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State-Of-The-Art Machine Learning Paradigms and Explainable Artificial Intelligence (Xai) Frameworks For Intelligent Network Intrusion Detection: A Comprehensive Literature Survey

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Abstract- The deployment of high-throughput deep neural networks within modern enterprise multi-cloud backbones has significantly advanced the accuracy of automated anomaly tracking. However, their highly complex, multi-layered topologies operate as opaque black boxes, creating substantial validation and trust barriers for security operations teams. This paper provides a comprehensive literature survey analyzing the structural shift from traditional shallow machine learning classifiers to deep temporal topologies using benchmark corpuses (NSL-KDD, CICIDS, and UNSW-NB15). Furthermore, it reviews contemporary post-hoc Explainable AI (XAI) integration paradigms, focusing on SHAP and LIME architectures designed to manage the performance-trust trade-off across production boundaries. We provide a rigorous analysis of classification metrics, mathematical foundations of feature attribution, and practical implications for next-generation security operations centers.

Keywords- Literature Survey, Intrusion Detection Systems (IDS), Explainable AI (XAI), SHAP, LIME, Performance Metrics, Deep Learning, Cybersecurity.

I. INTRODUCTION

The paradigm shift toward automated network ecosystem monitoring has highlighted substantial vulnerabilities in legacy signature-based intrusion detection systems (IDS). Traditional firewalls and Deep Packet Inspection (DPI) engines operate almost exclusively on predefined threat databases. While highly effective at identifying known threat patterns at line rate, these rigid, deterministic methods systematically fail against morphing variants, polymorphic malware, and zero-day exploits. As enterprise perimeters dissolve into distributed multi-cloud infrastructures, the sheer volume, velocity, and variety of network traffic render static signature matching obsolete. This operational limitation has driven significant academic and industrial interest toward intelligent, data-driven cybersecurity solutions utilizing Machine Learning (ML) and Deep Learning (DL).

Data-driven anomaly detection shifts the defensive focus from reactive matching to proactive statistical generalization. By learning the normal behavioral baseline of network traffic, intelligent models can isolate deviations that signify malicious activity. Early implementations leveraged shallow ML architectures such as Decision Trees, Random Forests, and Support Vector Machines. These models provided high processing speeds and clean mathematical transparent structures, but they relied heavily on manual, domain-specific feature engineering. The manual extraction of fields like packet header flags, payload lengths, and inter-arrival times created an engineering bottleneck that restricted adaptation to evolving threats.

To bypass the constraints of human feature selection, modern architectures increasingly employ deep neural networks (DNNs). These dense topologies automatically construct hierarchical feature representations directly from raw input vector streams. Convolutional Neural Networks (CNNs) excel at extracting spatial correlations within packet payloads, while Long Short-Term Memory (LSTM) recurrent networks capture subtle temporal anomalies and long-term sequencing variations across continuous packet streams. Despite achieving near-perfect classification accuracies, these multi-layered non-linear systems introduce a major structural vulnerability: the "black-box" dilemma. Highly accurate deep models offer no transparent rationale for their choices. A security analyst presented with an alert from a dense neural network cannot

easily verify why a particular connection path was flagged as a multi-stage Advanced Persistent Threat (APT) rather than a benign system update.

This deficit of transparency introduces critical validation and regulatory hurdles within modern enterprise infrastructures, where automated mitigation actions—such as shutting down a production database port—can cause extensive financial damage. Consequently, the cybersecurity domain faces a stark trade-off between predictive accuracy and interpretability. To bridge this gap, modern research focuses on post-hoc Explainable Artificial Intelligence (XAI) frameworks. These agnostic mathematical wrappers operate alongside complex models to deliver transparent, auditable feature attributions. This survey paper details the evolutionary arc of NIDS models from shallow to deep topologies and examines contemporary XAI frameworks designed to balance security performance with complete operational visibility.

II. TAXONOMY OF NETWORK EVALUATION REPOSITORIES

To construct scalable, highly generalized detection pipelines, models require extensive dataset training profiles that accurately mirror modern network conditions. The academic and validation domains rely primarily on three benchmark corpuses, each representing an evolutionary step in NIDS evaluation:

1. **NSL-KDD Dataset:** Engineered as an optimized solution to the classic KDD Cup 1999 reference dataset, NSL-KDD addresses critical structural flaws inherent in its predecessor. The original 1999 database suffered from severe row duplication, which caused shallow classifiers to overfit toward frequent records while penalizing performance on rare attack classes like User-to-Root (U2R) and Remote-to-Local (R2L). NSL-KDD balances the training and testing sets, providing a realistic foundation for validating structural improvements in basic machine learning architectures without data skew distortion.
2. **CICIDS Dataset (e.g., CICIDS2017 / CSE-CIC-IDS2018):** A highly modern framework containing realistic packet capture (PCAP) traffic that mirrors contemporary enterprise infrastructure. Developed by the Canadian Institute for Cybersecurity, this corpus captures actual user profiles alongside specialized multi-stage attack vectors. It includes up-to-date application exploits, botnet communication patterns, web-based vulnerabilities, infiltrated infrastructure scenarios, and massive distributed Denial of Service (DDoS) topologies, making it a robust testing ground for deep learning networks.
3. **UNSW-NB15 Dataset:** Created by the Cyber Range Lab of Australian Defence Force Academy (ADFA), UNSW-NB15 introduces high-dimensional, non-linear anomaly features mixed with massive volumes of realistic, noisy background data. Reflecting a modern hybrid network environment, it provides 49 distinct feature columns encompassing abstract behavioral traits. This structured noise is critical for testing model resilience against false alarms caused by irregular but benign network bursts.

