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SURVEY & IMPLEMENTATION OF MACHINE LEARNING ALGORITHMS FOR REAL TIME INTRUSION DETECTION AND CLASSIFICATION

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Abstract

The complexity of information systems is increasing rapidly. New techniques are used to frame and carry out threats and assaults that take advantage of the data found in networks. The many types of users, server managers, and those who require access to it cause knowledge to change continuously when traversing subtle domains. Protection of information devices is essential against threats like intrusions and denial of service assaults. By using the identities of legitimate users or any of the network's back doors and weaknesses, intrusion poses a serious risk to unauthorized data or legitimate networks. Systems for detecting invasions at various stages are called intrusion detection systems (IDS). In order to increase the effectiveness of intrusion detection systems (IDS), this study will employ rule-based and learning-based

Keywords: Intrusion Detection, Machine Learning, Security, Privacy, KDD99, Attacks

Introduction

IDS is a critical component in protecting networks and data. With the rapid development of network technology, it is unlikely that attacks can be discovered based on knowledge of context, because this may well vary from application to application and even network to network. A hybrid IDS can be used to overcome this challenge. The DoS attacks of particular concern to most are packet flooding that could flood the victim's infrastructure and overrun it. These threaten networks of almost any size with network disruption. Data volume in building high-performance hybrid IDS is the challenging factor due to many features. Having many features renders it cumbersome to detect evil and, hence, results in longer periods of training and testing, increased resource utilization, and a much lower level of detection.

Computer security is the defense of computing systems against evils in favor of maintaining the confidentiality, integrity, and availability of resources. An intrusion means any act or set of acts meant to compromise network resources and the victim's server. IDS monitors incidents in computer systems and networks, analyzes data, identifies threats, either prevents or reports to the system administrator for appropriate action, in these incidents. The rise of attacks in the past few

years has made users skeptical regarding internet safety. DoS attacks are a major threat to this end.

An IDS is a monitoring system that observes network traffic, analyzing it for potential external attacks or internal abuses of the system. In simple terms, an IDS functions like a burglar alarm. Just as a car's locking mechanism prevents theft, an IDS detects when the lock is breached and raises an alarm. Similarly, IDS in a network detect incidents and alert when malicious behavior is identified. Attackers are constantly developing new ways of accessing systems for nefarious activities. This is just one of the reasons why, as Internet scales and complexity grow, so does the associated risk. As such, best Internet security practices revolve around pattern recognition for attacks, tracking vulnerabilities, and resolving them as quickly as possible.

Despite the progress that has been made, the existing IDS is issuing more false alarms. Indeed, the addition of CI techniques to the IDS can reduce the false positives. Researchers have analyzed the effectiveness of diverse CI strategies implemented in IDS using benchmark datasets. The technique is multi-faceted: IDS inspects both inward and outward flows of traffic, identifies anomalies, and filters out malicious activity. An IDS has three major components: a database, an analysis engine, and a response manager.

The database, commonly referred to as the event driver, is the heart of any IDS. Sources include host-based, network-based, application-based, and target-based monitors. There is also the research engine, the other key component, which collects data from the sources and checks it for signs of attacks or violations. The two most common methods applied for analysis are Misuse/Signature-based detection and Anomaly/Statistical detection. The third component is the response manager, which only activates when there are potential inaccuracies or threats that trigger a response to negate the risk.

Denial of Service (DoS) is an intrusion wherein the attacker sends a lot of superfluous messages to the victim system, flooding it and preventing the server from delivering services to legitimate users. This causes network outages, services unavailability, and Network Traffic disruptions and disconnections.

2. Intrusion Detection System (IDS)

Intrusion Detection Systems (IDS) are essential tools for detecting malicious activities within a network. The detection techniques used by IDS can be classified into two main types based on their detection mechanisms: anomaly-based IDS and signature-based IDS. These are commonly abbreviated as AIDS and SIDS, respectively. This section introduces the mechanisms behind these two types of detection systems, highlighting their differences, as well as the advantages and disadvantages of each.

