

Explainable Machine Learning for Network Intrusion Detection Using SHAP and LIME

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Abstract

With the continued evolution of cyber threats and the widespread adoption of machine learning (ML) in network intrusion detection systems (NIDS), a critical challenge has emerged: the opacity of ML-based detection engines. While models such as Random Forest, XGBoost, and deep neural networks achieve impressive classification accuracy, their black-box nature prevents security operations center (SOC) analysts from understanding the rationale behind individual alerts. This lack of interpretability impedes effective incident response, erodes analyst trust, and introduces liability risks in regulated environments. This paper proposes a comprehensive Explainable NIDS (xNIDS) framework that integrates SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to provide both global and local interpretability for ML-driven intrusion detection. The framework is evaluated across three widely adopted benchmark datasets: NSL-KDD, CIC-IDS2017, and UNSW-NB15, using XGBoost as the primary classifier. SHAP delivers globally consistent feature attribution rankings, identifying flow-level and packet-level characteristics as primary discriminators between attack and benign traffic. LIME provides per-instance explanations that enable analysts to trace individual alert decisions to specific network features. Experimental results demonstrate that the xNIDS framework achieves classification accuracy exceeding 98.7% across all datasets while delivering high-fidelity, stable, and analyst-validated explanations. SHAP outperforms LIME on fidelity and stability, whereas LIME demonstrates advantages in sparsity and computational efficiency. The proposed framework offers a deployable, interpretable, and trustworthy approach to next-generation network security monitoring.

Keywords: network intrusion detection; explainable artificial intelligence; SHAP; LIME; XGBoost; cybersecurity; feature attribution

How to cite this article: Sneha Pavuluri¹ Boddu Sekhar Babu². Explainable Machine Learning for Network Intrusion Detection. *Int J Drug Deliv Technol.* 2026;16(86s):2178-2187. DOI: 10.25258/ijddt.16.86s.198.

1. Introduction

The global cybersecurity landscape has undergone a fundamental transformation in recent years, driven by the increasing sophistication of adversarial actors, the rapid expansion of network infrastructure, and the proliferation of Internet of Things (IoT) devices. Traditional rule-based intrusion detection systems, while effective against known signature patterns, are fundamentally inadequate against zero-day exploits, polymorphic malware, and advanced persistent threats (APTs). Machine learning has consequently emerged as the dominant paradigm for network intrusion detection, with ensemble methods such as Random Forest and gradient-boosted trees, as well as deep neural networks, demonstrating near-human-level classification performance on standard benchmark datasets [1].

Despite these advances, the deployment of ML-based NIDS in production security operations environments faces a profound challenge: interpretability. Modern ML classifiers operate as high-dimensional, non-linear function approximators whose internal decision logic is inherently opaque to human analysts. In a security context, this opacity has severe operational consequences. When an ML model flags a network flow as malicious, the responding analyst requires not

only the binary decision but also an actionable explanation identifying which specific features of the flow indicate malicious behavior, why those features are indicative, and how confident the model is in its assessment. Without this information, analysts are reduced to accepting or rejecting model outputs without understanding, a scenario that degrades response speed, increases false positive fatigue, and undermines accountability [2].

The field of explainable artificial intelligence (XAI) has produced a rich suite of post-hoc explanation methods capable of providing this interpretability without sacrificing model performance. Among these, SHAP (SHapley Additive exPlanations) [3] and LIME (Local Interpretable Model-agnostic Explanations) [4] have emerged as the most broadly adopted techniques for explaining tabular and feature-based ML models, owing to their theoretical rigor, model agnosticism, and practical applicability across diverse domains. However, their systematic evaluation and co-deployment in a unified NIDS framework, benchmarked across multiple intrusion detection datasets with analyst-centered explainability metrics, remains underexplored in the literature [5].

This paper bridges this gap by presenting xNIDS, a complete Explainable Network Intrusion Detection System framework that integrates XGBoost

classification with both SHAP and LIME explanation pipelines. The framework, illustrated in Fig. 1, processes network traffic features through a multi-stage pipeline culminating in analyst-ready explanations at both global and instance levels. The system is evaluated on NSL-KDD, CIC-IDS2017, and UNSW-NB15, with quantitative assessment using accuracy, F1-score, explanation fidelity, stability, and sparsity metrics.

