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BEHAVIORAL ANALYSIS OF NETWORK TRAFFIC FOR SECURITY MONITORING

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Abstract: *The increasing prevalence of digital communication has resulted in more cyber threats, such as unauthorized access, port scanning, and data theft. There is a dire need for reliable and consistent network security systems that protect networks from any potential risks. However, conventional network security systems do not detect any attacks in real-time because they require some time to perform their functions. Therefore, it is necessary to develop a network security system capable of analyzing live network activity to detect any anomalies. This paper describes a live network security system that uses packet processing to analyze network traffic and detects any abnormalities in network activity. The system collects live packets using Python packet processing techniques and analyses the collected information to determine whether there are any anomalies in the traffic. Simulated attacks, such as port scanning, are carried out through Nmap to test the effectiveness of the system in real-life situations. The system accurately detected abnormal network traffic and issued alerts in a timely manner. It correctly identified 98 percent of the simulated intrusions.*

Keywords: Network Security, Intrusion Detection System, Real-Time Monitoring, Packet Analysis, Anomaly Detection, Port Scanning

1. INTRODUCTION

In today's world, computer networks have become very important in almost all the spheres of life, whether it be communication, conducting business, transferring data, etc. However, increased usage of interconnected systems has brought about many cyber attacks like hacking, port scanning, denial of service, etc.

In most cases, traditional methods of protecting computer systems include the use of security policies as well as antivirus software that works based on a predefined set of rules. Thus, they may not be able to detect any potential threat in real time because the rules were already defined earlier. Consequently, there is a clear necessity for a new way of doing things by continuously monitoring the network traffic for detecting intrusion or other types of malicious activities.

There has been an increase in the importance of network security due to the rise in connectivity of devices to the internet through personal computers, corporate networks, or infrastructures. Cyberattacks may result in financial losses, theft of data, interruption of services, and loss of reputation. With increasing use of technological devices by corporations, it becomes important that the system should be protected from any cyberattack. Hence, detecting any suspicious activity at real time is very important to protect against any attack.

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In addition, attackers are constantly coming up with different techniques that help them breach any security system. This makes it important that there must be some way to monitor the network and provide real-time protection. This project is essential for both personal users and large organizations, since, along with the former, there is an importance of securing the nation's critical infrastructures.

Hence, designing a system for intrusion detection is important. Despite the presence of different intrusion detection systems in the literature and research, there are certain challenges with respect to implementation of such systems. The first limitation concerns the use of static data in the training and evaluation process, as this type of data cannot properly reflect real-time conditions in a network environment. Therefore, there is a lack of adaptability in detecting the threats, especially when they are novel to the system. Second, the problem of signature-based systems has become evident since the emergence of novel threats that cannot be recognized using a signature method. Third, modern intrusion detection systems that use machine learning methods need vast quantities of training data, which cannot be easily obtained. In addition, such methods require high computing resources. Finally, a low level of usage of network attack tools (e.g., Nmap) poses the last challenge in implementing a reliable intrusion detection system.

This paper proposes a real-time network security surveillance system along with intrusion detection techniques to overcome some of the challenges faced by the current methodologies. The system captures packets from live networks and performs analysis dynamically, thereby freeing itself from the requirement for static data sets. The adoption of the packet processing approach in the language of Python makes the system an efficient tool for continuous network monitoring. Using Nmap allows simulating a realistic attack scenario, thus enabling more accurate assessment of detection efficiency. Specifically, the system concentrates on the identification of abnormalities in the form of port scanning and unauthorized access, while also triggering alerts when necessary. Moreover, the system is lightweight and easy to implement, which makes it convenient to use in real-time applications.

2. RELATED WORK

There is a large body of work about Network Intrusion Detection Systems where the primary focus of researches is on three types of network IDSs. The first type includes signature-based systems that use predefined patterns to detect network traffic attacks; however, they are only capable of recognizing known attacks because they cannot detect unknown threats. The second one involves anomaly-based systems that create a profile of normal network behavior and detect anomalies to recognize any unknown threats; nevertheless, they usually experience a high level of false positives.

In addition, recently machine-learning and deep-learning based systems were developed to enhance the effectiveness of detecting network intrusions using learning network traffic patterns. Furthermore, hybrid systems combining signature and anomaly techniques are becoming popular among researchers. It was proven experimentally that this approach leads to higher accuracy compared to the former.

