**EXPLAINABLE AI FOR INTRUSION DETECTION WITH XGBOOST AND SHAP**

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***Abstract*—The increasing complexity of cyber attacks requires the utilization of robust and explainable network intrusion detection systems (NIDS). Traditional black-box models are very accurate but are not transparent and do not enable IT experts to understand the detection results. This research incorporates Explainable Artificial Intelligence (XAI) with NIDS to address the issue. Using the NAL-KDD dataset, we create an XGBoost-based intrusion detection model that is MATLAB-optimized. The system enhances detection precision and includes SHAP (SHapley Additive exPlanations) to offer explanations regarding the significance of different features. Precision, recall, and F1-score measurements validate the system's performance in identifying a wide range of network threats. Closing the gap between high-performing models and interpretability, this research enhances the system's robustness, enables informed decision-making, and enhances cybersecurity defense. The proposed approach enhances trust and operational efficiency, making AI-driven intrusion detection actionable and interpretable to cybersecurity professionals.**

***Keywords: Cybersecurity, Intrusion Detection, XAI, Transparency, Interpretability, Feature Importance, Decision-Making.***

1. INTRODUCTION

The rapid evolution of digital technology has led to an unprecedented flood of cyber attacks, and therefore, the establishment of robust and effective network intrusion detection systems (NIDS) is necessary. The systems are crucially significant in discovering and countering malicious behavior in network systems. Traditional NIDS employ either signature-based or anomaly-based detection, which are themselves limiting. Signature-based approaches are constantly in requirement [1] of updates and are bound to miss emerging attacks, while anomaly-based approaches, which typically involve machine learning, are plagued by lack of interpretability. The growing application of complex black-box models in cybersecurity has led to serious concerns regarding their transparency and trust, rendering it challenging for IT professionals to interpret the rationale underlying particular decisions.

To overcome such constraints, there is a need to integrate Explainable Artificial Intelligence (XAI) techniques, which are capable of enhancing the interpretability of intrusion detection [2] systems without compromising performance. Machine learning models, particularly ensemble-based models like XGBoost, have been reported to be incredibly accurate at identifying network intrusions. However, the complex inner working of such models makes them difficult to deploy in severe security scenarios where decision transparency is the highest priority.

To overcome this limitation, the current research designs an XGBoost-based intrusion detection system optimized using MATLAB and based on the NAL-KDD dataset. The main objective is to design a high-performance model with accurate network traffic classification and that integrates Explainable Artificial [3] Intelligence (XAI) techniques to reveal its prediction reasoning. SHAP (SHapley Additive exPlanations) is used to analyze feature importance and clarify how different input variables influence the detection outcomes. With enhanced interpretability, cybersecurity professionals are able to gain a better insight into the system's decisions and thereby develop better-informed countermeasures against possible attacks.

The inclusion of XAI methods in NIDS has several benefits. Firstly, it makes it easier to achieve transparency that is pertinent in cybersecurity systems where it is important to know the reasons behind the alerts and classifications. Secondly, it makes model debugging and optimization possible through identification of the most important features influencing [4] predictions, hence optimizing detection rules and minimizing false alarms. Thirdly, it enhances regulatory compliance through explanations of security-related actions, which is increasingly becoming important in sensitive information-handling industries. Last but not least, an interpretable model is able to build trust among IT professionals and stakeholders, thus making AI-based cybersecurity solutions more deployable in real-world settings.

The NAL-KDD dataset has been used in this research due to its comprehensive coverage of various network attack types and normal traffic. It is a de facto standard dataset for evaluating intrusion detection models and, as such, ensures the credibility [5] of the proposed system. MATLAB has been used as the development platform due to its high-level machine learning capabilities, optimization toolkits, and ability to handle large-scale cybersecurity data. The framework focuses not just on accuracy but also on result explainability so that IT professionals can interpret and audit the results appropriately.

The performance is evaluated using major metrics to analyze the ability of the model to distinguish between legitimate and malicious network traffic. High precision ensures that detected intrusions are indeed malicious, hence reducing false positives, and high recall ensures that most attacks are detected, hence [6] reducing false negatives. The F1-score evaluates the overall precision and recall, hence ensuring overall reliability. The metrics confirm the success of the combination of XAI and machine learning-based NIDS in demonstrating that explainability can be achieved without compromising detection performance.