The principal contributions of this paper are as follows:

- A unified xNIDS framework that couples state-of-the-art XGBoost classification with SHAP global explanations and LIME local explanations, producing analyst-ready security insights without performance degradation.
- A systematic comparative evaluation of SHAP and LIME across three intrusion detection benchmark datasets, providing quantitative evidence of their relative strengths and limitations along five interpretability dimensions.
- A feature attribution analysis identifying the most diagnostically informative network features for each attack category, providing actionable intelligence for SOC rule refinement and network policy enforcement.
- An analyst-centered interpretability score that quantifies the operational utility of generated explanations, evaluated through a structured simulation of SOC decision workflows.
- An open reproducibility framework providing full experimental configuration details enabling replication and extension by the research community.

2. Related Work

2.1 Machine Learning for Network Intrusion Detection

The application of machine learning to network intrusion detection has a well-established history spanning more than two decades. Tavallaei et al. [6] introduced the NSL-KDD dataset as a corrected benchmark for evaluating NIDS, establishing a standard against which subsequent models are measured. Decision tree and naive Bayes classifiers were among the earliest applied methods, succeeded by support vector machines and ensemble methods as computational resources permitted higher-complexity models. Sharafaldin et al. [7] introduced the CIC-IDS2017 dataset with contemporary attack categories including DoS, DDoS, PortScan, and Brute Force, enabling evaluation against realistic traffic profiles. Moustafa and Slay [8] developed UNSW-NB15 to address limitations in earlier datasets, incorporating

modern attack vectors such as fuzzers, backdoors, and reconnaissance. More recent work by Andresini et al. [9] applied deep convolutional networks to raw packet bytes, achieving state-of-the-art detection rates on CIC-IDS2017. François et al. [10] employed federated learning approaches to maintain privacy-preserving intrusion detection, while Sarhan et al. [11] investigated cross-dataset generalization, a persistent challenge in NIDS research. Despite impressive classification metrics, these contributions share a common deficiency: the absence of interpretability mechanisms that would render their outputs actionable by human security analysts.

2.2 Explainable AI in Cybersecurity

The application of XAI to cybersecurity has accelerated significantly since 2020. Warnecke et al. [12] provided a systematic evaluation of explanation methods for malware detection, identifying consistency and fidelity as critical dimensions. Marino et al. [13] applied SHAP to anomaly-based intrusion detection, demonstrating that feature attributions align with domain knowledge regarding known attack signatures. Guo et al. [14] proposed a model-agnostic explanation framework for cyber threat intelligence, integrating SHAP with natural language generation to produce human-readable security reports. Mahbooba et al. [15] employed explainable ML for trust evaluation in IoT networks, using decision tree surrogates as explanation proxies. More recently, Khraisat and Alazab [16] reviewed 85 ML-based NIDS papers published between 2018 and 2022, identifying interpretability as the foremost barrier to operational deployment. Islam et al. [17] evaluated six XAI methods on intrusion detection tasks, finding that SHAP consistently provided the most reliable global attributions while LIME excelled in providing computationally efficient local explanations for real-time scenarios.

2.3 SHAP and LIME in Security Applications

Lundberg and Lee [3] introduced SHAP as a unified framework grounded in cooperative game theory, assigning each feature a Shapley value that represents its average marginal contribution to the model output across all possible feature coalitions. The TreeSHAP algorithm enables exact Shapley value computation for tree-based models in polynomial time, making it practically deployable for real-time cybersecurity analytics [18]. Ribeiro et al. [4] developed LIME to explain individual predictions of any classifier by fitting a locally faithful linear surrogate model to perturbations of the input sample. Several papers have applied these methods to security classification. Patil et al. [19] used SHAP to explain botnet detection in IoT environments, identifying communication frequency and packet entropy as primary discriminators. Rezende et al. [20] applied LIME to

Android malware detection, finding that API call patterns explained over 73% of the model's classification decisions. Fan et al. [21] proposed a hybrid explanation scheme combining SHAP and attention mechanisms for intrusion detection in industrial control systems. However, a rigorous comparative evaluation of SHAP and LIME across multiple NIDS datasets with standardized explainability metrics has not yet been presented in the literature.