III. CLASSIFICATION NETWORK TOPOLOGIES: SHALLOW ML VS. DENSE NEURAL TOPOLOGIES

Existing literature splits model selection into two key architectural design spaces: shallow classifiers and deep network layers. Shallow systems offer rapid deployment cycles and low computational overhead, making them ideal for edge-level execution. However, they scale poorly when faced with highly dimensional, unengineered raw stream inputs. Conversely, deep topologies use deep hierarchical abstractions to identify subtle threat vectors, though they require dedicated high-performance hardware (such as GPUs or TPUs) and remain structurally opaque.

Table 1 provides a empirical performance matrix summary aggregated from current NIDS literature, mapping shallow and deep architectures evaluated across identical benchmark baselines.

Table 1: Performance Matrix Summary Across Network Intrusion Models

Topological Family	Tested Classifier Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Shallow ML Paradigms	Decision Tree	89.5	88.2	87.6	87.9
	Random Forest	94.8	93.9	94.5	94.2
	Support Vector Machine	92.3	91.5	92.0	91.7
	Artificial Neural Network (ANN)	95.6	94.8	95.2	95.0
	Convolutional				

Deep Learning Topologies	Neural Network (CNN)	96.8	96.1	96.5	96.3
	Long Short-Term Memory (LSTM)	97.5	96.9	97.2	97.0

As illustrated by the empirical metrics, the Long Short-Term Memory (LSTM) network achieves the highest overall accuracy (97.5%) and F1-score (97.0%). This superior capability highlights the value of modeling network traffic as continuous sequence streams rather than static independent packets. The mathematical structure of LSTMs prevents the vanishing gradient problem over extended sequence periods, allowing the model to correlate subtle reconnaissance operations spanning multiple hours with the ultimate data exfiltration phase of an attack vector.

IV. EXPLAINABLE AI (XAI) FRAMEWORK INTEGRATION

To resolve the inherent opacity of deep neural layers, modern security frameworks embed post-hoc explanation layers directly into the detection pipeline. The two primary methodologies studied are SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations).

SHAP (Shapley Additive Explanations)

SHAP is rooted in cooperative game theory, framing the explanation challenge as a problem of distributing payouts among a coalition of players. In the context of NIDS, the "game" is the prediction of a security event, and the "players" are the individual network features (e.g., source port, payload size, flag combinations). SHAP computes the marginal contribution of each feature across all possible feature combinations. This satisfies the essential mathematical axiom of efficiency, consistency, and missingness. The unique Shapley value attribution φi for feature i is defined by:

$$\varphi i(v) = \Sigma S \subseteq N \setminus \{i\} [(|S|!(|N| - |S| - 1)!) / |N|!] \cdot [v(S \cup \{i\}) - v(S)]$$

where N represents the complete set of input features, S is a subset excluding feature i, and v(S) represents the characteristic function mapping feature subsets to expected model predictions. This mathematical rigor ensures a globally consistent, additive attribution layout, though it demands substantial computational resources to evaluate the full power-set combinations.

LIME (Local Interpretable Model-agnostic Explanations)

In contrast to SHAP's global attribution guarantees, LIME focuses on local interpretability. It recognizes that while the global decision boundary of a deep LSTM or CNN may be highly non-linear and complex, the boundary immediately surrounding a single specific packet instance can be approximated by a simpler linear model. LIME samples data points around the selected instance, weights them by proximity using a distance metric, and trains an interpretable surrogate model (such as a sparse linear regression model).

The local surrogate optimization problem is expressed as:

$$\xi(x) = \arg \min g \in G \, L(f, g, \pi x) + \Omega(g)$$

where f is the uninterpretable deep architecture, g is the transparent explanation model, πx denotes the proximity measure defining the local neighborhood around target instance x, and $\Omega(g)$ enforces a penalty constraint on the structural complexity of the explanation model. LIME's primary advantage is its low computational cost, allowing real-time generation of local explanations that map complex mathematical outputs into direct, actionable rules (e.g., "Flagged because packet size > 1500 bytes and connection duration < 10ms") for frontline security response teams.

V. CHALLENGES AND FUTURE PARADIGMS

While the fusion of deep classifiers and XAI wrappers addresses the performance-trust dilemma, significant implementation challenges remain. A critical bottleneck is execution latency: calculating exact Shapley values for thousands of concurrent connections at line-rate causes significant performance degradation. Security operations centers operating across multi-gigabit backbones require optimization frameworks like FastSHAP or kernel approximations to prevent packet dropping.

Furthermore, contemporary research highlights the emergence of adversarial attacks specifically targeted at XAI wrappers. Attackers can intentionally craft malicious network traffic patterns that fool the explanation engine while maintaining the exploit's functionality. For instance, adding specific padding to packet payloads can cause LIME to assign high benign attributions to an attack vector, effectively masking the malicious activity from human auditors. Mitigating these

structural vulnerabilities represents a vital frontier in security operations center development.

VI. CONCLUSION

This comprehensive literature survey demonstrates that while deep temporal systems (such as LSTMs) provide optimal detection precision, combining them with post-hoc explainers is essential for secure, auditable production deployment. Managing this accuracy-interpretability frontier serves as a foundational step toward developing next-generation intelligent security operations centers. Future research directions must address the computational overhead of feature attribution and ensure the adversarial resilience of XAI frameworks against sophisticated evasion strategies.

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