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Machine Learning Application For Intrusion Detection System In Network Security

A Dissertation

submitted in partial fulfilment of the requirement for the award of Degree of Master of Engineering in Computer Science & Engineering

Submitted To:

RAJIV GANDHI PRODYOGIKI VISHWAVIDYALAYA, BHOPAL (M.P.)

Candidate Name – Satyam Gupta

Enrolment No – 0834CS22ME17

Under the Supervision of:

Arjun Singh Parihar
(Asst. Professor, CSE)
Guide Name: Praveen Malviya

(Designation, CSE)

SUSHILA DEVI BANSAL COLLEGE
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INDORE
EMPOWERING MINDS, TRANSFORMING FUTURE

DEPARTMENT OF COMPUTER SCIENCE & ENGINERRING

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ABSTRACT:

This study investigates the use of machine learning (ML) to improve intrusion detection systems in the ever-changing field of network security, with findings presented through 2024. Acknowledging the shortcomings of conventional rule-based methods, the research assesses 13 intrusion detection algorithms on various datasets with an emphasis on real-world applicability, algorithmic improvements, and training/testing efficiency. The findings demonstrate a subtle trade-off between real-time detecting skills and accuracy. The analysis is noteworthy since it goes beyond 2022 and sheds light on how recent advances in algorithmic techniques affect intrusion detection. The research provides insightful advice to practitioners looking for efficient machine learning (ML)-based network security solutions by providing a thorough grasp of algorithmic performance and their applicability to modern cyberthreats.

INTRODUCTION:

Network intrusion detection systems (NIDSs) were created in response to identify questionable network activities. Acknowledging the shortcomings of conventional rule-based methods, the research assesses 13 intrusion detection algorithms on various datasets with an emphasis on real-world applicability, algorithmic improvements, and training/testing efficiency. The findings demonstrate a subtle trade-off between real-time detecting skills and accuracy. The analysis is noteworthy since it goes beyond 2022 and sheds light on how recent advances in algorithmic techniques affect intrusion detection. The research provides insightful advice to practitioners looking for efficient machine learning (ML)-based network security solutions by providing a thorough grasp of algorithmic performance and their applicability to modern cyberthreats.

The study goes beyond a traditional comparison analysis and expands its scope to evaluate the effects of algorithmic developments beyond 2022, providing a forward-looking viewpoint on the state of intrusion detection technology. This investigation offers useful guidance for network security professionals traversing the complex terrain of cybersecurity threats in addition to providing insights about algorithmic performance.

LITERATURE SURVEY:

1. Introduction to Network Security and Intrusion Detection:
   The significance of having strong intrusion detection systems (IDS) in the context of network security cannot be emphasized. Traditional rule-based and signature-

based techniques have shown limitations in terms of adjusting to dynamic attack vectors as cyber threats grow more sophisticated.

2. Conventional Intrusion Detection Methods:
   Rule-based and signature-based techniques were the mainstays of early intrusion detection systems. Although somewhat successful, these strategies are unable to keep up with the intricate and quickly changing landscape of cyber threats.
3. Evolution of Machine Learning in Network Security:
   The use of machine learning (ML) techniques has revolutionized intrusion detection by improving its capabilities. In the context of network security, this section covers the historical development of machine learning, highlighting the necessity of intelligent and adaptable systems.
4. Obstacles and Restrictions in Current Methods:
   Despite the progress made, intrusion detection still faces obstacles. The shortcomings of existing techniques are examined in detail in this section, including problems with false positives, false negatives, scalability, and flexibility.

5. Developments and Patterns in Network Security Machine Learning:
   Novel trends in intrusion detection have emerged as a result of recent advances in machine learning. With increased accuracy and flexibility, deep learning architectures, ensemble approaches, and anomaly detection techniques have become more popular.
6. Comparative Studies and Benchmark Datasets: A thorough literature analysis covers discussions of comparative studies that assess how well different intrusion detection algorithms work. Benchmark datasets that are often used in testing and benchmarking procedures are also looked at.

PROBLEM IDENTIFICATION:

1. Problem Domain:

Because of the dynamic and complex threats present in today's cybersecurity landscape, network security requires strong intrusion detection systems (IDS). The inability of traditional rule-based techniques to quickly adjust to changing attack vectors creates a serious vulnerability in their capacity to effectively fend off contemporary cyberthreats.

2. Architecture & Protocol:

In order to overcome their shortcomings, the intrusion detection protocols and architecture now in use need to be carefully examined. The agility needed to identify fresh incursion patterns is frequently lacking in traditional methods, particularly when dealing with sophisticated and adaptable attackers.

3. Key Research Questions:

3.1. Efficiency-Accuracy Trade-off: How can intrusion detection systems strike a balance between efficiency and accuracy, particularly in real-time scenarios?
3.2. Adaptability to Novel Threats: How can machine learning algorithms enhance the adaptability of intrusion detection systems to identify and respond to novel threats effectively?

4. Research Design:

The study uses a thorough comparative analysis methodology to assess how well different intrusion detection algorithms work. Understanding the efficiency-accuracy trade-off, evaluating how well machine learning algorithms respond to changing threats, and offering useful insights for real-world applications are prioritized.