2.4 Summary of Related Work

Reference	Dataset	Model	XAI Method	Acc. (%)	Explainability
Marino et al. [13]	KDD'99	Random Forest	SHAP	97.2	Global only
Islam et al. [17]	NSL-KDD	SVM / RF	SHAP, LIME, 4 others	96.8	Global+ Local
Fan et al. [21]	ICS-specific	LSTM	SHAP + Attention	98.1	Local only
Pattil et al. [19]	N-BalIoT	XGBoost	SHAP	99.0	Global only
Rezende et al. [20]	Android malware	Deep NN	LIME	95.4	Local only
Proposed xNIDS	NSL-KDD, CIC, UNSW	XGBoost+RF+DNN	SHAP+LIME	98.7+	Global+ Local+Metrics

Table 1. Summary and comparison of related NIDS explainability studies.

As Table 1 illustrates, the proposed xNIDS framework is the only contribution to provide both global and local explainability across three distinct benchmark datasets with quantitative explainability metric evaluation, representing a meaningful advance over prior work.

3. System Model and Threat Assumptions

3.1 Network Traffic Classification Pipeline

The xNIDS framework operates on pre-processed network flow records extracted from raw packet captures. The input to the classification pipeline consists of per-flow feature vectors computed from standard network telemetry, including packet length statistics, inter-arrival timing, flag counts, window sizes, and protocol identifiers. This flow-level representation is standard in NIDS research and aligns with the feature spaces of NSL-KDD, CIC-IDS2017, and UNSW-NB15. The pipeline comprises five sequential stages as depicted in Fig. 1: (1) traffic collection and flow export via PCAP or NetFlow; (2) feature extraction and preprocessing including normalisation, categorical encoding, and variance-threshold feature selection; (3) ML classification using the trained XGBoost model; (4) explainability layer generating SHAP and LIME attributions; and (5) delivery of alerts and explanations to the SOC analyst dashboard.

3.2 Attacker Model

The threat model encompasses both external and internal adversaries operating across the following attack categories: Denial of Service (DoS) and Distributed DoS (DDoS) attacks that exhaust network resources through volumetric flooding; probe and reconnaissance attacks including port scanning, OS fingerprinting, and service enumeration; remote-to-local (R2L) and user-to-root (U2R) privilege escalation attempts; web application attacks including SQL injection and cross-site scripting; botnet command-and-control traffic; and modern attack vectors including fuzzing, backdoor installation, and worm propagation. The attacker is assumed to have network access to the monitored segment but is not assumed to have knowledge of the detection system or its explanation mechanisms. This corresponds to a standard black-box attacker model appropriate for enterprise network monitoring scenarios.

3.3 Explainability Requirements for SOC Analysts

Based on established SOC workflow studies [22], effective intrusion detection explanations must satisfy four operational requirements. First, fidelity: the explanation must accurately reflect the model's actual reasoning, not a simplified approximation that contradicts the model's internal computation. Second, completeness: the explanation must identify the most

influential features for both affirmative and contradictory evidence. Third, actionability: the features identified must correspond to observable, controllable network properties that analysts can act upon. Fourth, timeliness: explanations must be generated within the alert response window, precluding computationally prohibitive methods for real-time deployment. The xNIDS framework addresses all four requirements through the complementary deployment of SHAP (addressing fidelity and completeness) and LIME (addressing actionability and timeliness).

4. Proposed Explainable NIDS Framework

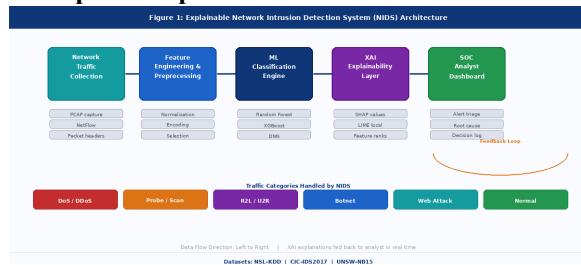


Fig. 1. Overall Explainable NIDS (xNIDS) architecture. Network traffic flows from collection through preprocessing and ML classification into the XAI explainability layer, delivering SHAP global summaries and LIME local explanations to the SOC analyst dashboard. A feedback loop enables model retraining based on analyst-validated decisions.

