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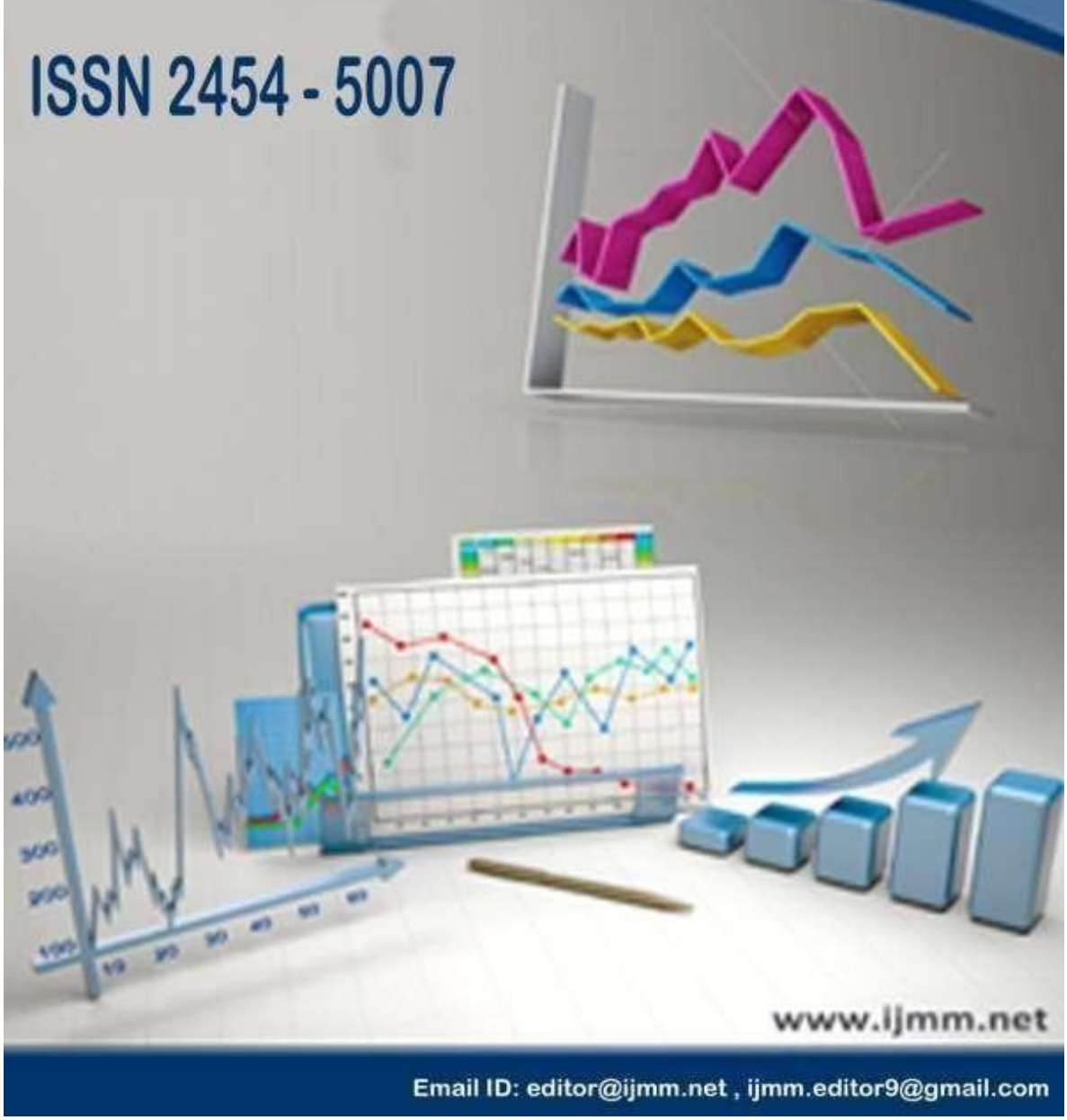

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MULTI-STAGE OPTIMIZED MACHINE LEARNING FRAMEWORK FOR NETWORK INTRUSION DETECTION