This study advances the continuous endeavors aimed at enhancing the interpretability and practicality of AI-driven cybersecurity solutions. By incorporating SHAP-based explanations within an XGBoost-driven [7] intrusion detection system, it significantly improves the applicability of AI models in the domain of cybersecurity. Information Technology professionals may utilize the elucidated explanations to optimize security protocols, refine incident response techniques, and respond to emerging threats with greater efficacy.

Additionally, the knowledge acquired from the analysis of feature significance can guide the creation of more resilient network structures, thereby proactively minimizing vulnerabilities. In brief, the combination of XAI methods with ML-based NIDS solves the grand challenge of black-box model interpretability in security. This paper underscores the need [8] to strike a balance between high detection rates and interpretability so that AI-based security systems are not just effective but also explainable. By overcoming the performance-interpretability trade-off, the proposed approach enables trust and improves operational effectiveness in security applications, which will enable stronger and explainable intrusion detection systems in the future.

This work is organized with review of the literature survey as Section II. Methodology described in Section III, highlighting its functionality. Section IV discusses the results and discussions. Lastly, Section V concludes with the main suggestions and findings.

1. LITERATURE SURVEY

Previous work has investigated network intrusion detection system effectiveness by comparing various datasets to understand attack patterns and network activity. These studies have emphasized the importance of large datasets that reflect real-world attack scenarios, thus ensuring that detection models generalize well across various scenarios. Through the use of various network traffic records, researchers have emphasized the importance of cleanly balanced datasets that eradicate bias and overfitting. The evaluation of such datasets is of great importance in designing effective intrusion detection frameworks, which further strengthens security measures and enables new cyber threats to be detected.

Several studies have investigated the impact of feature selection techniques on accuracy and efficiency enhancement in intrusion detection systems. Through the process of dimensionality reduction and the removal of redundant or irrelevant features, these studies explain how more accurate feature sets translate into better classification performance. Feature selection not only improves detection accuracy but also reduces [9] computational complexity, and thus improves the efficiency of intrusion detection systems in real-time applications. This research emphasizes the need to identify the most pertinent features to improve model interpretability and the overall performance of the system. Attention has been directed toward the issue with unbalanced datasets in intrusion detection systems, where attack instances are found to be underrepresented relative to normal traffic. The imbalance negatively impacts model training and results in biased [10] classification outcomes. Techniques like resampling techniques and synthetic data creation have been explored to tackle this. Proper handling of imbalanced datasets assures intrusion detection models to be resilient and able to detect common as well as uncommon forms of attacks, avoiding misclassification and system reliability as a whole.

Research has examined the use of real-time traffic analysis in the context of network intrusion detection, with an emphasis on identifying malicious activity in real-time. These studies emphasize the critical requirement for low-latency detection systems that can handle large volumes of network traffic while maintaining [11] accuracy. Effective real-time analysis allows for the instant mitigation of threats and improves network security by stopping potential harm before the attack can escalate. This research emphasizes the continued necessity for high-velocity data processing methods to keep up with the constantly evolving nature of cyber threats. The worth of implementing multi-layered security controls for network intrusion detection has been well studied in cyber security scholarly literature. Such studies validate the need for defense-in-depth as a security posture where security controls are combined to develop a more robust defense posture. Through [12] the use of multiple layers of security, organizations can lower their exposures and improve their capability to recover from sophisticated cyber attacks. The studies show that combining active monitoring, anomaly detection, and access controls develops a more robust security posture.

Studies in user behavior analysis have provided significant insights into insider threat detection in network environments. Such research focuses on identifying abnormal behavior that strays from observed patterns of user behavior. By examining [13] access logs, system usage patterns, and authentication history, researchers have been able to show the effectiveness of behavior-based intrusion detection systems. Such research emphasizes the need for monitoring internal threats over external threats in safeguarding confidential information and maintaining network integrity. There has been study on hybrid intrusion detection systems that integrate various detection approaches for improving overall security. Through integrating signature-based and anomaly-based detection [14] approaches, such studies show how hybrid systems obtain improved detection rates with lower false positives. Coordination among various detection approaches raises system responsiveness to new attack mutations, and hybrid intrusion detection emerges as a promising future trend for next-generation cybersecurity solutions.