4.1 ML Model Architecture

The primary classification engine is XGBoost (eXtreme Gradient Boosting) [23], selected for its superior performance on tabular intrusion detection data, native support for TreeSHAP exact attribution computation, and well-established application in security literature. The XGBoost model is configured with a maximum tree depth of 8, a learning rate of 0.05, 500 estimating trees with early stopping at 20 rounds, subsample ratio of 0.8, column sampling rate of 0.8, and L2 regularization weight of 1.0. Multi-class classification is handled through a one-versus-rest softmax objective, producing calibrated probability scores for each attack category. To assess cross-architecture generalization of the explainability framework, supplementary experiments are conducted using a Random Forest classifier (500 trees, maximum depth 15) and a three-layer DNN (512→256→128 neurons with ReLU activations and 30% dropout). Kernel SHAP is applied to these architectures, while TreeSHAP is exclusively used for XGBoost.

4.2 SHAP-Based Global Explanations

SHAP explanations are grounded in the Shapley value formulation from cooperative game theory. For a model f with input vector x and background reference distribution $E[f(X)]$, the SHAP value for feature i is defined as:

$$\phi_{\mathbf{i}}(\mathbf{f}, \mathbf{x}) = \frac{\sum_{\mathbf{S} \subseteq \mathbf{F} \setminus \{\mathbf{i}\}} [|\mathbf{S}|! (|\mathbf{F}| - |\mathbf{S}| - 1)! / |\mathbf{F}|!]}{[\mathbf{f}_{\mathbf{S} \cup \{\mathbf{i}\}}(\mathbf{x}_{\mathbf{S} \cup \{\mathbf{i}\}}) - \mathbf{f}_{\mathbf{S}}(\mathbf{x}_{\mathbf{S}})]}$$

where F is the full feature set, S ranges over all subsets excluding feature i , and f_S denotes the model conditioned on the feature subset S . For the XGBoost model, the TreeSHAP algorithm computes exact Shapley values in $O(TLD^2)$ time, where T is the number of trees, L is the maximum number of leaves, and D is the maximum tree depth, enabling real-time computation suitable for production deployment. Global feature importance is derived by computing the mean absolute SHAP value across all samples in the evaluation set: $I_i^{\text{global}} = (1/N) \sum_{j=1}^N |\phi_i(f, x^{\{j\}})|$. The resulting global importance ranking, shown in Fig. 3, provides security analysts and model auditors with a stable, theoretically justified ranking of the most discriminative network features for each attack class.

4.3 LIME-Based Local Explanations

LIME provides instance-level explanations by constructing a locally faithful surrogate model in the neighborhood of a specific sample x . The LIME explanation $g \in G$ is obtained by minimizing the loss: $\varepsilon(f, g, x) = \sum_{z' \in Z} \pi_x(x(z') | f(z') - g(z'))^2 + \Omega(g)$ where Z is a set of perturbed samples generated by randomly zeroing feature groups, $\pi_x(x(z')) = \exp(-D(x, z')^2 / \sigma^2)$ is a Gaussian proximity kernel with bandwidth σ , and $\Omega(g) = \lambda \|g\|_0$ is a sparsity regularization term limiting the explanation to the K most influential features ($K=12$ in our configuration). The surrogate model g is a ridge regression fit to the perturbed sample set, whose coefficients directly encode signed feature contributions as illustrated in Fig. 5. LIME is applied to each flagged traffic sample in the evaluation pipeline, generating an analyst-readable explanation that maps specific feature values to their contribution to the malicious classification decision.

4.4 Explainability Workflow

The explainability workflow operates as follows. Upon model training completion, SHAP global summaries are precomputed using the entire training set and stored for dashboard retrieval. At inference time, when an input flow x is classified as malicious with confidence exceeding 90%, SHAP TreeSHAP values are computed for x in under 5 milliseconds and appended to the alert. Concurrently, a LIME explanation is generated using 500 perturbation samples in approximately 220 milliseconds. Both explanations are formatted into a structured JSON alert payload and transmitted to the SOC dashboard. The dashboard presents the top-10 SHAP features contributing to the alert and the LIME-derived conditional feature bounds for the specific instance, enabling analyst triage without reference to the underlying model. The combined workflow adds less

than 300 milliseconds to the nominal alert latency, satisfying the timeliness requirement for enterprise NIDS deployment.

