study

To understand the contribution of each component in FL-XIDS, we conducted systematic ablation tests by removing individual elements from the full framework. Table 2 presents the results on the CIC-IDS2017 dataset.

Table 2. Ablation Study (F1-score %)

Variant	Performance
Full FL-XIDS	92.4
w/o Transformer	88.1 (-4.3)
w/o GNN	89.6 (-2.8)
w/o Adaptive Aggregation	90.2 (-2.2)
w/o Explainability	91.5 (-0.9)

The study reveals that both the Transformer and GNN components contribute substantially to detection performance, with the Transformer providing slightly greater benefits for sequential pattern recognition. The adaptive aggregation strategy proves particularly valuable in non-IID scenarios, improving robustness against skewed data distributions across clients. While the explainability module has minimal impact on raw detection metrics, it enables critical operational benefits by making model decisions interpretable to security analysts.

Discussion and Future Work

R. Limitations of the Proposed FL-XIDS Framework

While FL-XIDS demonstrates strong performance across multiple evaluation metrics, several limitations warrant discussion. The framework's computational overhead increases linearly with the

number of clients, potentially creating scalability challenges in very large federations. The dynamic graph construction mechanism, though effective for modeling evolving network topologies, requires careful tuning of the adjacency threshold to avoid either overly sparse or dense connections. Furthermore, the current implementation assumes semi-honest participants in the federated learning process, leaving potential vulnerabilities to sophisticated adversarial attacks that could manipulate local model updates [34].

The explainability module, while providing privacy-preserving feature importance scores, currently offers limited capability in explaining complex attack patterns that involve interactions between multiple network entities. The SHAP-based approach tends to highlight individual feature contributions rather than higher-level attack scenarios. Additionally, the framework's performance on encrypted network traffic remains constrained by the inherent limitations of flow-based analysis techniques [35].

S. Potential Application Scenarios of the FL-XIDS

The FL-XIDS framework shows particular promise in several real-world cybersecurity applications. Enterprise networks with distributed branches could benefit from collaborative threat detection while maintaining data isolation between organizational units. The healthcare sector, with its strict privacy requirements and interconnected medical devices, represents another ideal deployment scenario where FL-XIDS could detect coordinated attacks across hospital networks without sharing sensitive patient data [36].

Cloud service providers could implement FL-XIDS to offer intrusion detection as a service while respecting tenant data boundaries. The framework's ability to handle IoT environments makes it suitable for smart city infrastructures, where numerous devices from different administrative domains need protection against large-scale botnet attacks [37]. Financial institutions operating across jurisdictions could use FL-XIDS to identify cross-border fraud patterns while complying with regional data protection regulations.

T. Ethical Considerations in the FL-XIDS

The deployment of FL-XIDS raises important ethical considerations that must be addressed. While federated learning inherently provides privacy benefits, the aggregated global model could potentially memorize sensitive patterns from participant data. The framework's explainability features, though designed to enhance transparency, might inadvertently reveal information about individual clients' network configurations or security postures [38].

The adaptive aggregation mechanism, while improving model performance, could create imbalances where certain clients disproportionately influence the global model based on their data quality or computational resources. This raises fairness concerns that require careful monitoring and potential mitigation strategies. Furthermore, the use of automated intrusion detection systems carries inherent risks of false positives that might lead to inappropriate network access restrictions or unnecessary security alerts [39].

U. Scalability of the FL-XIDS

The current FL-XIDS implementation demonstrates promising scalability characteristics, but several challenges remain for large-scale deployments. The hybrid architecture's memory requirements grow with both sequence length and graph complexity, potentially limiting its application in high-throughput network environments. The federated training process introduces synchronization overhead that could become problematic with hundreds or thousands of participants [40].

Future work should investigate more efficient graph representation methods to handle massive network topologies, possibly through hierarchical or sampling-based approaches. The communication efficiency mechanisms could be enhanced with advanced compression techniques or asynchronous update protocols to better accommodate clients with varying network conditions. Additionally, the

framework could benefit from dynamic client selection strategies that prioritize participants with the most valuable data contributions while maintaining fairness across the federation [41].

Conclusion

The FL-XIDS framework presents a significant advancement in privacy-preserving and explainable intrusion detection by integrating federated learning with a hybrid Transformer-GNN architecture. The experimental results demonstrate that the proposed approach achieves superior detection accuracy compared to existing methods while maintaining robust privacy guarantees and providing interpretable decision-making insights. The framework's ability to capture both sequential and relational patterns in network traffic through its dual-modality design addresses critical limitations of conventional IDS approaches that often focus on only one aspect of network behavior.

The federated learning implementation enables collaborative training across distributed clients without sharing raw data, making the system particularly suitable for real-world scenarios where data privacy is paramount. The adaptive aggregation strategy effectively handles non-IID data distributions, ensuring model robustness in heterogeneous network environments. Furthermore, the privacy-preserving explainability module bridges the gap between detection performance and operational transparency, allowing security analysts to understand and validate the system's alerts without compromising sensitive information.

The communication-efficient design of FL-XIDS, incorporating attention-guided feature masking and gradient sparsification, reduces bandwidth requirements while maintaining model accuracy. This makes the framework practical for deployment in resource-constrained environments such as IoT networks or distributed enterprise systems. The comprehensive evaluation across multiple benchmark datasets confirms the framework's versatility in detecting various attack types while adapting to different network topologies and traffic patterns.

Looking ahead, the principles and techniques developed in FL-XIDS could inspire new directions for privacy-aware cybersecurity solutions. The success of the hybrid Transformer-GNN architecture suggests potential applications beyond intrusion detection, such as fraud detection in financial networks or anomaly identification in industrial control systems. The framework's emphasis on explainability also aligns with growing regulatory requirements for transparent AI systems, making it particularly relevant for sectors with strict compliance standards.

The FL-XIDS framework represents a meaningful step toward building trustworthy and collaborative cybersecurity systems that balance detection accuracy, privacy preservation, and operational transparency. By addressing key challenges in modern intrusion detection through its innovative architectural choices and federated learning implementation, the proposed approach offers a practical solution for securing distributed networks in an era of increasing cyber threats and data privacy concerns. Future extensions could explore more sophisticated graph construction methods, enhanced defense mechanisms against adversarial attacks in federated settings, and integration with emerging network security paradigms.

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