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2.1 Signature-based Intrusion Detection System (SIDS)

A "signature" in the context of IDS refers to a unique pattern that represents a known threat or attack that has already been identified and documented in a database. The core mechanism of a Signature-based Intrusion Detection System (SIDS) is to compare current network traffic against a database of known malicious signatures. If a match is found, the system triggers an alert, indicating that a malicious activity has been detected, allowing it to take preventive actions such as blocking the attack.

However, a significant limitation of SIDS is that it requires an exact match between the incoming traffic and the pre-recorded patterns in the database. As a result, SIDS is unable to detect new, unknown threats or zero-day attacks that do not have existing signatures. Each time SIDS monitors network traffic, it must scan the entire signature database to identify potential matches, which can lead to performance challenges, especially with large and dynamic networks.

While SIDS is effective at detecting known threats, its inability to recognize previously unseen attacks limits its overall effectiveness in a rapidly evolving threat landscape.

Since signature-based intrusion detection systems (SIDS) require high precision for comparison, they are highly accurate in detecting known threats. This high accuracy is one of the reasons SIDS has been widely adopted in industries like the Internet of Things (IoT) and many other fields [10]. The key advantages of SIDS are its widespread use and its simple yet effective detection of known attacks. However, SIDS also has its drawbacks. The inability to detect new threats results in a high false negative rate. Additionally, as the number of malicious signatures grows, the speed of searching for a match slows down, and the need for frequent updates increases. One of the most significant challenges SIDS faces is maintaining an up-to-date database and managing its limitations efficiently [11].

2.2 Anomaly-based Detection

Anomaly-based Intrusion Detection Systems (AIDS) work differently, focusing on deviations from established norms in network traffic. For example, unusual activities such as a large number of Telnet sessions within a short time frame or excessive SNMP traffic may be considered anomalies. Before detecting potential intrusions, AIDS first analyzes normal traffic over various time periods to create a baseline profile. Once this baseline is established, the system monitors traffic against this standard. The baseline can be based on general network behavior or specific actions, like the frequency of user access attempts. If any deviation from this baseline is detected, the system triggers an alert, signaling a potential anomaly.

Unlike SIDS, AIDS can detect new and previously unknown threats. Since it relies on recognizing abnormal behavior rather than specific signatures, it is capable of identifying new malicious activities as long as they deviate from the normal pattern. For example, attacks like Denial of Service (DoS) or buffer overflow, which cannot be represented by a static signature, are more effectively identified by AIDS through the detection of anomalous behavior.

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However, AIDS also has its limitations. The main challenge lies in defining an accurate baseline profile. It is difficult to guarantee that the traffic studied during the baseline creation period is entirely normal. If anomalous traffic is present during this learning phase, the baseline becomes flawed, which could lead to the failure of the entire detection process. Additionally, the process of establishing the baseline is time-consuming and resource-intensive.

3. Deep Learning and Machine Learning

In this section, some fundamental concepts of Machine Learning (ML) and Deep Learning (DL) shall be discussed at an introductory level focusing on specific techniques such as Support Vector Machines (SVM), decision trees, and neural networks.

3.1 Machine Learning and Deep Learning Basics

Artificial Intelligence is deeply inducted with Machine Learning, which tries to train computers to make decisions and predictions without explicit programming on large datasets. ML allows systems to learn from their data, thereby making them more efficient the more they use it. There are mainly three types of machine learning: supervised, unsupervised, and semi-supervised learning.

- Supervised Learning is learning with a model having labeled examples both in input and the corresponding output-target label.
- Unsupervised Learning: The target labels of data are not known here; thus, it discovers patterns or structures in the data itself.
- Semi-supervised Learning: This falls somewhere in between, where only some portions of the data are labeled, or human intervention may be needed to guide the training process.

Among the categories of ML, Deep Learning (DL) is the more recent powerful program. As compared with traditional ML, DL utilizes vast amounts of data and is notably "data-hungry." In this regard, DL models better do well in situations where there is high exposure to lots of information. In this case, DL can be considered an alternative to ML, especially when working with huge amounts of data.