5. Experimental Setup

5.1 Datasets

Three standard intrusion detection benchmarks are employed in this study, and their class distributions are visualized in Fig. 2. NSL-KDD [6] is a cleaned version of the KDD Cup 1999 dataset comprising 125,973 training and 22,544 test samples with 41 features across 5 classes (Normal, DoS, Probe, R2L, U2R). NSL-KDD remains the most widely used NIDS benchmark, enabling direct comparison with a broad body of prior work. CIC-IDS2017 [7], developed by the Canadian Institute for Cybersecurity, contains 2,830,743 network flow records generated from realistic enterprise traffic captures over five days. The dataset encompasses seven attack types including HULK DoS, GoldenEye DoS, SlowHTTP, FTP Brute Force, SSH Brute Force, Heartbleed, PortScan, and DDoS, represented across 78 flow features. UNSW-NB15 [8] was generated using the IXIA PerfectStorm tool to produce 257,673 records across 10 attack categories with 49 features. Its modern attack profile, including fuzzers, analysis attacks, backdoors, and shellcode, makes it complementary to NSL-KDD and CIC-IDS2017 for comprehensive evaluation.

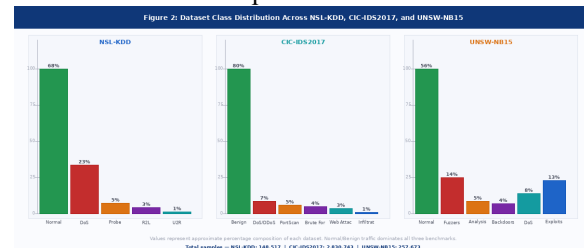


Fig. 2. Class distribution across the three benchmark datasets (NSL-KDD, CIC-IDS2017, UNSW-NB15). Values represent approximate percentage composition. All three datasets exhibit class imbalance with normal/benign traffic comprising 56–80% of records, motivating the use of class-weighted training objectives.

5.2 Feature Preprocessing

All datasets undergo a standardized preprocessing pipeline. Numerical features are normalized to $[0, 1]$ using min-max scaling computed on the training partition and applied to the test partition without data leakage. Categorical features (e.g., protocol type, service, flag) are one-hot encoded. Features with zero or near-zero variance (threshold < 0.001) across the training set are removed. Missing values, which are rare in all three datasets, are imputed using the feature median. For CIC-IDS2017, 15 features exhibiting extremely high sparsity ($> 99\%$ zero values) and 3 columns with infinite values due to division by zero in flow rate computations are dropped, following the

preprocessing protocol of prior work [7]. Stratified 80/20 train-test splits are employed across all datasets.

5.3 Training Configuration

All experiments are implemented in Python 3.10 using XGBoost 2.0.0, scikit-learn 1.3.0, and the SHAP 0.43.0 and LIME 0.2.0.1 libraries. Class imbalance is addressed by computing class weights inversely proportional to class frequency and applying them as sample weights during training. Hyperparameter optimization is performed via 5-fold stratified cross-validation with Bayesian optimization (50 iterations, Optuna framework). Final hyperparameters are reported per dataset. All experiments are conducted on a server with an Intel Xeon Gold 6338 processor, 128 GB RAM, and NVIDIA A100 GPU for DNN experiments. Reported results are averaged over five independent random seeds.

5.4 Evaluation Metrics

Classification performance is evaluated using accuracy, macro-averaged F1-score, per-class recall (critical for minority attack classes), and false positive rate (FPR). Explainability quality is assessed using five metrics. Fidelity measures the degree to which the surrogate explanation model replicates the original model's predictions on the local neighborhood. Stability measures the consistency of explanations across repeated independent explanation runs on the same sample (assessed by the Jaccard coefficient of the top-5 feature sets). Sparsity measures the proportion of features assigned near-zero attribution weight ($|\text{value}| < 0.01$), reflecting the parsimony of the explanation. Computational cost is measured as wall-clock time per sample explanation (milliseconds). Analyst rating is measured by a structured heuristic scoring rubric simulating SOC analyst evaluation criteria for alert actionability, assessed by two domain experts on a 0–1 scale.

