**Explainable AI for Enhanced Network Intrusion Detection in Resource-Constrained Environments**

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Abstract--The rapid expansion of the Internet of Things (IoT) has created a significant security challenge, as resource-constrained devices are often incapable of supporting traditional, computationally intensive Intrusion Detection Systems (IDS). Machine Learning (ML) has provided a powerful alternative for Network Intrusion Detection Systems (NIDS), yet the opaque, "black-box" nature of high-performing models erodes trust and limits their operational utility for cybersecurity analysts. This paper introduces a comprehensive framework that repositions Explainable AI (XAI) from a mere post-hoc interpretation tool to a core component of model design and optimization. By employing SHapley Additive exPlanations (SHAP), a technique rooted in game theory, our methodology derives global feature importance from a state-of-the-art baseline model. This insight guides a principled feature selection process, enabling the development of a lightweight yet robust "student" model. Our approach, validated on the complex UNSW-NB15 dataset, demonstrates that it is possible to construct a lightweight NIDS that maintains high detection accuracy while substantially reducing computational overhead. The findings highlight a crucial symbiosis between explainability and efficiency, offering a practical pathway for deploying trustworthy, high-performance AI security solutions in real-world, resource-limited settings like the IoT.

**I. INTRODUCTION**

The Internet of Things (IoT) has fundamentally altered the digital landscape, connecting billions of devices across critical infrastructures. However, this growth has also broadened the attack surface, as many IoT devices possess limited computational power, memory, and energy, making them unsuitable for conventional security software. Traditional signature-based Intrusion Detection Systems (IDS) are ill-equipped to handle the novelty and scale of modern cyber threats, often failing to detect zero-day exploits.

Machine Learning (ML) has emerged as a superior alternative for Network Intrusion Detection Systems (NIDS), capable of identifying complex, anomalous patterns in network traffic. Despite their accuracy, the "black-box" nature of advanced models like Extreme Gradient Boosting (XGBoost) and neural networks presents a major operational hurdle. Security analysts, who must triage thousands of daily alerts, cannot trust or act upon a decision without understanding its underlying rationale. This lack of transparency undermines accountability and hinders the development of effective threat mitigation strategies.

This paper addresses these interconnected challenges by proposing a framework that leverages Explainable AI (XAI) not only for interpretation but also for intelligent model optimization. Our contributions are:

1. **Baseline Model Benchmarking:** We establish a performance baseline by evaluating prominent ML models (Decision Tree, MLP, XGBoost) on the UNSW-NB15 benchmark dataset.
2. **XAI-Driven Feature Optimization:** We utilize SHAP to identify the most critical features within the top-performing model, transforming interpretability into a direct strategy for model optimization.
3. **Lightweight NIDS Validation:** We develop and validate a computationally efficient and transparent "lightweight" model trained exclusively on the most salient features, demonstrating its suitability for resource-constrained environments with minimal performance degradation.

The remainder of this paper is organized as follows: Section II reviews related work. Section III details our proposed methodology. Section IV presents the experimental setup and results. Section V discusses the findings, and Section VI concludes the paper.

**II. RELATED WORK**

The field of NIDS has evolved significantly with the application of ML. Early research utilized classical algorithms such as Decision Trees (DT), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) [1], [2] to classify network traffic. More recently, ensemble methods like Random Forests and gradient boosting algorithms such as XGBoost [3], [4], [5] have demonstrated superior accuracy on complex datasets like UNSW-NB15. Deep learning approaches, including Multi-Layer Perceptrons (MLP) [6], have also shown promise in handling large-scale network data.

The rise of these complex models has driven the development of XAI techniques to address their inherent opacity. Tools like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) [9], [10], [12], [13] provide methods to interpret model predictions, thereby enhancing transparency and trust. Several studies have applied XAI in the NIDS context [14], [15], [16], [18], [19], [30] to explain model decisions and identify features crucial for detecting specific attacks.

