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Automated Detection Of Network Intrusions Using Machine Learning in Real-Time Systems

Aulia Novi[1*], Ryan Satria[2]
[1-2]Hasanuddin University (UNHAS), Indonesia

Abstract.*Network intrusion detection is crucial for maintaining the integrity of real-time systems. This paper evaluates various machine learning algorithms, including support vector machines (SVM) and decision trees, for real-time intrusion detection. Through extensive testing on simulated datasets, the study highlights the advantages of automated detection in reducing response times and enhancing network security.*

Keywords: *Intrusion detection, Real-time systems, Machine learning, Support vector machine, Network security, Decision tree*

1. INTRODUCTION

The rise of sophisticated cyberattacks has emphasized the need for robust, real-time intrusion detection systems (IDS) in network security. Traditional intrusion detection methods, though effective, often struggle to keep up with the speed and volume of modern threats. Machine learning (ML) offers an automated approach to detect network intrusions with greater accuracy and faster response times. This paper explores the application of ML models in real-time IDS, focusing on SVM and decision tree algorithms, and demonstrates their effectiveness in enhancing network security.

2. BACKGROUND AND RELATED WORK

A robust IDS is essential for identifying malicious activity within a network. Traditional IDS rely on signature-based or anomaly-based methods, which require substantial manual effort and are often unable to adapt to evolving threats. Machine learning has shown promise in automating the detection of intrusions through pattern recognition, anomaly detection, and real-time analysis, enabling adaptive security mechanisms that reduce human intervention.

Related Work:

Signature-Based IDS: Signature-based systems identify threats by matching incoming traffic patterns with known signatures. However, these systems struggle with zero-day attacks and require frequent updatesd IDS**: Anomaly-based methods detect deviations from normal behavior but often produce high false-positive rates without sufficient training.

3. MACHHMS FOR INTRUSION DETECTION

Machine learning models such as SVM and decision trees offer the potential to improve IDS by identifying complex patterns within data and making near-instantaneous decisions.

Support Vector Machine (SVM)

SVMs work by creating a hyperplane to separate different classes of data, making them effective for binary classification tasks such as intrusion detection . This section discusses the implemf SVM in IDS, focusing on the model's training requirements, feature selection, and computational efficiency.

Decision Tree

Decision trees are widely used due to their simplicity and interpretability. They classify data by partitioning the feature space and are known for low computational costs in prediction, making them suitable for real-time IDS applications.

4. EXPERIMENTAL SETUP

The modesimulated dataset derived from real-world network traffic data. The dataset includes various types of attacks, such as Denial of Service (DoS), probing, and unauthorized access attempts.

Data Preprocessing

Data preprocessing included feature extraction, normalization, and splitting of training and test datasets. By isolating key attributes, we aimed to improve model accuracy and minimize computational overhead.

Model Training and Evaluation

The models were eecision, recall, accuracy, and F1 score. We also measured latency to assess the models' ability to operate in real-time systems.

5. RESULTS

The SVM and decision tree models demonstrated high acculightly outperforming decision trees in precision. Decision trees, however, provided faster response times due to lower computational requirements.

Accuracy: SVM achieved 95% accuracy, while decision trees reached 92% .

Latency: Decision trees processed data with minimal delay, achieving an average latency of 0 per request.

6. DISCUSSION

Our findings suggest that machine learning-based IDS can significantly enhance netwy in real-time systems by automating the detection of intrusions. The trade-off between accuracy and latency presents an opportunity for hybrid models, where high-accuracy models like SVM are supplemented with low-latency decision trees to achieve optimal performance .

7. CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of SVM and decision tree algorithmsme intrusion detection. Future research could explore hybrid models and ensemble techniques to further improve detection speed and accuracy, as well as adapting these models for emerging threats in evolving network environments.

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