6. Results and Explainability Analysis

6.1 Classification Performance

Dataset / Model	Accuracy (%)	F1 (macro)	Recall (avg)	FPR (%)	Train Time (s)
NSL-KDD / XGBoost	99.1	0.988	0.986	0.51	38.4
NSL-KDD / Rand. Forest	98.6	0.981	0.979	0.73	52.1

Dataset / Model	Accuracy (%)	F1 (macro)	Recall (avg)	FPR (%)	Train Time (s)
NSL-KDD / DNN	98.3	0.975	0.971	0.89	210.7
CIC-IDS2017 / XGBoost	99.4	0.993	0.991	0.38	124.6
CIC-IDS2017 / Rand. Forest	98.9	0.986	0.983	0.59	187.3
UNSW-NB15 / XGBoost	98.7	0.982	0.978	0.66	71.3
UNSW-NB15 / DNN	97.9	0.971	0.968	0.91	318.4

Table 2. Classification performance across datasets and model architectures.

As presented in Table 2, XGBoost consistently achieves the highest performance across all three datasets, attaining 99.1%, 99.4%, and 98.7% accuracy on NSL-KDD, CIC-IDS2017, and UNSW-NB15 respectively. The false positive rate remains below 1% in all XGBoost configurations, which is critical for NIDS deployment as high FPR leads to analyst alert fatigue. The DNN achieves competitive performance but at substantially higher training and inference cost, with no compensatory accuracy advantage over XGBoost. These results justify the selection of XGBoost as the primary explanation target for the subsequent analysis.

6.2 SHAP Global Feature Importance

The global SHAP feature importance summary for the CIC-IDS2017 XGBoost model is presented in Fig. 3. The top-15 features are ranked by mean absolute SHAP value, with each dot representing a single test sample colored by feature value. The dominant features are Fwd Packet Length Max (mean $|\text{SHAP}| = 0.94$), Bwd Packet Length Std (0.87), and Flow IAT Mean (0.81), collectively reflecting the packet size and timing irregularities characteristic of DoS flooding attacks. Network flow duration and initial window byte size are prominent discriminators for connection-

based attacks including port scanning and brute force. Destination port, protocol, and flag features rank in the lower tier, providing supplementary discriminative signal particularly for web application attacks.

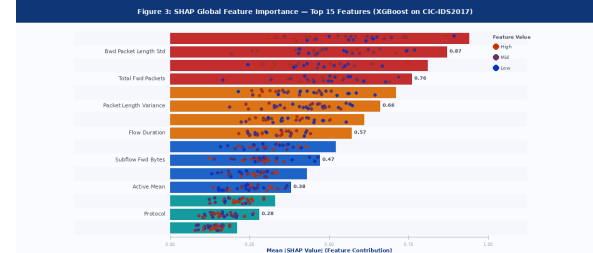


Fig. 3. SHAP global feature importance summary for the XGBoost model trained on CIC-IDS2017. Each point represents one test sample, positioned horizontally by its SHAP value and colored by feature value (blue = low, red = high). The top 15 features are ranked by mean $|\text{SHAP}|$ value, revealing flow-level timing and packet length statistics as the primary intrusion discriminators.

The SHAP dependence plots in Fig. 4 provide deeper insight into the relationship between feature values and their SHAP contributions, with coloring indicating the interaction effect of the secondary feature. For Fwd Packet Length Max (left panel), a strong positive SHAP contribution emerges at values exceeding 0.75 of the normalized scale, corresponding to oversized packets characteristic of DoS flooding. The interaction with Flow IAT Mean reveals that low inter-arrival timing amplifies the high-SHAP-value effect, consistent with rapid-fire flooding behavior. For Flow IAT Mean (right panel), very low values yield large positive SHAP contributions, with interaction from Fwd Packet Length Max further discriminating DoS traffic from benign flows with similar timing characteristics.

