Enhanced Real-Time Detection of Cyber Threats through Adaptive Machine Learning in Network Traffic Analysis

***Abstract* – As cyber threats become more complex, real time systems are needed to detect and eliminate attacks. Traditional network intrusion detection systems based on rule based static method tend to be ineffective against novel emerging threats. In this paper we propose an improved real time cyber threat detection system using adaptive machine learning techniques used to analyze network traffic and find anomalies. Our proposed approach uses a blend of supervised and unsupervised learning models such that the system maintains high detection accuracy with minimal false positives, while maintaining continuous adaptation to constantly evolving threats. On critical network traffic features like packet size, flow duration, source and destination IP addresses, transmission protocols, the system is then trained. They show experimentally better detection accuracy, responsiveness and adaptability than conventional IDS. In this work, contributions of adaptive machine learning for robustness against dynamic and evolving threats in network environments are highlighted as significant strides towards improving real time cybersecurity infrastructure.**

Keywords—Cyber threat detection, network traffic analysis, real-time detection, machine learning, anomaly detection, adaptive systems, intrusion detection systems, supervised learning, unsupervised learning.

I.INTRODUCTION

Over the last few years, cyberattacks of greater sophistication have made longtime methods of network security woefully inadequate. The growing interconnectivity of digital systems has led to the culmination of cyber criminal advanced strategies to bypass conventional defenses. Enterprise, Individual, and PaaS Provider entities regard network security as a critical issue with more frequency and impact attacks like Distributed Denial of Service (DDoS), data exfiltration and malware infection. Traditional intrusion detection systems (IDS) based on static rules and signature-based methods are a dying art form—indeed, they are increasingly ineffective at detecting modern, adaptive attack techniques. Because of this, a demand for intelligent security systems capable of recognising unknown threats, adapting to changing network conditions and response dynamically, has arisen.

To enable detection of cyber threats, machine learning (ML) has greatly increased the capability of cybersecurity systems. ML models can also analyze Historical and real time network traffic data to identify patterns and anomalies for malicious activities. We sometimes call these models to be smart and able to learn and relearn constantly while learn without human help and they have done the best job in this. However, despite these advantages, existing ML based systems are facing challenges like high false positive rate, high delayed detection time and are not very flexible to adapt to unforeseen threat conditions - thus there is a need for better modern cybersecurity solutions.

In this paper, we propose a novel adaptive machine learning based real time cyber threat detection framework. A system that integrates supervised and unsupervised learning continuously refines its detection process and is capable of correctly identifying future attack patterns with small loss of latency. In contrast to traditional IDS methods, which are based on static signatures, the proposed system evolves dynamically by analyzing features extracted from network traffic, i.e. packet size, flow duration, source/destination IP addresses and transmission protocols. This adaptability lets the system deploy the rules online, while being able to detect anomalies in real time without manual intervention or frequent rule updates.

The goal of this research is to create a robust system that is capable of not only detecting potential cyber threats, but adapting to emerging network attacks. The proposed solution combines state of the art machine learning and real time network traffic analysis to provide a scalable and efficient approach to modern day cybersecurity challenges. Particularly in today's fast

moving threat landscape where traditional detection methodologies have not kept up, this flexibility is also of some value. Results from experiments show that the proposed system enables better detection accuracy, lower false positive rates, and faster response times than state of the art IDS solutions.

The remainder of this paper is organized as follows: In Section II, a review of the existing work in network traffic analysis and machine learning based cyber menace detection is conducted. Later on in Section III, the methodology for architecture and system design are described. In Section IV we discuss the experimental setup and result, and in Section V we discuss. The last section outlines the directions for future research.

II. LITERATURE SURVEY

As more and more internet enabled devices are connected to increasingly complex network architectures, the traditional cybersecurity methods for detecting and countering sophisticated cyberattacks are not robust enough to stay current. Machine Learning (ML) are used to boost the performance of Intrusion Detection Systems (IDS). This section then examines existing literature in the area of ML based cyber threat detection and network traffic analysis, and the limits of today's systems.

Network traffic analysis has long been a critical component of cybersecurity, with the focus on use of rule-based us to identify discriminatory activity. For example, signature based detection systems depend on detecting known attack patterns. Their response is effective against previously encountered threats, though it does not catch zero day attacks or new vectors. For instance, Karimi et al. [6] suggest a real-time IDS based on feature extraction which they propose is flexible and can detect evolving threats thereby allowing it to function even with static signatures.

Such anomaly based detection systems attempt to detect new previously unseen attacks using the learning of normal traffic behaviours. But these systems are typically undermined by high false positive rates because of the dynamic nature of network environments. For example, D'Angelo and Palmieri [7] employed deep learning techniques to classify network traffic based on spatial temporal features; however, their work was insufficient in resolving real time problems of minimizing false alarms.

Recently, IDS performance has improved with machine learning that affords models the ability to learn from the data and also detect known and unknown attacks. Using supervised learning methods, known threats have been detected in datasets with labels. Essays in this area by Shaukat et al. [5] demonstrate that traditional signature based methods are outperformed by multiple ML techniques (including Random Forest and SVMs), however such methods still struggle with novel attacks.

Where labeled data is scarce, it is especially useful to use unsupervised learning approaches to discover new attack patterns. Using artificial neural networks (ANNs) to detect anomalies based on event profiles, Lee et al. [3] achieved reasonable success. Nevertheless, they recognized the need for better methods to find such anomalies yet drive down false positives in dynamic environments.