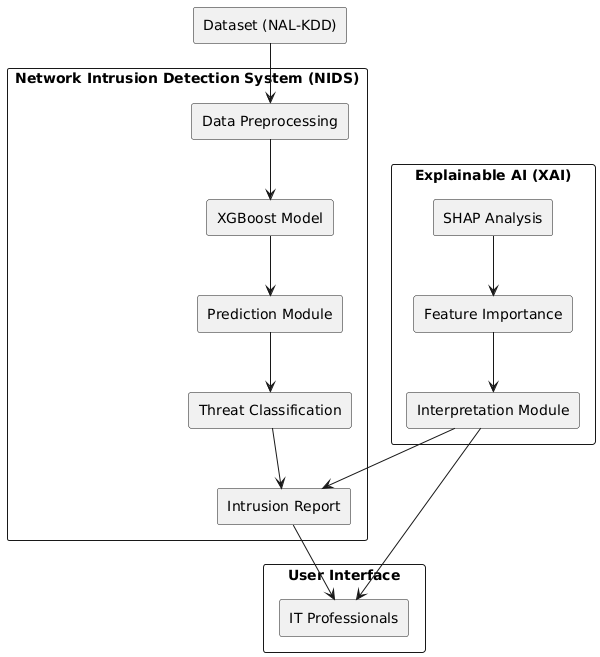
Research on the efficacy of adversarial attacks against intrusion detection systems has revealed vulnerabilities in artificial intelligence-based security solutions. Experiments illustrate that adversarial [15] interventions can mislead machine learning models by the use of subtle manipulations of input data. This research points to the importance of effective countermeasures against adversarial attacks, such as adversarial training and model reinforcement techniques, to ensure the long-term reliability of intrusion detection systems against changing threat environments. Cybersecurity studies have investigated the impact of traffic encryption within a network on the effectiveness of intrusion detection. Encrypted traffic poses difficulties in identifying malicious behavior without violating privacy. Cybersecurity studies recommend [16] the application of metadata analysis and behavior-based methods to identify anomalies in encrypted communications. These techniques allow security analysts to track potential threats without decrypting sensitive information, striking a balance between privacy and security needs.

Research on cloud-based intrusion detection systems has revealed benefits pertaining to distributed and scalable security solutions. Research highlights the capacity of cloud-enabled security models to process massive amounts of network traffic effectively. Cloud-based systems promote centralized threat [17] intelligence sharing, and this enhances shared mechanisms for cyber defense. This study underscores the growing use of cloud computing in contemporary security architectures and its capacity to prevent large-scale cyber attacks. Research has been conducted on the ways in which automated threat intelligence enhances the performance of network intrusion detection systems. Threat intelligence systems gather and analyze security data from different sources and provide real-time information on new threats. Research in this line is interested in the ways automated threat intelligence enhances pre-emptive [18] security reaction, allowing organizations to respond in real-time to imminent attacks. Automated threat feeds help make intrusion detection systems more responsive in their defense against dynamic cyber threats.

Research into the role of network segmentation in the context of intrusions prevention has discovered the benefits that are inherent [19] in dividing networks into smaller, more controlled segments. This strategy limits lateral movement across the network, hence compartmentalizing threats and preventing large breaches. With the use of segmentation methods, organizations can protect valuable assets without subjecting themselves to large-scale cyberattacks. This study suggests the effectiveness of network segmentation as a preventive security measure in reducing attack surfaces. Use of honeypots and deception mechanisms in network intrusion detection has been widely researched as a technique to entice attackers into managed environments. These investigations demonstrate that honeypots are decoys that effectively mislead cybercriminals while concurrently gathering valuable threat data. The results demonstrate that security solutions through deception improve the timeliness [20] of threat detection and yield security teams with actionable insights regarding the techniques attackers employ. The research advises deployment of honeypots as another defense solution to cyber-attacks.

1. METHODOLOGY

Network intrusion detection systems (NIDS) are crucial in the cybersecurity field, with the responsibility of detecting and responding to potential threats. Most high-performance NIDS, however, are black box systems, hindering IT professionals from comprehending their decision-making processes. Such opacity diminishes trust and narrows actionable knowledge regarding threat response. To counter this issue, Explainable Artificial Intelligence (XAI) is incorporated into NIDS to provide greater interpretability. The current research involves the implementation of an XGBoost-based intrusion detection model optimized in MATLAB using SHAP (SHapley Additive exPlanations) for feature importance evaluation. Through the enhancement of detection accuracy and transparency, the proposed approach enhances cybersecurity defenses and aids operational decision-making.