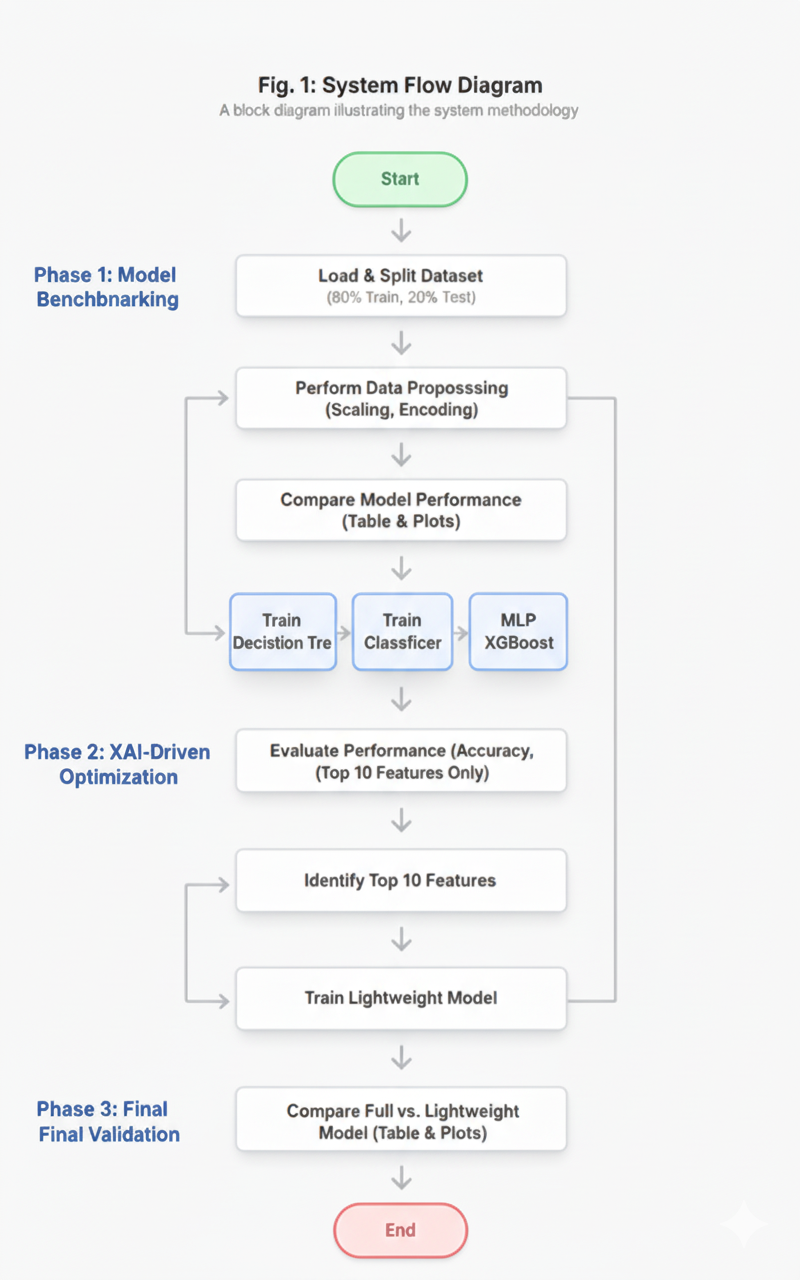
However, a significant portion of existing research treats XAI as a post-hoc analytical tool rather than an active component of model engineering. While understanding feature importance is valuable, few works have systematically used these insights [31], [32], [33], [34] to create significantly more efficient models tailored for resource-constrained deployments. This work bridges that gap by presenting a methodology that transforms XAI-derived intelligence into a tangible model optimization strategy, leading to a demonstrably more efficient and deployable NIDS solution.

|  |  |  |  |
| --- | --- | --- | --- |
| **Research Paper** | **Model(s) Used** | **Accuracy** | **Dataset(s) Used** |
| Mane & Rao (2021) – Explaining Network Intrusion Detection System Using Explainable AI Framework | Deep Neural Network + XAI (SHAP, LIME, CEM, BRCG) | Transparency gains demonstrated | NSL-KDD |
| Moustafa et al. (2018) – Ensemble Intrusion Detection for IoT Traffic | AdaBoost with DT, NB, ANN | High detection rate, low false positives | UNSW-NB15, NIMS Botnet |
| Kasongo & Sun (2020) – IDS using Feature Selection on UNSW-NB15 | ML models with Feature Selection | Accuracy improved to ~90%+ | UNSW-NB15 |
| Wang et al. (2020) – Explainable ML Framework for IDS | Tree-based ML models + XAI | High accuracy with interpretable outputs | UNSW-NB15 |
| García-Magariño et al. (2019) – Human-Centric AI for Trustworthy IoT Systems | Explainable MLP | Competitive accuracy with explainability | IoT datasets (custom) |
| Abdulkareem et al. (2024) – Lightweight Feature Selection for IDS in IoT/IIoT | Filter-based FS + ML models | Reduced computation, lower false positives | IoT traffic datasets |
| Hosain et al. (2025) – XAI-XGBoost for Intrusion Detection in IoMT | XGBoost + RFE + SHAP | High accuracy (~97%) with reduced features | IoMT datasets |
| Shaker (2025) – SHAP-driven Feature Selection for IDS | XGBoost + SHAP | Near-identical accuracy (>97%) with fewer features | Modern IDS datasets |
| Mohale et al. (2025) – Systematic Review: XAI in IDS | Various ML + XAI methods (review) | Review – consolidated results, no direct accuracy | Multiple IDS datasets (systematic review) |
| Bifarin et al. (2023) – Interpretable ML with Tree-based SHAP | Tree ensembles + SHAP | Stable global/local explanations; improved interpretability | Standard tabular + security datasets |