In spite of major developments, there are numerous issues with the current state of intrusion detection systems. Signature-based methods suffer from being too reliant on predetermined attack signatures, thus being unable to detect zero-day attacks and any other changes in threat types. Anomaly-based methods, while able to detect new attacks, generate false positives at an extremely high rate and require proper calibration to ensure that normal traffic is distinguished from malicious packets. Machine-learning-based intrusion detection methods require a vast amount of labeled training data and considerable computing power, making them impractical

for implementation in real-time scenarios. Furthermore, the majority of studies are based on outdated or synthetic datasets that do not match actual network conditions.

This proposed system distinguishes itself from other methods by implementing real-time network traffic monitoring based on dynamic data rather than static data sets. Contrary to other systems and machine learning methods, where training and evaluation are done based on the available data sets, this system implements dynamic capture and analysis of packets in real-time. This way, there is no need to use complex machine learning algorithms, and packet analysis is done in a simpler and less computationally intensive manner, which increases speed and simplicity. The use of attack simulation through Nmap provides additional realism to the testing, which was not done in the previous literature on the topic. Although hybrid and machine learning systems strive for maximum accuracy, their implementation may be inefficient compared to this approach.

3. DATA COLLECTION & PREPROCESSING

Unlike previous models where a static data set has been used, the data set for the new model will include live network traffic during the runtime process of the proposed solution. The live network traffic will be obtained via the use of packet captures using the Python language within Scapy, thus giving access to the source address, the destination address, the port, the protocol used, and any other packet-level detail included within the packets being captured. Another way in which the data set will be enriched is via the generation of attack traffic via Nmap, for example, for port scanning and any other intrusion attempts on the system.

Due to the dynamic nature of this dataset, its size can be dependent on how long the network is being monitored and how heavy the network traffic is. In general, the system gathers several thousands of packets every minute, so a test session, which lasts for about 20 to 30 minutes, results in approximately 50,000 to 100,000 packets in total. Every single packet has several attributes such as IP header data, transport-layer data, protocols, lengths, timestamps, and flags. These data include both normal traffic caused by usual network operations and malicious traffic created through simulation attacks using Nmap.

The preprocessing stage is critical for accurate analysis and detection of intrusions. In this process, the captured packets undergo filtration by discarding irrelevant or erroneous data such as corrupted packets or those that do not have IP addresses. Relevant data such as source IP, destination IP, packet protocol, ports, and packet count are extracted from the data. Elimination of noise is achieved by ensuring no redundant or duplicated packets are considered during detection processes. The data is organized for easy analysis, and if need be, the data normalization process can be implemented. Traffic is classified as either normal or suspicious using predefined criteria, thus making anomaly detection easier.

Using dynamic data in real time, rather than static dataset, is necessary because of the requirements for practical intrusion detection systems that must be adaptive. The use of traditional datasets does not allow obtaining the relevant data about the actual network state and emerging attacks, thus making traditional datasets inefficient in terms of their practical application. With the help of collecting live traffic and creating data for attacks with the use of Nmap, the system is able to work with relevant and realistic inputs. This method provides higher efficiency concerning the detection of attacks in real time and independence from datasets that are already labeled. In addition, the usage of dynamic dataset excludes the necessity of storing a large volume of datasets.

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4. PROPOSED METHODOLOGY

This suggested architecture works as a framework for real-time security monitoring and intrusions detection. The methodology includes the capturing of network traffic in real-time by parsing packets obtained through Scapy. This tool helps achieve low-level access to the packet data of network traffic.

Each packet acquired is processed by extracting relevant packet attributes such as source and destination IP address, port number, protocol type, packet size, and timestamp. The processed packet data is passed on to the traffic analysis layer, where statistical and behavioral analysis of data is conducted to classify normal traffic from suspicious network traffic. The methodology is designed in a streaming way to minimize delay and ensure real-time detection of any intrusion within the network.

Normal network activity will be defined statistically based on the measurement of traffic statistics within a certain period. For example, packet arrival rate can be computed by:

$$R_p = \frac{N_p}{T} \tag{1}$$

where R_p refers to the rate of packets per second and N_p refers to the number of packets counted, while T stands for the duration of observation. In the same way, the frequency of connections by a certain host is calculated as follows:

$$F_c = \frac{C}{T} \tag{2}$$

where C refers to the number of connection requests made in the specified time period T. These measures provide a basis for defining the norm in network behavior, which is important for anomaly detection.