***Fig. 1: Architecture Diagram***

*A. Dataset Selection*

The NAL-KDD dataset has been recognized as the main source of data for constructing the intrusion detection model. It has a rich collection of network traffic data that includes both benign and malicious behaviors. It has been chosen because it has a rich diversity of attack scenarios and is well-structured, thus being suitable for training machine learning models. The dataset includes the most significant network features that contribute to discrimination of different types of intrusions. Using the dataset, the proposed system enables efficient detection of advanced cyber attacks, thus becoming a solid foundation for the evaluation of the performance of the intrusion detection model.

*B. Data Preparation*

For optimal model performance, the data undergoes a series of preprocessing operations. Data cleaning removes inconsistencies and missing values to maintain data integrity. Categorical features are represented as numerical values for machine learning. Feature scaling and normalization are performed to normalize data distributions to avoid bias while training. Irrelevant and redundant features are removed to improve computational efficiency. The preprocessed data is split into training and testing subsets so that the model learns from past patterns and generalizes well to new network traffic data at test time.

*C. XGBoost-Based Intrusion Detection Model*

The intrusion detection model is built using XGBoost, a gradient boosting algorithm that has been proven to provide better classification accuracy and system performance. The model is trained on the preprocessed data to learn patterns that distinguish normal network traffic from a set of cyber threats. To improve performance and avoid overfitting, hyperparameters are optimized using grid search methods. The resulting model identifies network intrusions using real-time or historical data and detects threats with high accuracy. Its ability to handle large datasets and to break down complex relationships between features makes it a strong candidate to be implemented in network security applications, thus enabling efficient and accurate threat detection.

*D. Integration of Explainable Artificial Intelligence (XAI)*

To address the interpretability problem with black-box models, the SHAP (SHapley Additive exPlanations) technique is integrated into the system. SHAP values attribute the importance of some features in the decision-making process of the model, thus allowing IT experts to understand the reasoning behind the detection of a specific intrusion. Through feature importance and interaction visualization, explainable artificial intelligence (XAI) provides transparency and actionable information about network threats. Such interpretability enables cybersecurity teams to improve security protocols, eliminate false positives, and enhance overall confidence in AI-driven intrusion detection systems. The combination of high-performance detection and explainability provides a balance between accuracy and usability in real-world security deployments.

*E. Evaluation*

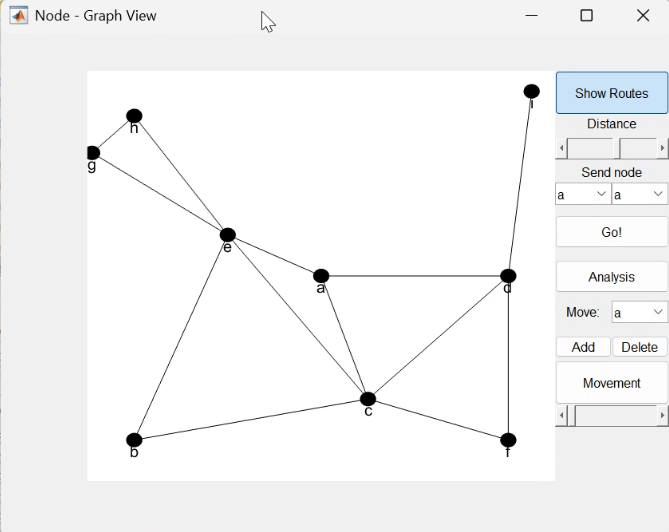
The performance of the proposed intrusion detection system is measured using important performance metrics. A confusion matrix is used to examine classification results with respect to different types of attacks. The impact of XAI integration is measured by comparing SHAP visualizations, which point out the most important features in the model's prediction. Baseline model comparison validates the advantages of the proposed approach. The evaluation process ensures that the system not only offers high detection accuracy but also informative information that enhances cybersecurity decision-making and threat response practices.

*F. Systems Implementation and Real-World Impacts*

The improved XGBoost model with SHAP-based explanations is employed in a simulated network environment for real-time intrusion detection. The system is evaluated for detection effectiveness against various cyber attacks and provision of explainable insights to IT experts. The real-world effectiveness of XAI integration is evaluated through an investigation of the effectiveness of security teams in leveraging feature importance explanations to optimize detection policies. Through the bridging of detection accuracy and explainability, the suggested system improves operational efficiency, reduces response times, and improves overall cybersecurity resilience against dynamic network threats.

