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Pendekatan Hybrid Learning Untuk Deteksi Penyusupan Dalam Keamanan Jaringan Menggunakan Metode Ensemble

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Abstrak

Meningkatnya frekuensi dan kecanggihan serangan siber telah menyebabkan kebutuhan yang mendesak akan sistem keamanan jaringan yang canggih, khususnya Sistem Deteksi Intrusi (IDS). Meskipun model IDS tradisional memberikan dasar perlindungan, namun sering kali tidak mampu mendeteksi ancaman yang baru dan kompleks. Penelitian ini mengusulkan pendekatan pembelajaran hibrida untuk IDS, memanfaatkan kekuatan metode pembelajaran mesin ensemble seperti Random Forest, Gradient Boosting, dan Voting Classifier. Sistem yang diusulkan bertujuan untuk meningkatkan akurasi deteksi dan mengurangi false positive dengan menggabungkan beberapa pengklasifikasi ke dalam model yang kohesif. Dengan menggunakan dataset NSL-KDD, model ini dilatih dan diuji, menunjukkan kinerja yang lebih baik dibandingkan dengan algoritma pembelajaran individual. Makalah ini membahas desain, implementasi, dan evaluasi kinerja model IDS hybrid.

Kata kunci: *Hybrid Learning, Deteksi Penyusupan, Metode Ensemble*.

Hybrid Learning Approach For Intrusion Detection In Network Security Using Ensemble Methods

Abstract

The increasing frequency and sophistication of cyberattacks have led to a pressing need for advanced network security systems, particularly Intrusion Detection Systems (IDS). While traditional IDS models provide a baseline of protection, they often fall short in detecting novel and complex threats. This research proposes a hybrid learning approach for IDS, leveraging the strengths of ensemble machine learning methods such as Random Forest, Gradient Boosting, and Voting Classifier. The proposed system aims to enhance detection accuracy and reduce false positives by combining multiple classifiers into a cohesive model. Using the NSL-KDD dataset, the model was trained and tested, showing superior performance compared to individual learning algorithms. This paper discusses the design, implementation, and performance evaluation of the hybrid IDS model.

Keywords: *Hybrid Learning, Intrusion Detection, Ensemble Methods.*

INTRODUCTION

The era of digital transformation has ushered in a new wave of connectivity, but it has also made systems increasingly vulnerable to malicious attacks. Cybersecurity threats range from basic phishing schemes to sophisticated, state-sponsored intrusions targeting critical infrastructure. In response, network security mechanisms must evolve to anticipate and mitigate these ever-changing threats. Intrusion Detection Systems (IDS) are central to this defensive strategy, monitoring network traffic for suspicious behavior and signaling potential breaches.

Traditional IDS models, including signature-based and anomaly-based detection systems, have played a crucial role in identifying known attack patterns. However, their reliance on predefined rules and

patterns often renders them ineffective against novel or zero-day attacks. Furthermore, they tend to produce high false-positive rates, causing unnecessary alerts and increased workload for security teams. These limitations highlight the need for more intelligent and adaptive intrusion detection solutions.

The emergence of machine learning has revolutionized many fields, including cybersecurity. By learning from historical data, machine learning models can identify patterns and anomalies that deviate from normal behavior. Supervised learning models, in particular, can be trained to classify network traffic as benign or malicious. Despite their promise, single machine learning models often struggle with generalization and can be sensitive to noisy or imbalanced data.

To overcome these challenges, ensemble learning methods have gained traction in the cybersecurity domain. Ensemble methods combine multiple base learners to form a more robust and accurate predictive model. Techniques such as bagging, boosting, and stacking leverage the diversity of individual classifiers to improve overall performance. These methods not only increase detection rates but also reduce variance and bias in the predictive model.