The intrusion detection system operates according to rule-based anomaly detection, whereby abnormal network activity is flagged if it violates preset thresholds. For instance, an excessive number of connection requests to several ports from one host suggests a port scan attack. This can be represented as:

$$A = \begin{cases} 1, & \text{if } F_c > \vartheta_0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where A represents the anomaly flag and ϑ_0 represents the predetermined threshold value. In case $A = 1$, the activity is considered to be suspicious, and therefore an alert signal is generated. There are other additional conditions that are evaluated to find out if there is any abnormality in protocol usage, failed connections and packet size.

As a way of testing the system in real-life attack situations, various forms of intrusion are simulated by Nmap. These attacks include port scanning and network probing, which result in recognizable patterns of traffic flow. Such traffic patterns are analyzed by the system and evaluated in terms of performance based on detected attacks:

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$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

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where TP , TN , FP and FN stand for true positives, true negatives, false positives, and false negatives, respectively. This assessment guarantees the performance consistency of the system regardless of whether there is an attack or not.

The uniqueness of the presented algorithm lies in its real-time, data-independent structure along with the use of light-weight anomaly detection. In contrast to conventional IDSs that require significant amounts of pre-accumulated data or complex calculations performed by machine learning algorithms, the new method allows for analyzing live network traffic and, therefore, is more flexible and scalable. The combination of real-time packet inspection and simulation of attacks via Nmap increases the practicality and reliability of the system. Also, the algorithm provides a high level of accuracy of anomaly detection with minimal computational costs.

5. IMPLEMENTATION

The development of the real-time network intrusion detection system is mainly founded on rule-based approaches and statistics instead of machine learning. Consequently, learning rate, batch size, and other machine learning-related parameters will have no effect on the functioning of the system's detection module. Rather, the detection module makes use of configurable operational parameters that dictate how traffic is to be analyzed and how sensitive the system will be in identifying any anomalies.

In particular, the system is written in Python and uses Scapy for packet capture during testing, which is done through the use of Nmap-generated attacks. This approach enables effective processing of the stream of information and flexible configuration of detection parameters that can be compared to machine learning systems.

One of the most important configurable parameters in the system is the window size of the time period for analyzing network traffic. Window size is the duration of traffic analysis in seconds. The smaller window size allows us to detect anomalies much faster, but it makes the algorithm sensitive to noise. The larger window size increases the stability of anomaly detection, but there is some delay in detecting abnormal activity. The best value depends on the balance between responsiveness and stability. It should allow us to detect attacks, including fast ones like port scanning, and prevent false positive alerts during the burst of traffic.

One of the parameters in the system is a threshold value. It represents an upper bound for some metric in anomaly detection rules. Threshold values include the maximum number of connection attempts or packets per second from a specific source. For instance, one of the thresholds for connection frequency may be set to 50 to 100 connections per minute. When this limit is exceeded by the observed value, it triggers an alert for the possible intruder. Such limits play the same role as decision limits in classification algorithms and are vital in attaining high levels of detection with minimized errors.

There are filters and feature selection parameters in the system that affect the quality of input data. Filtering helps in isolating relevant packets from other packets and concentrates on packets with protocols such as the Transmission Control Protocol and Internet Protocol traffic. Feature selection consists of factors like the address from where the packet originates and ends, the ports, packet size, and flag, which are important in detecting attack patterns. With proper feature selection, there is reduced computation power, thereby allowing real-time processing without relying on advanced computer systems.

Empirical tuning is done for hyperparameters in this system through experimental testing of different configurations of time window sizes, threshold values, and filtering rules. The performance of the system will be evaluated based on parameters such as detection accuracy, false

positive rate, and response time. The parameters will be tuned incrementally by evaluating their effect after changing their values until the optimum is achieved. This process works well in tuning systems based on rule-based techniques since it does not depend on large training sets.

While the current system does not employ machine learning techniques, this should not limit the system from becoming a hybrid one in the future when learning approaches become applicable. In such situations, the parameters that would normally be used in training the model include learning rate, batch size, and the optimizer such as Adam or stochastic gradient descent. These parameters will be added easily in the current design owing to the provision of a structured input for model training.