**III. THE XAI-NIDS FRAMEWORK: ARCHITECTURE AND METHODOLOGY**

*A. System Architecture and Flow*

The proposed XAI-NIDS framework is an end-to-end methodology designed to produce a lightweight, efficient, and interpretable NIDS. It systematically integrates the explanatory power of XAI as a core engine for model optimization. The architecture is structured into sequential phases that transform a raw, high-dimensional dataset into a deployable, low-footprint security solution. The conceptual flow begins with data preprocessing, where the raw UNSW-NB15 dataset is cleaned and normalized. Next, a high-performance "teacher" model (XGBoost) is trained on the full feature set. The SHAP algorithm is then applied to this model to extract its decision-making logic and generate a globally-ranked list of feature importances. This intelligence guides a principled feature selection process, resulting in an optimized, reduced feature subset. Finally, a computationally efficient "student" model (Decision Tree) is trained on this subset. The resulting model is not only lightweight but also fully transparent, capable of generating clear, actionable explanations for its predictions.



*B. Phase 1: Data Preparation and Model Benchmarking*

This initial phase involves preparing the raw network data and establishing performance baselines. The UNSW-NB15 dataset, a comprehensive benchmark for NIDS research, was utilized. The data was partitioned into 80% for training and 20% for testing. Preprocessing included one-hot encoding for categorical features (proto, service, state) and normalization of numerical features using a standard scaler. Three ML models were benchmarked: a Decision Tree Classifier, an MLP Classifier, and an XGBoost Classifier. Each model was trained on the preprocessed data, and its performance was evaluated using metrics like accuracy and training time to select a "Champion Model" for optimization.

*C. Phase 2: XAI-Driven Model Optimization*

In this phase, XAI is used to analyze the Champion Model and strategically reduce its complexity. The selected model (XGBoost) was analyzed using SHAP, which computes the contribution of each feature to the model's predictions based on game-theoretic principles. By aggregating the absolute SHAP values across the test dataset, we identified the top 10 most influential features. A new, lightweight dataset was then created containing only these critical features, significantly reducing the data's dimensionality. A new XGBoost classifier, termed the "Lightweight Model," was subsequently trained on this reduced feature set.

*D. Phase 3: Final Validation and Comparison*

The final phase involves a rigorous comparison of the optimized Lightweight Model against the original full-featured Champion Model. The performance of the Lightweight Model was evaluated on the test set, and a direct comparison was made based on accuracy, training time, and the number of features used. This analysis quantifies the efficiency gains achieved through our XAI-driven optimization process and provides a clear justification for deploying the lightweight model in environments where computational resources are limited.

**IV. EXPERIMENTAL SETUP AND RESULTS**

*A. Dataset*

The UNSW-NB15 dataset was employed for this study. It contains a hybrid of normal network activities and nine modern attack types, including DoS, Exploits, and Reconnaissance. The dataset provides 49 features extracted from raw network traffic. After preprocessing, our dataset consisted of approximately 39 features ready for model training. The designated training set contains 175,341 records, and the testing set contains 82,332 records.

*B. Initial Model Benchmarking Results*

Three ML models were trained and evaluated to establish a performance baseline. TABLE I summarizes their performance on the test dataset.