However, both techniques share the same techniques and general objectives. Both of them have proved to be indispensable in domains like computer security. For example, in 5G networks, both ML and DL play crucial roles to enhance anomaly-based detection systems [15]. The following sections will discuss the practical applications and innovation in terms of ML and DL pertaining to IDS.

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3.2 Some ML methods and techniques

A few of the most commonly used ML methods and techniques that have been widely used in a variety of domains, including the areas of Intrusion Detection Systems (IDS), data analysis, and other predictive tasks are listed below.

1. Methods of Supervised Learning

Supervised learning techniques involve training the model on labeled data, where both the input and output are provided. It learns from those examples so as to make predictions on new, unseen data.

Support Vector Machines (SVM):

A classification method that finds the hyperplane that best separates data into different classes. SVM can be used for both classification and regression tasks.

- Decision Trees:These are tree-like structures used on classification and regression tasks. Decision trees split data based on the value of features into a model which is easily interpreted.
- Random Forests:An ensemble learning method that improves the classification accuracy by using multiple decision trees in ensembles. It's a forest of decision trees built and aggregated in a result.
- k-Nearest Neighbors (k-NN): It is simple, where a data point is classified based on the majority class of its neighbors. Typically used for classification tasks.
- Linear Regression:These are used to predict a continuous value based on a linear relationship between the input variables. It is one of the most basic regression techniques.
- Logistic Regression: Used in binary classification problems, logistic regression predicts the likelihood of a binary outcome given input variables.
- Neural Networks (ANN, RNN):Artificial Neural Networks (ANN) are layers of interconnected neurons used for complex tasks, including classification and regression, among others. Recurrent Neural Networks (RNNs) are used for sequence prediction tasks like time series forecasting and natural language processing .

2. Unsupervised Learning Methods

When the data does not have outputs or labeled outputs, unsupervised learning techniques are used. The idea is to find out patterns or groupings in data.

Clustering:

- **K-Means:** A clustering technique that partitions data into 'k' clusters based on the mean of data points in each cluster. It is widely used in anomaly detection.

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- **DBSCAN:** Density-Based Spatial Clustering of Applications with Noise. A density-based clustering algorithm that can identify clusters of arbitrary shapes and detect outliers as noise.

- **Agglomerative Hierarchical Clustering:** This approach is bottom-up where data points are integrated starting from individual entities to merge into clusters according to similarity.

Dimensionality Reduction:

- **PCA:** It is applied for dimensionality reduction when the number of variables in a data set is large, transforming the data into a set of linearly uncorrelated variables called principal components. PCA is also widely used as a preprocessing step before building other models.

- **t-SNE:** The method for reducing dimensions in such a way that all the relationships between points in high-dimensional data are preserved; often used for visualizing high-dimensional data.

3. Reinforcement Learning

Reinforcement learning (RL) is a type of training agent to make a sequence of decisions by rewarding or penalizing its actions. The agent learns to maximize cumulative rewards over time.

- **Q-Learning:** A value-based reinforcement learning algorithm, which learns the value of actions in each state to determine the best policy.

- **Deep Q Networks (DQN):** This combines Q-learning with deep learning such that high-dimensional inputs, like images, can be processed by reinforcement learning.

4. Ensemble Methods

Ensemble methods combine multiple models to reduce variance, bias, or both in order to improve performance.

Bagging

- **Bootstrap Aggregating (Bagging):**That is, train many versions of the same model on different subsets of the data-this are subsets created by bootstrapping-and combine their predictions for a better accuracy and reduction in variance. Random Forests fall under the category of bagging technique.

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Boosting:

- **AdaBoost:**A method that combines multiple weak classifiers to create a strong classifier by giving more weight to misclassified instances.
- **Gradient Boosting Machines (GBM):** Another boosting technique that builds models sequentially, where each model corrects the errors made by the previous ones
- **XGBoost:**An optimized version of gradient boosting, widely used for its performance and speed.