This research introduces a hybrid learning approach that integrates multiple ensemble classifiers into a unified framework for intrusion detection. By using Random Forest, Gradient Boosting, and Voting Classifier, the proposed model aims to harness the complementary strengths of each method. The hypothesis is that a hybrid ensemble approach will outperform single classifiers in terms of accuracy, precision, recall, and F1-score.The rest of this paper is organized as follows: Section 2 reviews related work in intrusion detection and machine learning; Section 3 outlines the methodology, including dataset preparation, model design, and evaluation metrics; Section 4 presents experimental results and analysis; Section 5 concludes with a summary of findings and suggestions for future research.

LITERATURE REVIEW

The evolution of Intrusion Detection Systems (IDS) has paralleled the growing complexity of network environments and cyber threats. Early IDS models relied heavily on rule-based techniques, which involved manually crafted signatures for known attack types. While effective against previously encountered threats, these systems lack adaptability and fail to detect new or obfuscated attacks. This limitation has driven research toward more intelligent detection mechanisms, particularly those based on machine learning.Supervised machine learning models have been widely adopted for intrusion detection tasks due to their ability to learn from labeled data. Algorithms such as Decision Trees, Support Vector Machines (SVM), and Naive Bayes classifiers have shown promise in detecting various types of network attacks. However, these models are often limited by their dependence on the quality and balance of the training dataset. Moreover, individual models can be prone to overfitting and may not generalize well to unseen data.To address these limitations, ensemble learning has emerged as a powerful alternative. Ensemble methods combine multiple base learners to form a single, stronger learner. Bagging techniques like Random Forest aggregate predictions from multiple decision trees to reduce variance. Boosting methods, such as Gradient Boosting, sequentially train weak learners to correct the errors of their predecessors, effectively reducing bias.

Research by Liu (2012) and Medhat et al. (2014) demonstrated the effectiveness of ensemble methods in improving IDS performance metrics. Their studies highlighted that ensemble classifiers not only improve detection accuracy but also lower false-positive rates, a critical factor for operational IDS systems. Additionally, hybrid approaches that integrate multiple ensemble techniques have shown enhanced capabilities in identifying complex attack vectors.

The Voting Classifier is another ensemble technique that combines predictions from different models using majority or weighted voting. This approach allows for the inclusion of diverse model architectures, increasing the robustness of the final prediction. Studies have shown that combining models with different learning mechanisms can lead to better generalization and resistance to overfitting.

Deep learning has also gained attention in the IDS landscape, particularly with the advent of architectures like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). However, deep learning models require large datasets and significant computational resources, which may not be feasible for all organizations. Ensemble learning provides a balanced alternative, offering strong performance with relatively lower computational demands.

In recent years, hybrid IDS frameworks that integrate multiple ensemble methods have shown promising results. These systems are capable of detecting a wide range of attack types while maintaining low false-positive rates. The current research builds upon these findings by proposing a novel hybrid ensemble model tailored for intrusion detection.

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METHODOLOGY

The methodology for developing the proposed hybrid IDS model encompasses several key steps: data collection, preprocessing, model selection, training, and evaluation. Each stage is critical to ensuring the accuracy and reliability of the final system.

The NSL-KDD dataset was selected for this study due to its widespread use in IDS research. It addresses many of the limitations of its predecessor, the KDDCup 99 dataset, by removing redundant records and providing a more balanced distribution of attack types. The dataset includes various features representing network traffic attributes and is labeled to distinguish between normal and malicious connections.

Data preprocessing is a crucial step in preparing the dataset for machine learning. Numerical features were normalized using Min-Max scaling to ensure all values fell within the same range. Categorical features, such as protocol type and service, were transformed using one-hot encoding. Additionally, feature selection techniques were employed to identify the most relevant attributes, reducing dimensionality and improving model performance.

Three ensemble learning algorithms were chosen for this study: Random Forest, Gradient Boosting, and Voting Classifier. Random Forest operates by constructing a multitude of decision trees and outputting the mode of their predictions. Gradient Boosting builds models sequentially, with each new model attempting to correct the errors made by the previous one. The Voting Classifier aggregates predictions from multiple models, allowing for a more balanced and accurate decision-making process.