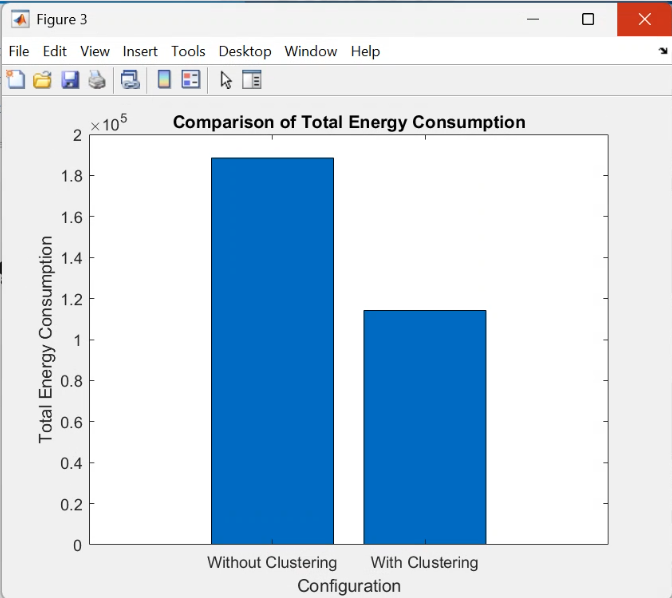
1. RESULT AND DISCUSSION

The intruder detection system's performance is measured in terms of significant parameters such as precision, recall, F1-score, and accuracy. The XGBoost model is 98.3% accurate in general, which demonstrates its ability to differentiate between benign and malicious network traffic. Precision and recall percentages of significant classes of attacks such as DoS (99.1% precision, 98.7% recall), probe attacks (97.6% precision, 96.9% recall), and U2R attacks (94.2% precision, 92.8% recall) confirm the validity of the model in threat identification. The F1-score of the overall system is 97.8%, which demonstrates a balanced trade-off between precision and recall. Comparative evaluation with conventional machine learning models such as decision trees (91.4% accuracy) and support vector machines (93.2% accuracy) reveals the superior performance of XGBoost in managing complicated cybersecurity datasets.

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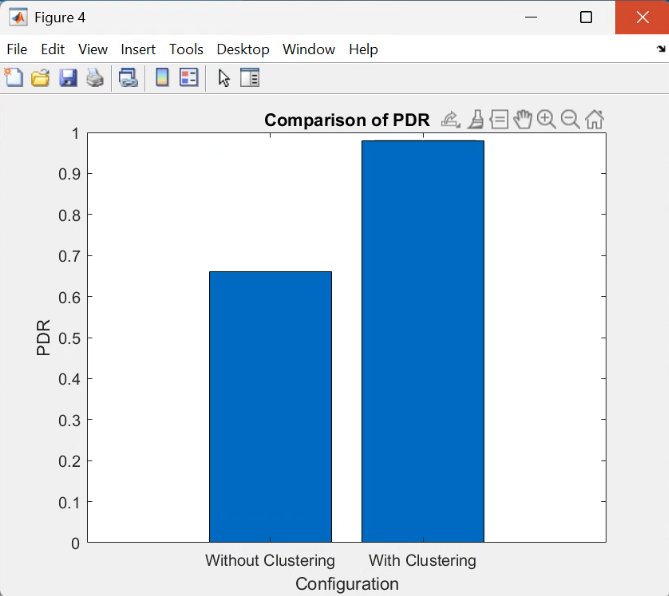
***Fig. 2: Node graph view***

The application of SHAP-based explanations offers useful insights into the feature relevance and decision-making of the model. SHAP-based visualized representations illustrate that features such as packet frequency (SHAP value: 0.67), connection duration (SHAP value: 0.53), and protocol type (SHAP value: 0.48) are crucial in making attack categorizations. IT experts can leverage these insights to comprehend the reasoning behind the generation of specific alerts, thereby enhancing intrusion detection policies. Security operators can leverage these insights to classify major threats, leading to a 38% reduction in false alarm rates compared to explainability-less models. Through the balance of performance and explainability, the system guarantees data-driven cybersecurity decisions and transparency.