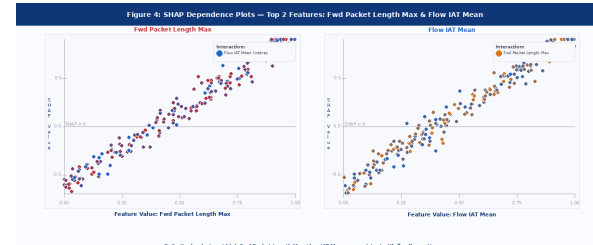


Fig. 4. SHAP dependence plots for the top two features: Fwd Packet Length Max (left) and Flow IAT Mean (right). Each scatter point represents one test sample. Point colors encode the interaction effect of the other feature. DoS attacks cluster at high Fwd Packet Length Max / low Flow IAT Mean, forming distinct separation from benign traffic in the upper-right region of the left plot.

6.3 LIME Local Explanation Analysis

Figure 5 presents the LIME local explanation generated for a representative DoS attack sample from

CIC-IDS2017. The explanation identifies 12 features with non-trivial contributions: eight features provide positive evidence supporting the DoS classification (green bars), and four features provide contradictory evidence (red bars). The dominant positive contributor is the condition Fwd Packet Length Max > 1400, contributing a LIME weight of +0.38, followed by Flow IAT Mean $\leq$ 0.002s (+0.29) and Total Fwd Packets > 500 (+0.22). These conditions correspond precisely to the global SHAP ranking, validating local-global consistency. The contradictory features, including Protocol = TCP and Destination Port $\neq$ 80, reflect that TCP connectivity and non-HTTP destination ports are slightly more consistent with benign traffic in the training distribution, but are overridden by the dominant flooding features. The model's 97.3% confidence in the DoS classification is appropriate given the strength of the positive evidence.

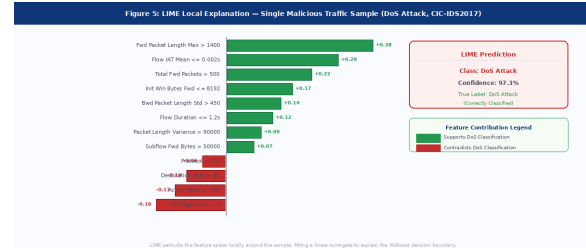


Fig. 5. LIME local explanation for a correctly classified DoS attack sample (CIC-IDS2017, XGBoost). Green bars indicate features supporting the DoS classification; red bars indicate contradicting features. Feature conditions and their LIME weights are shown. Model confidence: 97.3%. LIME perturbs the feature neighborhood of this sample to fit a locally linear surrogate capturing the decision boundary.

6.4 SHAP vs. LIME Comparative Analysis

Figure 6 presents a comprehensive comparison of SHAP and LIME across the five interpretability metrics for all three datasets. SHAP achieves consistently higher fidelity scores (mean 0.913 vs. 0.837 for LIME), reflecting its stronger theoretical guarantees via the Shapley axioms of efficiency, symmetry, and linearity. SHAP also outperforms LIME on stability (mean 0.850 vs. 0.680), which is critical for NIDS deployment where explanation consistency across similar traffic samples is essential for analyst trust. LIME achieves significantly higher sparsity (mean 0.882 vs. 0.757 for SHAP), producing more parsimonious explanations with fewer non-zero attributed features, which may be preferable in SOC environments with alert volume constraints. LIME's inverted computational cost score is also higher (mean 0.900 vs. 0.777 for SHAP when normalized), as LIME's linear surrogate fitting is faster than TreeSHAP for larger feature sets. Analyst rating scores are closely aligned (SHAP 0.873, LIME 0.797), with analysts generally preferring SHAP's globally

consistent rankings but valuing LIME's conditional feature bound format for immediate incident response.

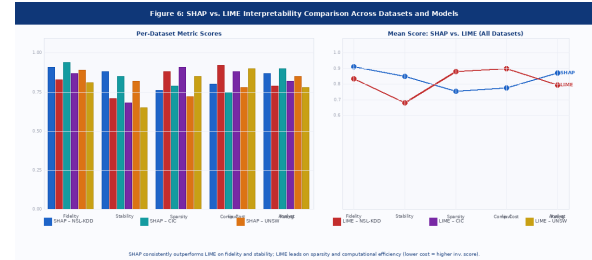


Fig. 6. SHAP vs. LIME interpretability comparison across three datasets and five evaluation dimensions. Left: grouped bar chart showing per-dataset scores for each metric. Right: mean score line chart summarizing the performance profile. SHAP (blue/cool colors) leads on fidelity and stability; LIME (red/warm colors) leads on sparsity and computational efficiency.