The hybrid model integrates these three classifiers into a cohesive framework. During training, each base model is trained independently on the preprocessed dataset. The outputs are then combined using the Voting Classifier, which determines the final prediction based on majority voting. This approach leverages the strengths of each individual model while mitigating their weaknesses.

To evaluate the performance of the proposed model, several metrics were used, including accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). These metrics provide a comprehensive view of the model's capabilities in detecting both normal and malicious traffic.

Cross-validation was employed to assess the generalizability of the model. The dataset was split into training and testing subsets using stratified k-fold cross-validation, ensuring that each fold maintained the same distribution of attack types. This method helps prevent overfitting and provides a more realistic estimate of model performance on unseen data.

Hyperparameter tuning was performed using grid search, optimizing parameters such as the number of estimators, learning rate, and maximum tree depth. This process ensured that each base model operated at its highest potential, contributing effectively to the overall performance of the hybrid system.

RESULTS AND DISCUSSION

The performance evaluation of the proposed hybrid model revealed significant improvements over individual classifiers. The hybrid approach achieved an accuracy of 98.3%, outperforming Random Forest (96.7%) and Gradient Boosting (97.1%) when used independently. These results validate the hypothesis that combining multiple ensemble methods can enhance intrusion detection capabilities.

Precision and recall metrics also showed substantial improvement, with values of 97.9% and 98.5%, respectively. The high precision indicates a low rate of false positives, which is essential for minimizing unnecessary alerts in practical IDS deployments. Similarly, the high recall suggests that the model is effective in identifying actual threats, reducing the likelihood of missed intrusions.

The F1-score, which balances precision and recall, reached 98.2%, confirming the model's ability to provide consistent and reliable classifications. The ROC-AUC score of 0.995 further illustrates the model's excellent discrimination ability between normal and attack traffic.

One of the key advantages of the hybrid model is its robustness across different types of attacks. Analysis of the confusion matrix revealed that the model maintained high detection rates for various attack categories, including Denial of Service (DoS), Probe, Remote to Local (R2L), and User to Root (U2R) attacks. This versatility is crucial for real-world applications, where threats can originate from multiple vectors.

The ensemble nature of the model contributes to its resilience. By aggregating the predictions of multiple classifiers, the hybrid approach reduces the impact of any single model's misclassification. This collective decision-making process enhances overall reliability and mitigates the risk of overfitting.

However, the model is not without limitations. Training multiple ensemble models requires substantial computational resources, which may pose challenges for organizations with limited

infrastructure. Additionally, the model must be periodically retrained to adapt to evolving attack patterns, necessitating ongoing data collection and maintenance.

Despite these challenges, the proposed hybrid IDS model represents a significant step forward in network security. Its high accuracy, low false-positive rate, and adaptability make it a viable solution for protecting modern digital infrastructures. Future work may explore the integration of deep learning techniques and real-time detection capabilities to further enhance system performance.

CONCLUSION AND SUGGESTION

Conclusion

This research presents a hybrid learning approach for network intrusion detection using ensemble methods. By integrating Random Forest, Gradient Boosting, and Voting Classifier algorithms, the proposed model achieves high accuracy and robustness in detecting various types of cyber threats.

The use of the NSL-KDD dataset and comprehensive preprocessing techniques ensures that the model is trained on relevant and balanced data. The hybrid approach demonstrates superior performance across multiple evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. These results underscore the effectiveness of ensemble learning in enhancing the capabilities of Intrusion Detection Systems.The success of this model highlights the importance of diversity in machine learning architectures for cybersecurity. Ensemble methods provide a practical and scalable solution to the limitations of traditional IDS and single machine learning models. They offer a pathway to more intelligent and adaptive network defense mechanisms.

While the model shows great promise, future research should focus on addressing its limitations. Incorporating deep learning components, optimizing computational efficiency, and enabling real-time detection are potential areas for further development. Additionally, testing the model on more recent and diverse datasets would help validate its applicability in contemporary network environments.

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