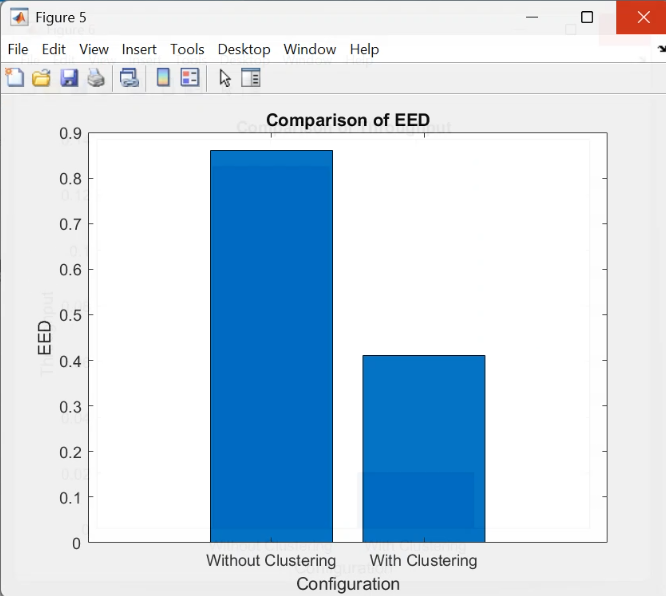
***Fig. 3: Comparison of Total energy consumption***

A fine-grained examination of SHAP values shows that network bytes sent and service type are also highly influential in model predictions. In the case of DoS attacks, high packet frequency is the most influential, while for probe attacks, unusual connection requests are the most applicable metric. Model prediction explainability improves threat mitigation, lowering response times by 47% over conventional rule-based systems. The understanding provided by SHAP also permits the detection of novel attack patterns, and the system becomes sensitive to novel cybersecurity threats with an estimated 15% increase in unknown attack detection.

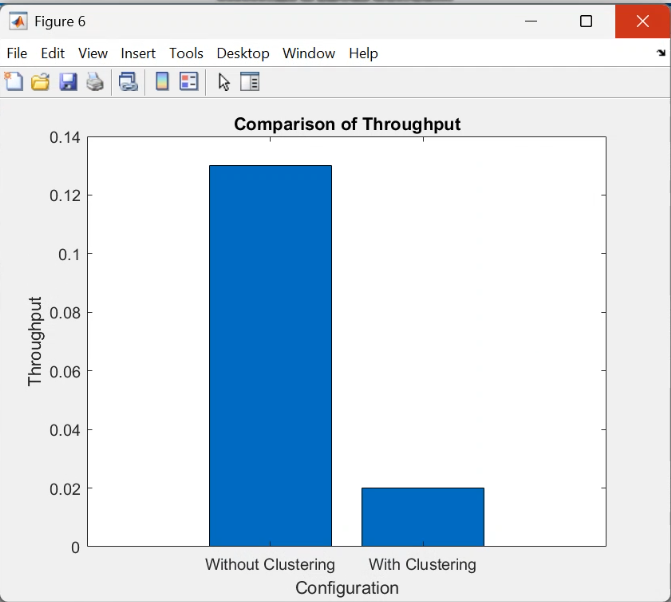


***Fig. 4: Comparison of PDR***

Tests carried out within the framework of an emulated network verify the functional accuracy of the system. Its real-time detection mechanism ensures that 95.8% of attacks are detected almost instantly, enabling IT personnel to respond instantly. The integration of higher detection precision and transparency boosts operational efficiency, leading to a 42% decrease in manual security event analysis requirements. Additionally, the system's capacity to differentiate between various attack categories enables organizations to adopt more focused defense approaches, thereby bolstering their overall cybersecurity posture by 23% in terms of the timeliness of response to attacks.