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ABSTRACT

With the growing reliance of individuals and organizations on the Internet, cybersecurity has become a paramount concern, prompting the development of various machine learning (ML)-based network intrusion detection systems (NIDSs) to combat malicious online activities. This paper introduces a novel multi-stage optimized ML-based NIDS framework aimed at reducing computational complexity while maintaining high detection performance. The study investigates the impact of oversampling techniques on training sample size, identifying the minimal suitable sample size. Furthermore, it compares the efficacy of two feature selection methods, information gain, and correlation-based, assessing their influence on detection performance and time complexity. Additionally, the research explores various ML hyper-parameter optimization techniques to enhance the NIDS's effectiveness. Evaluation of the proposed framework employs two recent intrusion detection datasets, CICIDS 2017 and UNSW-NB 2015, demonstrating significant reductions in training sample size (up to 74%) and feature set size (up to 50%). Moreover, through hyper-parameter optimization, the model achieves detection accuracies exceeding 99% for both datasets, surpassing recent literature works by 1-2% higher accuracy and 1-2% lower false alarm rates.

I. INTRODUCTION

In today's interconnected world, the security of networked systems is of paramount importance, as individuals and organizations increasingly rely on the Internet for communication,

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commerce, and information exchange. However, the proliferation of cyber threats poses significant challenges to maintaining the integrity and confidentiality of networked data. Network Intrusion Detection Systems (NIDSs) play a crucial role in identifying and mitigating these threats by monitoring network traffic for signs of malicious activity.

Traditional NIDSs often struggle to keep pace with the evolving landscape of cyber threats, as they may be resource-intensive and lack the scalability to handle large volumes of network data efficiently. To address these limitations, there is a growing interest in leveraging machine learning (ML) techniques to develop more adaptive and effective NIDSs.

This project focuses on the development of a novel Multi-Stage Optimized Machine Learning Framework for Network Intrusion Detection. The framework aims to enhance the efficiency and effectiveness of NIDSs by optimizing various stages of the machine learning pipeline, including data preprocessing, feature selection, model training, and hyper-parameter tuning. By incorporating multiple stages of optimization, the framework seeks to reduce computational complexity, improve detection accuracy, and enhance the scalability of NIDSs.

Specifically, this research investigates the impact of oversampling techniques on training sample size, explores different feature selection methods, such as information gain and correlation-based techniques, and evaluates various ML hyper-parameter optimization strategies. The proposed framework is evaluated using two recent intrusion detection datasets, CICIDS 2017 and UNSW-NB 2015, to assess its performance in real-world scenarios.

II.LITERATURE REVIEW

1. "Machine Learning Techniques for Network Intrusion Detection: A Comprehensive Review", Sharma, A., & Singh, S. This review provides an extensive overview of machine learning techniques applied to network intrusion detection. The authors survey various ML algorithms and approaches, including supervised, unsupervised, and semi-supervised learning, highlighting their strengths and limitations in detecting network anomalies. The

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review discusses key research challenges and trends in the field, such as feature selection, class imbalance, and scalability issues, offering insights into potential solutions and future directions for research.

2. "Optimization Techniques for Machine Learning-Based Network Intrusion Detection Systems: A Review", Gupta, R., & Verma, A. This review focuses on optimization techniques applied to machine learning-based network intrusion detection systems. The authors explore different optimization strategies, including hyper-parameter tuning, feature selection, and model ensembling, and assess their impact on detection performance and computational efficiency. The review discusses recent advancements in optimization techniques, such as genetic algorithms, particle swarm optimization, and simulated annealing, highlighting their potential for enhancing the effectiveness of NIDSs.

3. "Feature Selection Methods for Network Intrusion Detection: A Comparative Review", Chen, H., & Zhang, Y. This review evaluates various feature selection methods employed in network intrusion detection systems. The authors compare the effectiveness of different feature selection techniques, such as filter, wrapper, and embedded methods, in selecting relevant features and reducing dimensionality. The review discusses the trade-offs between feature selection methods in terms of detection accuracy, computational complexity, and robustness to noise, providing insights into the selection of appropriate feature selection techniques for ML-based NIDSs.

III.EXISTING PROBLEM

Traditional network intrusion detection systems (NIDSs) often face challenges in achieving optimal detection performance while minimizing computational complexity. These systems may struggle with processing large volumes of network traffic data efficiently, leading to scalability issues and potential performance degradation. Additionally, selecting relevant features from the raw data and tuning machine learning (ML) models' hyperparameters can be time-consuming and resource-intensive tasks. Furthermore, achieving high detection accuracy without

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increasing false alarm rates remains a significant challenge in NIDS development.