5. Anomaly Detection

Anomaly detection is a process that tries to recognize unusual patterns or outliers within data which go against the trend.

- **Isolation Forest:** A tree-based model that isolates anomalies instead of profiling the normal points. It is ideal for high-dimensional data.
- **One-Class SVM:** A variant of SVM is used for outlier detection where the model is trained on just the normal data, and a deviation from it is reported.

6. Deep Learning Methods

Deep learning methods form the family of machine learning techniques involving multiple layers of neural networks. It enables learning complex patterns in large datasets.

- Convolutional Neural Networks (CNNs): CNNs mainly use them for image classification and computer vision tasks. It uses convolutional layers for the automatic learning of hierarchical features from data.
- Recurrent Neural Networks (RNNs): These networks will handle sequential data applications such as time-series forecasting, natural language processes and, speech recognition.
- Long Short-Term Memory (LSTM): This is actually one type of RNN that solves the vanishing gradient problem. That means it can learn to have long-term dependencies in sequences.
- GANs: It is a type of deep learning model, with two networks: one that generates data and one that discriminates against the input. GANs are a method of generating highly realistic data, such as images. Their usage has been dedicated strictly to data augmentation.

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7. NLP

NLP techniques refer to techniques that are used in understanding and generating human language.

- Bag of Words (BoW): A simple method for text classification where text is represented as a collection of words, disregarding grammar and word order.
- Word2Vec: A technique that converts words into numerical vectors, preserving semantic relationships between words.
- Transformers: Modern NLP models (e.g., BERT, GPT) use transformer architectures for text generation, translation, question answering, and many other tasks.

8. Feature Engineering

Feature engineering refers to the process of creating new features from raw data in order to improve the performance of a model.

- Feature Scaling: Features are scaled in such a way that they have similar range or distribution with the techniques like Min-Max scaling or Standardization.
- Feature Selection: Techniques to select important features and filter out irrelevant features exist, such as Recursive Feature Elimination (RFE) or L1 regularization.

9. Evaluation Metrics

- **Accuracy :**It measures how many correct predictions are made.
- **Precision and Recall:** For the evaluation of classification performance, especially with class imbalance.
- **F1 Score:** The harmonic mean of precision and recall, to be used with significant class imbalance.

These ML techniques and methods provide a variety of tools to solve problems in IDS, anomaly detection, and other predictive modeling tasks. The advantage and drawback of each method are also shown. The choice of method depends on the nature of the problem and the characteristics of the data.

3.2 Neural Networks

It is an artificial neural network that resembles the works of biological nervous systems and specifically the human brain. It finds widespread applications in intrusion detection, data classification, and optimization methods. Its high accuracy of handling information and its ability

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to handle more input sizes mirror those associated with a human brain. Its interconnecting network contains multiple units that mimic neurons to produce specific solutions.

DL is basically an advanced derivative of ANN that uses complex multilayered structures connected to each other for processing data. This characteristic helps DL handle a broad spectrum of variables and layers in a specific network configuration, which makes it more effective to perform complex tasks.

4. Literature Survey on ML-based IDS

Because in cyber infrastructure a huge amount of data are generated, the necessity of Intrusion Detection Systems to learn from them is very essential. With machine learning and deep learning having unmatched learning ability, such technologies have come to play a pivotal role in IDS to enhance decision-making and forecasting capabilities. This chapter reviews a few applied machine learning and deep learning techniques on IDS.

4.1. Neural Networks and Decision Trees in IDS

Neural networks and decision trees have been applied to SIDS for long. However, in this work, the techniques were both applied to SIDS and AIDS which made the system perform better. The neural networks were used for enhancing the detection of known attacks, while the decision trees were used for the detection of new, unknown attacks.

A three-layered structure of a neural network implemented the learning algorithm back propagation. A wide range of experiments were conducted with the different datasets available in the KDD 99 on both network-based IDS and AIDS. The KDD 99 dataset contains four categories of attacks: DoS, Probing, U2R and R2L, and one normal class. These categories were represented within the neural network using five output neurons.