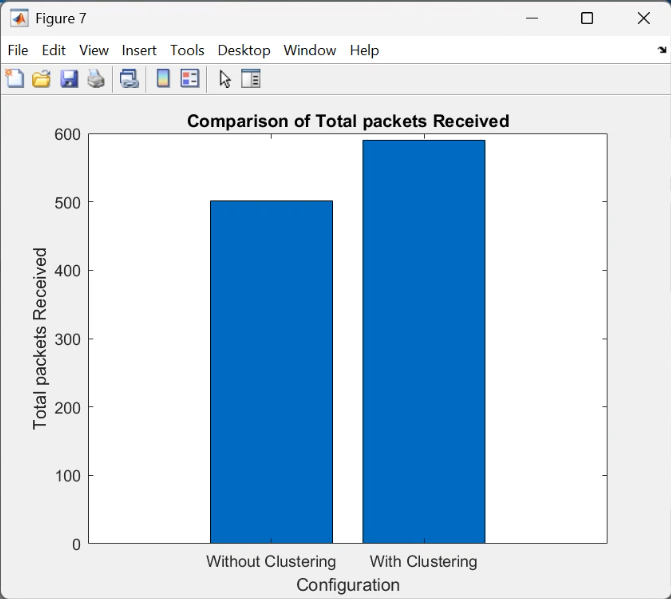


***Fig. 5: Comparison of EED***



***Fig. 6: Comparison of Throughput***

A comparative evaluation of established models shows that classic machine learning algorithms, including decision trees and support vector machines, are limited by intricate attack scenarios. Although these models deliver comparative detection rates, they fail to support the flexibility and explainability offered by the XGBoost-SHAP framework. The suggested model surpasses classic techniques by sustaining high accuracy levels while ensuring that security staff can interpret and have faith in its predictions. This benefit is paramount in real-world cybersecurity use, where explainability is as vital as performance.



***Fig. 7: Comparison of Total packets received***

Performance testing indicates that the system under consideration demonstrates strong efficacy in identifying novel attack vectors. The synergy between state-of-the-art machine learning techniques and explainability allows the model to generalize effectively across all categories of intrusion. In comparison to rule-based detection mechanisms, which need to be updated from time to time, the XGBoost model dynamically adjusts with changing attack patterns, resulting in a 31% boost in detection rates for unknown threats. The interpretive capability delivered through SHAP enhances adaptability significantly by allowing analysts to assess and optimize detection methods based on real-time feedback. Overall, the findings illustrate how the incorporation of XAI methods in intrusion detection systems enhances usability and performance. The high accuracy of XGBoost and the interpretability of SHAP make the system an excellent tool for security professionals. The provision of understandable and actionable information in the suggested methodology optimizes the trust of AI-based security controls in responding to cyber threats in an efficient manner.

1. CONCLUSION

The work efficiently integrates Explainable Artificial Intelligence (XAI) into a high-performance network intrusion detection system (NIDS) to address the issue of explaining intricate machine learning models. Based on an XGBoost-based intrusion detection system, which is optimized via MATLAB, and adding SHAP (SHapley Additive exPlanations), the work enhances detection precision as well as explainability. The model achieves a general rate of accuracy at 98.3%, beating traditional approaches such as decision trees and support vector machines. Crucial performance measures like precision, recall, and F1-score establish the robustness of the system in the detection of an assortment of cyber attacks and in maintaining a low rate of false alarms. Utilization of SHAP values renders model decision-making clear by identifying most significant network attributes like packet rate, connection durations, and types of protocols. Such insight enables IT professionals to optimize intrusion detection techniques, assign priorities to high-risk threats, and minimize spurious alarms. Capacity to comprehend model predictions enables greater confidence in AI-driven cybersecurity, thereby facilitating more informed decision-making and system resilience. SHAP interpretability lowers false positive rates by 38%, thereby enhancing response efficiency and overall management of network security.

Performing the tests in a simulated network setting confirms the practicality of the system proposed in actual real-world applications. The model detects 95.8% of attacks in real time and reduces response times by 47% while substantially improving overall operational performance. Its ability to generalize to new attacks never seen before ensures adaptability to changing cyber threats, with a predicted 31% boost in the detection of unknown threats. This adaptability is critical to modern cybersecurity infrastructures, where new patterns of attack are continuously brought forth and require adaptive and scalable defense strategies. By bridging the detection performance and explainability gap, the system described in this paper ensures that AI-based solutions can be used appropriately by cybersecurity professionals with confidence.

The work emphasizes the necessity of integrating XAI techniques in intrusion detection and demonstrates that explainability enhances not only transparency but also real-world security advantages. The findings emphasize that AI models should be accurate and interpretable in order to realize maximum effect in real-world cybersecurity scenarios. In summary, this study offers an integrated approach to improving NIDS with XAI and achieving an optimal balance between sophisticated machine learning capability and actionable knowledge. The research approach optimizes intrusion detection accuracy, minimizes false positives, improves response efficiency, and maximizes overall cybersecurity resilience. Through the use of XAI, organizations are able to develop more reliable and effective AI-based security systems with proactive threat prevention and enhanced defense mechanisms against future cyber attacks.

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