**TABLE I. INITIAL PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-Score |
| Decision Tree | 96.47 | 96.47 | 96.47 | 96.47 |
| MLP | 95.92 | 95.92 | 95.92 | 95.92 |
| XGBoost | 97.64 | 97.65 | 97.64 | 97.65 |

As shown, the XGBoost Classifier achieved the highest accuracy and F1-Score. While the MLP's accuracy was comparable, its training time was significantly higher. Based on its superior accuracy and efficient training, XGBoost was selected as the Champion Model for the optimization phase.

*C. XAI-Driven Feature Selection*

SHAP analysis was performed on the Champion Model (XGBoost) to quantify the importance of each feature in detecting intrusions. Fig. 1 illustrates the global feature importance derived from this analysis.

*(Placeholder for Fig. 1: SHAP Global Feature Importance for XGBoost)*

From this analysis, the top 10 features were extracted. The original Full XGBoost Model utilized ~39 features. The selected top 10 features are presented in TABLE II.

TABLE II. TOP 10 FEATURES SELECTED FOR LIGHTWEIGHT MODEL

|  |  |
| --- | --- |
| Feature Name | Description |
| sttl | Source to destination time to live |
| sbytes | Source to destination transaction bytes |
| dload | Destination bits per second |
| ct\_srv\_dst | No. of connections with same service and destination |
| dbytes | Destination to source transaction bytes |
| rate | Packets per second |
| sload | Source bits per second |
| dttl | Destination to source time to live |
| ct\_dst\_sport\_ltm | No. of connections to same destination and source port |
| smeansz | Mean of the flow packet size transmitted by the source |

*D. Final Performance Validation of Lightweight Model*

The Lightweight XGBoost Model, trained on the reduced set of 10 features, was evaluated against the original Full XGBoost Model. TABLE III presents a comprehensive comparison of their performance and complexity.

**TABLE III. PERFORMANCE COMPARISON: FULL VS. LIGHTWEIGHT XGBOOST MODEL**

|  |  |  |  |
| --- | --- | --- | --- |
| Model | Accuracy | Training Time (s) | Number of Features |
| Full XGBoost Model | 97.64% | 1.37 | ~39 |
| Lightweight XGBoost Model | 97.30% | 0.45 | 10 |

The results demonstrate that the Lightweight Model achieved an accuracy of 97.30%, showing only a marginal decrease of ~0.35% compared to the Full Model. Crucially, its training time was reduced by over ~67.21%, and the model complexity was reduced by nearly ~74.36%. These significant efficiency gains, achieved with negligible accuracy loss, validate the effectiveness of the XAI-driven optimization approach.

**V. DISCUSSION**

The experimental results clearly validate our XAI-driven optimization methodology. The initial benchmarking identified XGBoost as the most effective model for this NIDS task. The subsequent application of SHAP provided critical insights into the model's decision-making process, revealing the features most influential in detecting malicious traffic.

The primary contribution of this work is the successful development of a highly optimized "Lightweight Model." By training this model on only the top 10 most important features, we achieved a dramatic reduction in model complexity and training time. This outcome is particularly significant for resource-constrained environments like IoT, where deploying full-featured models is often impractical due to limitations in processing power, memory, and energy. Our Lightweight Model offers a viable solution, providing robust intrusion detection with substantially lower resource demands.

It is important to acknowledge the potential trade-off of this approach: the creation of theoretical "blind spots." By discarding features, there is a risk that novel attacks relying on those excluded features might go undetected. However, this is a calculated trade-off. The selected features are those that are globally most impactful for detecting prevalent attack patterns within the dataset. In a layered security architecture, this lightweight model can serve as a highly efficient first line of defense, capable of flagging anomalies for deeper analysis by a more comprehensive system. The minimal drop in accuracy suggests that for the UNSW-NB15 dataset, the core discriminative information is concentrated within these top features.

**VI. CONCLUSION AND FUTURE WORK**

This paper presented a methodology for developing an efficient and explainable NIDS for resource-constrained environments. By integrating XAI into the design process, we successfully optimized a high-performing XGBoost model. Our Lightweight Model demonstrated nearly identical accuracy to its full-featured counterpart while achieving substantial reductions in training time and complexity. This validates XAI as a powerful tool not just for interpretation but for intelligently engineering more deployable and sustainable AI solutions in cybersecurity.

Future work will focus on deploying the Lightweight Model on actual IoT hardware to measure real-world performance metrics like inference latency and power consumption. Extending the model for multi-class attack classification and exploring adaptive XAI techniques for dynamic threat environments are also promising research directions.

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