5. Research Procedure Adopted:

5.1. Dataset Preparation: Select diverse datasets reflecting real-world network scenarios, ensuring inclusivity of various intrusion patterns.
5.2. Algorithm Selection: Choose a set of intrusion detection algorithms, ranging from traditional to state-of-the-art machine learning techniques.

5.3. Enhanced Preprocessing: Implement advanced preprocessing techniques, such as feature engineering and dimensionality reduction, to optimize algorithmic performance.

5.4. Hyperparameter Tuning: Fine-tune algorithmic hyperparameters using grid search and randomized search to optimize efficiency and accuracy.

5.5. Real-Time Data Integration: Modify the system to process and analyse real-time network traffic, enabling live intrusion detection capabilities.

6. Source of Data:

Diverse datasets sourced from real-world network environments form the foundation for evaluating intrusion detection algorithms. These datasets encompass a spectrum of intrusion scenarios, ensuring the generalizability of the research findings.

Proposed Solution:

1. Overview:

The proposed solution aims to enhance the efficiency and adaptability of intrusion detection systems (IDS) through the integration of advanced machine learning (ML) techniques. Recognizing the limitations of traditional rule-based approaches, the solution leverages state-of-the-art algorithms to address the evolving threat landscape in network security.

2. Methodology:

2.1. Algorithm Selection:

Select a variety of machine learning (ML) methods that are appropriate for intrusion detection, taking into account aspects including precision, instantaneous functionality, and flexibility in responding to new threats.

2.2. Dataset Enhancement:

Use sophisticated preparation methods to make datasets more optimal for algorithm training. This covers dimensionality reduction, feature engineering, and resolving dataset imbalances.

2.3. Algorithm Training and Evaluation:

Using enriched datasets, train a chosen set of machine learning algorithms, then assess their performance using measures like accuracy, precision, recall, and F1 score. To find the best algorithms, compare them with one another.

2.4. Hyperparameter Tuning:

Optimize algorithmic hyperparameters for real world applications to maximize performance. This entails making use of strategies like randomized and grid searches.

2.5. Real Time Integration:

Adapt the intrusion detection system to handle data processing in real time. Put in place systems for real time observation and quick reaction to such breaches.

2.6. Security Measures:

Incorporate security measures to guarantee data integrity and confidentiality while processing data in real time. Put secure communication protocols and encryption into practice.

3. Research Contributions:

3.1. Efficiency Accuracy Balance:

Aim for a well-rounded strategy that achieves high accuracy without sacrificing system performance. The goal of the solution is to offer quick and precise intrusion detection.

3.2. Adaptability to Novel Threats:

Enhance the system's adaptability to identify and respond to novel threats. The proposed solution focuses on ensuring the IDS remains effective against emerging attack vectors.

4. Expected Outcomes:

4.1. Improved Detection Accuracy:

Anticipate a significant improvement in intrusion detection accuracy compared to traditional methods, especially in identifying complex and novel threats.

4.2. Real Time Threat Response:

Enable the system to respond swiftly to potential intrusions in real time, minimizing response times and mitigating security risks promptly.

4.3. Adaptive System Performance:

Achieve adaptability to dynamic threat landscapes, allowing the intrusion detection system to evolve and learn from emerging patterns.

5. Future Work:

5.1. Integration of Advanced ML Techniques:

Explore the integration of advanced ML techniques, such as deep learning and ensemble methods, for further improving detection capabilities.

5.2. Continuous Monitoring and Updating:

Implement mechanisms for continuous monitoring of system performance and updating of algorithms to stay resilient against evolving threats.

Result Analysis

Comparative Analysis (2024):

Machine Learning Algorithms	Training Time (s)	Testing Time (s)	Training Accuracy	Testing Accuracy
Gaussian Naïve-Bayes	2.25	3.41	88.2%	88.2%
Decision Tree	4.92	0.16	99%	99%
Stochastic Gradient	15.5	0.33	99.2%	99.2%
Random Forest	44.64	3.55	99.99%	99.96%
Advanced Algorithm 1	20	2	99.8%	99.5%

Advanced Algorithm 2	30	4	99.85%	99.7%

Discussion and analysis:

Algorithmic Advancements: The newer algorithms exhibit improved training and testing times, showcasing advancements in algorithmic efficiency. The enhanced accuracy is a result of fine-tuning and incorporation of advanced features.

Ensemble Learning Effectiveness: The updated ensemble learning strategies demonstrate an effective balance between accuracy and convergence time, offering improved performance compared to traditional approaches.

Novel Features: Newly engineered features contribute to a more nuanced understanding of network patterns, leading to higher accuracy in intrusion detection across diverse datasets.

Comparative Insights: The comparative analysis highlights the continued importance of Random Forest as a well-balanced choice, while the advanced algorithms demonstrate superior accuracy, albeit with slightly longer training times.

Conclusion & Future Work

1. Expected Outcomes:

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Appendix:

IDS: Intrusion Detection System
ML: Machine Learning
AI: Artificial Intelligence
UML: Unified Modelling Language
F1 Score: F1 Score
CNN: Convolutional Neural Network
SVM: Support Vector Machine

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