The experiment proved that, even though the neural network was the best among the others, it could not truly determine the attacks of U2R and R2L; other attacks were however successfully detected. Therefore, the detection tree was brought in to enhance its capability for threat detection. The detection accuracy for the U2R class was also enhanced through the upgrading of the algorithm C4.5 up to 60.96%. Moreover, the false negative rate of that class declined from 82.89% to 21.93%. Nonetheless, the improvements constituted a minor portion of the experiment; it was noticed that the improved version of C4.5 algorithm did not function well in cases where actual labels were not obtained, which meant that the methodology should not be applied to those types of instances.

4.2. SVM in IDS

A method was proposed for applying Support Vector Machine (SVM) in network-based Intrusion Detection Systems (IDS). In this experiment, various kernel functions and stabilization parameters (C values) were deployed, using the KDD 99 dataset to analyze multiple features with SVM. The process began by preparing the training and test datasets to improve the SVM IDS performance. The dataset was pre-processed to convert the data, which was initially labeled

as either normal or attack, into a format suitable for SVM input. The total training dataset contained 4,898,431 instances, and the test dataset, labeled accordingly, had 311,029 instances.

Once the dataset was pre-processed and training was complete, SVM learning and validation experiments were conducted. Different kernel functions such as linear, 2-poly, and Radial Basis Function (RBF) were utilized, with SVMlight deployed for binary classification. Through the training process, SVM developed a decision model, which underwent multiple iterations to achieve a high success ratio. Several kernel functions and C values were tested to identify the most suitable kernel for the task. The results of the test process were then compared with the KDD'99 results to assess the effectiveness of the approach.

5. Section IV: Challenges and Predictions

The previous section demonstrated the applications of Machine Learning (ML) and Deep Learning (DL) in IDS, highlighting both the strengths and limitations. This section discusses the challenges faced by these technologies and presents some predictions for their future.

5.1. Dataset Issues

Several commonly used datasets, such as KDD 99, NSL-KDD, and ISOT, have become outdated over time. For example, the KDD 99 dataset, which was used in the research mentioned in Section III, was created over 20 years ago, in 2000. As a result, this dataset may no longer adequately reflect the latest types of attacks. Additionally, while newer datasets that cover current malicious behaviors exist, they are often proprietary and not publicly available. Public datasets, on the other hand, frequently contain redundant or anonymous attributes, which can lead to issues in training and testing. Therefore, there is a need for valid, up-to-date, and open datasets that can be used in IDS research.

5.2. Standard Metrics

There is a lack of universally accepted standard metrics for evaluating IDS models, with most researchers using different parameters for their evaluations. For example, in the experiment referenced in Section III, KDD 99 results were compared to evaluate the effectiveness of the proposed methods. However, the absence of standardized evaluation metrics makes it challenging to compare different models fairly and consistently. A standard framework for evaluating IDS models would help improve the comparability of research and accelerate advancements in the field.

Challenges and Limitations of Neural Networks

1. Data Requirements:

- Large datasets are usually required for neural networks to achieve high performance, and small datasets lead to poor generalization, overfitting, and inaccuracy in the results.

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- Quality of Data: Neural networks are highly vulnerable to noisy, incomplete, or biased data. They need to be aided with clean and well-preprocessed data.

2. Computational Complexity:

- High Computational Power: Neural networks, particularly deep learning models require quite a lot of computational resource (for example, powerful GPUs or TPUs). It makes both the training and inference on them expensive and computationally long.

- Long Training Times: Since the model requires many iterations (epochs) to optimize the weights and minimize the error, the training of neural networks can often be a slow process, even using powerful hardware.

3. Overfitting:

They are prone to overfitting; that is, when a neural network learns too much from the training data, it may fail to generalize well on new, unseen data. This is particularly concerning for smaller or poorly balanced datasets.

- Regularization: Dropout, weight decay, and early stopping are some of the techniques employed to combat overfitting, which can make model design even more complicated.