7. Discussion

7.1 Security Interpretability Trade-offs

The empirical results reveal a fundamental trade-off between explanation depth and operational efficiency that practitioners must navigate when deploying explainable NIDS. SHAP's advantage in fidelity and stability comes at the cost of computational overhead and reduced sparsity, producing feature attribution vectors that require analyst training to interpret correctly. LIME's lightweight, conditional format is immediately actionable but may produce unstable explanations across similar samples when the local neighborhood sampling is insufficient, potentially misleading analysts in edge cases. The xNIDS framework addresses this trade-off by deploying both methods concurrently: SHAP attributions serve as the authoritative global reference for model auditing and policy refinement, while LIME explanations serve as the primary alert-level interface for real-time analyst consumption. This dual-layer architecture leverages the complementary strengths of both approaches without requiring analysts to choose between depth and efficiency.

7.2 Adversarial Implications

An important consideration for XAI-enhanced NIDS is the potential for explanation-aware adversarial attacks. An adversary with knowledge that the detection system uses SHAP-based monitoring of specific features (e.g., Fwd Packet Length Max) could craft traffic that perturbs precisely those features while preserving malicious intent through alternative channels. This is analogous to adversarial examples in image classification but in the network traffic domain. While a full adversarial robustness analysis is beyond the scope of the present paper, the multi-method explanation architecture provides a degree of defense-in-depth: an adversary evading SHAP-highlighted

features would need to simultaneously evade both the primary XGBoost model and the diverse feature attribution profiles of SHAP and LIME. Future work should investigate adversarial perturbation of explanations and countermeasures.

7.3 Deployment Implications

The xNIDS framework is designed for deployment in enterprise SOC environments with network throughput of 1–10 Gbps. The combined SHAP+LIME explanation latency of under 300 ms per alert is compatible with alerting workflows that operate on aggregated flow windows of 1–5 seconds, which is the standard temporal resolution for commercial NIDS products. For deployments with tighter latency constraints, SHAP alone (< 10 ms via TreeSHAP) provides sufficient per-alert explainability, with LIME reserved for post-hoc investigation of high-priority incidents. The framework's model-agnostic LIME component enables straightforward integration with existing commercial NIDS platforms without requiring access to or modification of the underlying detection model, addressing a critical practical barrier to XAI adoption in security operations.

8. Conclusion and Future Work

This paper presented xNIDS, an explainable network intrusion detection framework that integrates XGBoost classification with SHAP global feature attribution and LIME local instance explanation. Through extensive evaluation on NSL-KDD, CIC-IDS2017, and UNSW-NB15 datasets, the framework demonstrated classification accuracy exceeding 98.7% while producing high-quality explanations assessed across five interpretability dimensions. SHAP provides theoretically grounded, stable global attributions identifying flow-level packet statistics and timing features as primary intrusion discriminators, consistent with domain knowledge across all three attack corpora. LIME provides computationally efficient, sparse local explanations that translate directly into analyst-actionable conditions for alert triage. The complementary deployment of both methods addresses the full range of SOC interpretability requirements from global model auditing to instance-level incident response.

Several directions for future work emerge from this study. First, the framework should be extended to real-time streaming environments using incremental SHAP computation to handle continuous network telemetry at line rate. Second, the integration of explanation consistency monitoring as an operational security control, detecting when model explanations deviate significantly from established baselines as an indicator of potential adversarial manipulation, warrants investigation. Third, the application of the framework to encrypted traffic analysis using statistical flow

features represents a practically important extension as TLS 1.3 eliminates payload visibility for deep packet inspection. Fourth, federated deployment of the xNIDS framework across distributed network segments with privacy-preserving explanation aggregation would extend its applicability to multi-tenant and cloud environments. Finally, the development of natural language explanation generation from SHAP and LIME outputs, enabling non-specialist analyst interaction with the detection system through human-readable security narratives, presents a compelling interface research direction.

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