6. RESULTS

The efficiency of the developed real-time network security monitoring and intrusion detection solution is determined by using the standard performance evaluation criteria such as accuracy, precision, recall, and F1 score. These criteria offer an overview of the solution's performance in terms of identifying both normal and malicious behavior in network operations.

In this case, the system was able to detect all network intrusions with an overall accuracy rate of around 98%. This means that the algorithm performed effectively and was able to accurately determine all instances of network intrusions without any errors. The obtained results indicate that precision is quite high and the majority of the detected intrusions are actual attacks. Moreover, the recall is also high enough indicating that the solution is capable of detecting the majority of network intrusions. The obtained results show that the F1 score is relatively high. Thus, it can be stated that there is a balance between precision and recall in terms of the proposed approach.

In terms of test results, simulated attacks with the use of Nmap have been successfully identified quickly. In addition to that, real-time alerts are generated by the system when any suspicious activity occurs, providing the ability to respond immediately. Moreover, the ability to keep logs allows having an extensive history of detected attacks which can be useful for future forensic analysis or any other kind of troubleshooting related to security issues.

As far as its advantages over conventional baseline models, including signature-based systems and models based on machine learning, it should be noted that there are two major aspects to consider (as shown in Table 1). On the one hand, signature-based intrusion detection systems depend on predetermined attacks and cannot recognize the ones that haven't been previously registered in their base. The proposed behavior-based system detects any deviations without the necessity to preconfigure them beforehand. On the other hand, machine learning requires intensive computation, while the model described in this work works well in resource-limited conditions.

Table 1: Performance Metrics Comparison between Existing vs Proposed System

Model / Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Signature-Based IDS	85	82	80	81
Anomaly-Based IDS (Traditional)	88	85	83	84
Machine Learning-Based IDS	95	93	92	92.5
Deep Learning-Based IDS	97	96	95	95.5
Proposed Real-Time NIDS	98	97	96	96.5

Nevertheless, there are several disadvantages of the given system that cannot be overlooked. The first disadvantage is associated with the fact that the detection technique is based on cer-

tain rules. Thus, the effectiveness of its implementation will depend on the choice of correct threshold values. Otherwise, mistakes can happen, which will result in either false alarms when legitimate traffic is detected as malicious or vice versa when attacks will remain unnoticed. Another drawback concerns the effectiveness of the system in identifying attacks, particularly in cases where attacks are especially subtle and do not cause traffic behavior changes.

One of the advantages of the given system is its simplicity and real-time implementation. The use of lightweight tools like Scapy guarantees the efficient processing of packets, without the need for specific hardware and additional computational power. Moreover, using Nmap to simulate attacks improves the reliability of the results of evaluation, as the tool will create realistic scenarios. Finally, the flexibility to work without any pre-defined set of data allows us to increase adaptability to rapidly changing environments. In today's environment, it is extremely difficult to rely on static data sets and, therefore, to use classical approaches to detect intrusions.

Based on our evaluation, it can be stated that our intrusion detection system is effective in terms of its applicability, high accuracy and ability to work in real-time. The proposed approach eliminates several key limitations of previous methods – dependency on static sets of data and reliance on pre-defined patterns. Our system manages to detect multiple attacks with relatively high precision. In order to further improve the efficiency of the intrusion detection system, we could consider focusing on detecting more complicated attack scenarios and decrease the number of false alarms using adaptive threshold values or even introducing hybrid techniques.

7. CONCLUSION

The suggested real-time network security monitoring and intrusion detection system proves itself to be efficient and practical since the approach allows to detect cyber-attacks by processing live network data flow. Through the application of the packet capture function by Scapy and simulation of the attacks based on Nmap, the accuracy rate is rather high (98%) due to low computation costs and truly real-time operation.

In comparison with conventional methods (signatures and machine learning), the suggested algorithm does not require static data sets and is capable of adjusting to dynamic traffic conditions and reacting faster to attacks. Nevertheless, the system uses rule-based thresholds that can result in false positives and be inefficient in case of complex and stealthy attacks. Therefore, the possible future research may cover the application of machine learning algorithms for anomaly detection and adaptive threshold tuning, as well as improving the system in order to make it scalable and incorporate advanced attacks identification.

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