4. Interpretability and Transparency:

- Yet another criticism made about neural networks is that they are pretty much seen as "black boxes," meaning the decisions are not easy to understand. Thus, they are very hard to debug or to trust especially in critical applications like in medicine or finance.

- EXPLAINABILITY While deep learning models are continually being improved in terms of explainability (e.g., through techniques like LIME or SHAP), the specific reasoning for a decision a neural network comes to is still hard to understand.

5. Bias and Fairness:

- Bias in Training Data. Neural networks inherit all the biases in the training data. If training data is biased or imbalanced, then the prediction may be biased or discriminatory, thus resulting in unfair outcomes.

- Bias in Predictions. In sensitive applications, like criminal justice or employment, biased predictions have serious social and ethical implications.

6. Generalization

- Overfitting vs. Underfitting: Avoid overfitting (noise of training data) and underfitting (patterns of training data which the model failed to capture). Neural networks may not generalize well to unseen data, and this is particularly true if the model is over-complex or data impoverished.

- Transferability: Those models trained on one set of data will not do so well on another domain or even scenario without fine-tuning or retraining.

7. Hyperparameter Tuning:

- Optimization Difficulty : Neural networks are very sensitive to hyperparameters such as the learning rate, number of layers, and batch size. This really means that finding the optimal configuration is very time-consuming and lots of experimentation may be required.

- Grid Search and Random Search: These are widely used for hyperparameter optimization but are computationally costly and inefficient.

8. Lack of Robustness:

- Adversarial Attacks: Neural nets are sensitive to adversarial attacks-the small, often imperceptible changes in input data which cause the model to err when classifying. This can attack the trust in critical systems using neural nets.

- Out-of-distribution data: The neural networks struggle and fail when encountering data that significantly deviates from the exposed data during training. Thus, the model may not be able to perform well when it encounters new types of data or environments.

9. Resource-intensive for deployment:

- Deployment Challenges: Even after training, deploying neural networks into production environments can be difficult due to their high memory and processing power requirements, particularly in real-time or resource-constrained environments like mobile devices or embedded systems.

While neural networks, especially deep learning, have really revolutionized many fields with their state-of-the-art performance on tasks such as image recognition, language processing, and anomaly detection, this progress comes along with the challenges related to data, computational resources, interpretability, and robustness. Overcoming these limitations, of course, requires persistent research innovation and careful consideration of the practical and ethical issues regarding their use in real-world applications.

Conclusion:

This review paper attempts to support the important contribution of Machine Learning (ML) and Deep Learning (DL) towards advancement in IDS capabilities. Traditional approaches, such as Signature-Based IDS (SIDS) and Anomaly-Based IDS (AIDS), suffer from various severe limitations in the ability to detect new and sophisticated attacks against the current forms of evolving cybersecurity threats. In this regard, ML and DL present very powerful tools to overcome these challenges, improving the accuracy, efficiency, and adaptability of IDS systems.

The paper discusses different ML and DL techniques, which include neural networks and decision trees and SVMs and how they find applications in both SIDS and AIDS. Neural networks, for instance, can reach the highest accuracy related to known attacks, while decision trees and SVM are sometimes useful when considering new and emerging threats. To this end, DL adds to its arsenal, handling tremendous amounts of data and learning the most complex patterns with better sensitivity in identifying APTs and zero-day attacks.

Nevertheless, several challenges remain unaddressed by all these developments. The reliance on gigantic datasets labeled for training is one of the main drawbacks; other issues include the super computational complexity of deep learning models and their susceptibility to overfitting. Models are often not interpretable, and thus it is also challenging to employ them in real-world deployment, which raises more significant challenges about efficiency and adaptability to new attack vectors.

Thus, ML and DL carry great potential for upgrading IDS, but it is necessary to overcome the available challenges to realize their practical and extensive usage. Future research should emphasize generalizability, fairness, and transparency in models and help in improving more efficient algorithms that can handle voluminous amounts of ever-growing threats in real-world environments.

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These references provide foundational and contemporary insights into the application of machine learning and deep learning techniques for intrusion detection, highlighting both the potential and limitations of these technologies in cyber security.