
An Explainable Deep Learning-Based Intrusion Detection System Using SHAP and LIME for Enhanced Transparency

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Abstract.

Deep learning-based Intrusion Detection Systems (IDS) provide effective detection of complex cyber threats but often lack transparency and interpretability. This study proposes an interpretable IDS framework integrating deep learning with SHAP and LIME for global and local explanations. The framework is evaluated using NSL-KDD and CICIDS2017 datasets, achieving high detection performance while improving feature interpretability and model transparency. The proposed approach enhances decision validation, trust, and explainability, supporting applications in network security monitoring, Security Operations Centres, and anomaly detection.

Keywords. Explainable Artificial Intelligence (XAI), SHAP, LIME, Deep Learning, Intrusion Detection System (IDS), Cybersecurity, Anomaly Detection

1. INTRODUCTION

Modern networks face increasingly sophisticated cyber threats, making Intrusion Detection Systems (IDS) essential for network security. Deep learning improves attack detection but often lacks transparency. Explainable AI (XAI) techniques such as SHAP and LIME provide global and local explanations. This study proposes an interpretable IDS framework combining deep learning with SHAP and LIME, evaluated on NSL-KDD and CICIDS2017, to improve transparency without compromising detection performance and support practical cybersecurity applications.

2. BACKGROUND AND RELATED WORK

For intrusion detection many Deep learning models such as CNN, RNN, LSTM, and Bi-LSTM etc. have been analysed in a few research works. For example, based on benchmark datasets like NSL-KDD and CICIDS2017, investigators have shown that hybrid models that consist of RNN and Bi-LSTM have successfully captured both sequential attack and temporal dependencies patterns which improve detection accuracy. In a similar manner, by using CNN-based techniques for feature extraction have enhanced classification performance in high-dimensional network traffic data. Using the CICIDS2017 dataset, Chen

et al. (2024) introduced an intrusion detection method that integrates a Deep Neural Network (DNN) with the LIME (Local Interpretable Model-agnostic Explanations) technology [1]. This work's main contribution is the use of LIME to generate instance-level (local) explanations, which aid in understanding the model's classification of a particular network traffic instance as malicious or normal. As a result, DNN's individual predictions are easier to understand. But drawback of this method was lack of global interpretability. Using the UNSW-NB15 dataset, Singh et al. (2023) introduced an intrusion detection method that combines conventional Machine Learning (ML) models with SHAP (SHapley Additive explanations). This work's primary contribution is the use of SHAP for feature importance analysis, which allows for a thorough comprehension of how various input features affect the model's predictions [2]. By emphasizing the most important factors influencing intrusion detection conclusions, this increases transparency.

Table 1. Proposed System comparison with existing System

Author (Year)	Method Used	Dataset	Key Innovation	Limitation
Zhang et al. (2021)	CNN-based IDS	NSL-KDD	Improved feature extraction	No explainability
Kumar et al. (2022)	LSTM	CICIDS2017	High detection accuracy	Black-box model
Ali et al. (2023)	RNN + Bi-LSTM	NSL-KDD	Captures temporal patterns	Limited interpretation
Singh et al. (2023)	SHAP + ML	UNSW-NB15	Feature importance analysis	No deep learning
Chen et al. (2024)	LIME + DNN	CICIDS2017	Local explanation	No global insight
Proposed Work	DL + SHAP + LIME	NSL-KDD, CICIDS2017	Global + Local interpretability	—

3. KEY CONTRIBUTION

To enhance transparency in intrusion detection, an interpretable intrusion detection system that combines Explainable AI approaches (SHAP and LIME) with deep learning is proposed in this system. By delivering both fine-grained, instance-level explanations (using LIME for predictions) and global explanations (using SHAP for feature importance), multi-level model interpretability was attained. This ensured that there is no appreciable decline in classification efficacy, maintaining high detection performance and increasing model interpretability [5][6]. This method's robustness and improved generalization performance using benchmark datasets like NSL-KDD and CICIDS2017.

4. METHOD, EXPERIMENTS AND RESULTS

The suggested architecture offers a transparent intrusion detection system that integrates deep learning with interpretability methods to improve transparency and confidence. As shown in figure 1 at first, network traffic data from datasets like NSL-KDD and CICIDS2017 is introduced into the system, where it

undergoes preprocessing tasks such as data preprocessing, feature encoding and normalization to maintain data quality. The transformed data is subsequently sent through a feature engineering phase, where crucial features are chosen and modified for effective learning. The foundation of the system is an integrated deep learning model that consists of an RNN and Bi-LSTM, which effectively identifies temporal and sequential patterns in network traffic to identify it as normal or malicious. In the prediction of system, the explanation layer is implemented, which serves as the significant contribution of the model is its capability. SHAP delivers global interpretability by identifying the most significant features that affect the model throughout the full dataset, whereas LIME provides local interpretability by providing explanations for individual predictions through understandable surrogate models. Ultimately, the system provides not just the detection outcome but also provides valuable explanations, such as assessing the significance of features in classification outcomes and instance-specific insights, enhancing transparency, interpretability, and decision-making in cybersecurity contexts.



Figure 4.1: System Architecture for IDS using integrating Bi-LSTM with SHAP and LIME

5. RESULTS

The practical results show that proposed model achieves high efficiency and performance across all evaluation metrics. Proposed model attained an accuracy of 97.2%, outperforming LSTM (95.1%), CNN (93.5%), Random Forest (91.2%) and SVM (88.5%) shown in table 2.

Table 2 Performance Comparison of existing System proposed System

Model	Accuracy (%)	Precision	Recall	F1-Score	FPR
SVM	88.5	0.86	0.85	0.85	0.08
Random Forest	91.2	0.90	0.89	0.89	0.06
CNN	93.5	0.92	0.91	0.91	0.05
LSTM	95.1	0.94	0.94	0.94	0.04
Proposed Bi-LSTM + XAI	97.2	0.97	0.96	0.96	0.02

6. CONCLUSION

In this system we are using an explainable Intrusion Detection System (IDS) based on Bi-LSTM integrated with SHAP and LIME has been used to address the limitations of existing intrusion detection approaches. The proposed model leverages the strength of Bi-LSTM in

capturing bidirectional temporal dependencies in network traffic, resulting in improved detection of complex and previously unseen cyber-attacks. In this method we are evaluating standard benchmark datasets that demonstrate that in proposed system achieves high performance in terms of all feature like accuracy, precision, recall, and F1-score, while significantly reducing the false positive rate. These improvements highlight the effectiveness of the model in providing reliable and robust intrusion detection in proposed system.

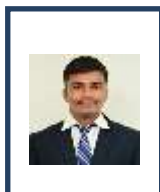
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Biographies



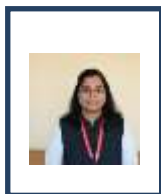
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