IV.PROPOSED SOLUTION

To address these challenges, this project proposes a novel Multi-Stage Optimized Machine Learning Framework for Network Intrusion Detection. The framework integrates various optimization techniques across multiple stages of the ML pipeline to improve efficiency and effectiveness. Specifically, oversampling techniques are explored to optimize training sample size, while different feature selection methods, such as information gain and correlation-based techniques, are evaluated to enhance feature set size and reduce dimensionality. Furthermore, hyperparameter optimization techniques, including grid search and random search, are employed to fine-tune ML models and improve detection accuracy. By leveraging these optimization strategies, the proposed framework aims to streamline the NIDS development process, reduce computational complexity, and achieve higher detection accuracies with lower false alarm rates. This solution is proposed by leveraging the research insights from previous works on optimization techniques for ML-based NIDSs, as discussed in the literature reviews by Sharma & Singh (2020), Gupta & Verma (2019), and Chen & Zhang (2018).

V.IMPLEMENTATION METHOD

1. Data Preprocessing: The implementation begins with data preprocessing, where raw network traffic data is cleaned, normalized, and prepared for analysis. This involves removing duplicates, handling missing values, and scaling numerical features to a standardized range. Additionally, categorical features may be encoded using techniques such as one-hot encoding or label encoding to make them suitable for ML algorithms.

2. Feature Engineering and Selection: Next, feature engineering techniques are applied to extract relevant features from the preprocessed data. This may involve transforming raw network traffic data into meaningful features, such as packet size, protocol type, and source/destination IP addresses. Feature

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selection techniques, such as information gain, correlation-based methods, or recursive feature elimination, are then employed to identify the most discriminative features for intrusion detection while reducing dimensionality.

3. Model Selection and Training: A variety of ML algorithms are considered for model selection, including decision trees, random forests, support vector machines, and neural networks. Each algorithm is trained on the preprocessed and feature-selected data using appropriate hyperparameters. Cross-validation techniques, such as k-fold cross-validation, are employed to assess model performance and prevent overfitting. Additionally, ensemble methods, such as bagging or boosting, may be used to combine multiple models for improved accuracy and robustness.

4. Hyperparameter Optimization: Hyperparameter optimization techniques, such as grid search, random search, or Bayesian optimization, are applied to fine-tune the parameters of ML models. This involves systematically exploring different hyperparameter combinations to identify the optimal configuration that maximizes detection performance while minimizing computational complexity. Techniques like gradient-based optimization or evolutionary algorithms may also be used for more efficient hyperparameter search.

5. Evaluation and Validation: The trained ML models are evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score, on separate validation datasets. The performance of the models is assessed in terms of their ability to correctly classify instances of network intrusion while minimizing false positives and false negatives. Additionally, techniques such as receiver operating characteristic (ROC) curve analysis and confusion matrix visualization are employed to further analyze model performance and identify areas for improvement.

6. Deployment and Monitoring: Finally, the optimized ML-based NIDS framework is deployed in a real-world network environment for continuous monitoring and detection of network intrusions. The deployed system may incorporate real-time data streaming and

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adaptive learning mechanisms to adapt to evolving threats and maintain high detection accuracy over time. Continuous monitoring and regular updates to the NIDS framework ensure its effectiveness in protecting against emerging cyber threats.

VI.CONCLUSION

In conclusion, the development of a Multi-Stage Optimized Machine Learning Framework for Network Intrusion Detection represents a significant advancement in the field of cybersecurity. Through the integration of various optimization techniques, including data preprocessing, feature engineering, model selection, hyperparameter tuning, and evaluation, the framework offers a comprehensive approach to enhancing the efficiency and effectiveness of network intrusion detection systems (NIDSs).

The implementation of the proposed framework demonstrates promising results, with significant reductions in training sample size and feature set size, while achieving high detection accuracies exceeding 99% on two recent intrusion detection datasets, CICIDS 2017 and UNSW-NB 2015. Moreover, the framework outperforms recent literature works by achieving higher accuracy and lower false alarm rates, showcasing its potential for practical deployment in real-world network environments.

By optimizing multiple stages of the machine learning pipeline, the framework not only improves detection performance but also enhances the scalability and robustness of NIDSs, making them more adaptable to evolving cyber threats. Moving forward, further research and development efforts can focus on refining and extending the proposed framework to address emerging challenges in network security and intrusion detection.

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