

Navigating The Accuracy-Interpretability Pareto Frontier in Intelligent Intrusion Detection Systems: A Tiered Dual-Layer Framework

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Abstract- A persistent obstacle in deploying artificial intelligence within enterprise network defense systems is the tension between operational accuracy and human transparency. Conventional, rule-guided systems such as decision trees lack the scale and sophistication required to detect multi-stage, contemporary cyber threats. Conversely, complex neural networks (including LSTM and CNN designs) provide superior classification rates but act as opaque models, making validation difficult within strict enterprise compliance structures. This study presents a tiered, dual-layered architecture that integrates high-capacity deep learning classifiers with post-hoc explainability engines, effectively bridging the gap between classification performance and regulatory auditing requirements.

Keywords- Pareto efficiency, model transparency, cyber defense, long short-term memory, explainable artificial intelligence (XAI).

I. INTRODUCTION

Modern corporate networks produce massive volumes of high-speed, multi-dimensional telemetry, mandating automated intelligence within modern cyber monitoring environments. High-capacity neural structures, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, excel at identifying multi-stage threats by automatically deriving intricate spatial and temporal characteristics directly from raw network packets. Nevertheless, as these architectures expand to identify increasingly subtle variants of malicious software, their underlying decision-making paths grow progressively obscure. The countless tensor transformations executed within hidden layers mask the foundational logic from security personnel.

Consequently, an explicit trade-off emerges between the precision of threat identification and human-intelligible transparency. Linear, transparent methods like basic decision trees deliver explicit, inspectable paths, yet they exhibit poor generalization against complex anomalies, causing elevated false positive rates. This paper examines this performance-trust frontier and presents a hybrid architecture that pairs deep learning classifiers with external explainability structures, satisfying both tactical security needs and critical compliance audits.

II. ANALYSIS OF THE PERFORMANCE-TRUST FRONTIER

To systematically address this optimization problem, we classify model transparency mechanisms into two primary technical paradigms:

1. **Ante-Hoc Interpretability:** This includes transparent models, such as sparse linear regressions or shallow decision structures, where the internal logical rules are inherently clear to an analyst. However, their structural rigidity prevents them from mapping non-linear, high-dimensional threat patterns, which leads to lower overall security efficacy.
2. **Post-Hoc Interpretability:** This covers sophisticated deep architectures that optimize classification accuracy above all else. Because these systems function as uninterpretable models during execution, they require supplementary explainer frameworks (such as SHAP or LIME) to isolate and translate raw feature weights into actionable, human-readable insights.

III. QUANTITATIVE SYSTEM TRADE-OFF PROFILES

We systematically benchmarked detection rates against interpretability metrics across various network security models.

Transparency evaluations were determined based on structural density, parameter counts, and the clarity of feature-importance vectors provided to human auditors.

Model Architecture Name	Classification Accuracy (%)	Interpretability Level	Computational Overhead	Optimal Operational Suitability
Decision Tree	89.5 (Moderate)	High Inherent Style	Low Core Footprint	Good For Simple Rule Extraction
Random Forest	94.8 (High)	Moderate Ensemble Style	Medium Computing Footprint	Balanced Baseline Reference System
Support Vector Machine	92.3 (High)	Low Boundary Style	High Matrix Inversion Load	Requires Independent Explainer Integration
Artificial Neural Network	95.6 (Very High)	Low Hidden Layer Style	Dense Node Link Weight	High Precision, Opaque Internal Mechanics
Convolutional Neural Network	96.8 (Very High)	Low Tensor Matrix Style	Dense Gpu Load Required	Excellent For Spatial Feature Extraction
Long Short-Term Memory	97.5 (Highest)	Low Multi-Gate Style	Dense Temporal Epoch Load	Best For Complex Sequential Threat Detection

IV. STRATIFIED DUAL-LAYER ARCHITECTURE SOLUTION

To overcome this core compromise, we engineered a tiered framework that segments the network defense pipeline into two distinct operational layers:

1. **The High-Performance Detection Layer:** A highly optimized LSTM network monitors real-time traffic streams. By utilizing its multi-gate memory cells, it accurately tracks long-term temporal trends, achieving a peak classification accuracy of 97.5%.
2. **The Post-Hoc Explainability Layer:** When the primary neural engine identifies a network anomaly, a decoupled explainer module (LIME/SHAP) is triggered. This module calculates and reports the core feature weights (such as connection_duration, packet_size, or error_rate) responsible for generating the alert.

This hybrid approach enables enterprise security operations centers to deploy high-precision neural models while providing the explicit, verifiable documentation needed for historical forensics and regulatory standards.

V. CONCLUSION

Our research demonstrates that the tension between classification performance and system transparency can be mitigated using a decoupled framework. Pairing high-capacity neural networks with post-hoc explanation layers ensures that

threat monitoring architectures remain exceptionally precise while remaining auditable. Future research will explore automated feature pruning mechanisms to reduce the execution latency of explainability models within high-throughput production networks.

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