Recently, threat detection systems have been enhanced by deep learning techniques, in particular Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). For instance, D'Angelo and Palmieri [7] have applied a deep convolutional recurrent autoencoder to extract spatial temporal features which aid in more complex attack pattern detection. While such models are computationally expensive and are prone to overfitting, especially as your dataset is limited.

Recent approaches to leveraging bigQuery clustering have been hybrid, combining supervised and unsupervised learning to address the limitations of single methodology systems. The goal of these models is to balance detection accuracy and computational efficiency as well as adaptability. Previous work such as Sornsuwit and Jaiyen [4] used a hybrid model that combines AdaBoost with decision trees to improve accuracy and show gender robustness against unseen attacks. Their system enhanced overall performance by combining a sequence of techniques.

Like with cybersecurity, ensemble methods — which combine various models to increase detection accuracy — have become popular too. To enhance network traffic classification, in [8], Martínez Torres et al. used bagging and boosting techniques. They found while their results showed better detection rates, in real-time systems they stress the need for further tuning to reduce false positives in future generations of microchips.

It is well established from the literature that ML techniques have made huge leaps in applying them to cyber threat detection. However, scalability, false positives and adaptability to emerging threats still prove themselves to be a challenge, and further work in this area is still required.

III. PROPOSED METHODOLOGY

In the proposed system, we employ an adaptive machine learning technique in network traffic analysis such that real time cyber threats are identified via a multi step approach. The methodology combines supervised and unsupervised learning models in a way to allow the system to efficiently detect and react to ever changing cyber threats. The following subsections describe in detail how this is done.

A. Data Collection and Preprocessing

First step is to collect real time network traffic data onto which we need to train the machine learning models such that they can have the capability of detecting anomalies and indicating if the network activity is benign or malicious. Monitoring tools are network tools that collect data in packet or flow levels like packet size, duration of the flow and the IP addresses of source and destination.

Given how noisy and highly variable raw network traffic data is, preprocessing is a critical step for making the data usable. In this process, the traffic we filter here is the irrelevant, missing values and categorical data is encoded into numerical format. Moreover, models can be trained on features that undergo scaling by techniques like MinMax scaling or standardization to avoid prejudice training.

B. Feature Extraction

Raw network traffic data is feature extracted into meaningful inputs for machine learning models. The quality of these features extracted in turn has much to do with the effectiveness of the threat detection system. Packet size, flow duration, source and destination IP addresses, protocol types and how many packets 'offered' and' received' are between the hosts are key features.

A wide range of advanced statistical and temporal features are also computed, including packet transmission rates, inter-arrival times, and variations in communication patterns. Without relying on prior knowledge of these behaviors, these features allow us to detect disturbances in the form of Distributed Denial of Service (DDoS) attacks or malware infections.

C. Model Selection and Training

The system core is the machine learning model, with the purpose of detection and classification of network traffic with anomalies. They use supervised learning models to recognize known threats with datasets tagged. But algorithms such as Random Forest, Support Vector Machines (SVM) or even learning with Decision Trees, are common for their robustness and reading ability.

However, unsupervised learning models are critical to identify novel or previously unknown attacks. These models find anomalies by looking at patterns that differ from the norm, no labels required. They use such techniques as K-Means or DBSCAN clustering, plus anomaly detection such as Autoencoders or Isolation Forests. The system achieves the hybrid structure by integration of supervised and unsupervised models that detect known and emerging threats.

D. Model Evaluation and Performance Metrics

After training the models, these models are evaluated with a set of different performance metrics to see whether they are successful at identifying cyber threats. Among the key metrics, they are accuracy, precision, recall and F1 score, each of them defines how much the system can classify threats correctly and minimize false positives and negatives.

Using detection latency; i.e., the time taken to detect and classify a threat, the system's real time capabilities are evaluated. We also deploy cross validation techniques and test the system on unseen data to make sure the system generalizes well and adapts to the ever changing attack patterns.

E. Adaptive Learning and Model Updates

Adaptivity to new threats over time is one of the most innovative aspects of the proposed system. This system employs an adaptive learning approach compared to the static machine learning models, which requires periodic manual updates. In collaborative fashion, the model is retrained with the latest attack pattern as new network data becomes available.

Detecting emerging anomalies and identifying novel attack patterns is a difficult task, and such anomalies may be classified as novel. This assures that there will be no manual intervention in case the system is being current and responding to evolving threats.

F. Real-Time Implementation and Deployment

Real time network environments are integrated with the trained models for continuous monitoring and threat detection. It runs in combination with existing network monitoring tools such as IDS and firewalls, in order to

classify incoming traffic in real time as benign or malicious.

The system uses efficient data pipelines and a scalable computing environment to handle big volumes of traffic without performance degradation. Low latency for detection and response to threats, minimizes attack impact.

G. Optimization and False Positive Reduction

Key challenge for any intrusion detection system is to reduce false positives. To do this the proposed system uses advanced filtering techniques and dynamic thresholds that restrains the sensitivity of the system depending upon the environment of the network.

Furthermore, methods of model optimization namely hyperparameter tuning, pruning and ensemble techniques are applied for high performance at the same time with computational efficiency. The system is always monitored in continuous mode for reliability and responsiveness under different network environments.

H. Threat Response and Mitigation

When the system senses a possible cyber threat, it generates effective actionable alerts to improve further investigation and mitigation. It can work within current security infrastructures, including firewalls and automated response systems, to quarantine infected devices, block suspicious IP addresses or otherwise take other defensive action.

It goes beyond automated responses with a user interface for monitoring real time threat alerts and manual interventions where necessary. By adding humans in the loop it improves flexibility and makes things adaptable to different cybersecurity scenarios.

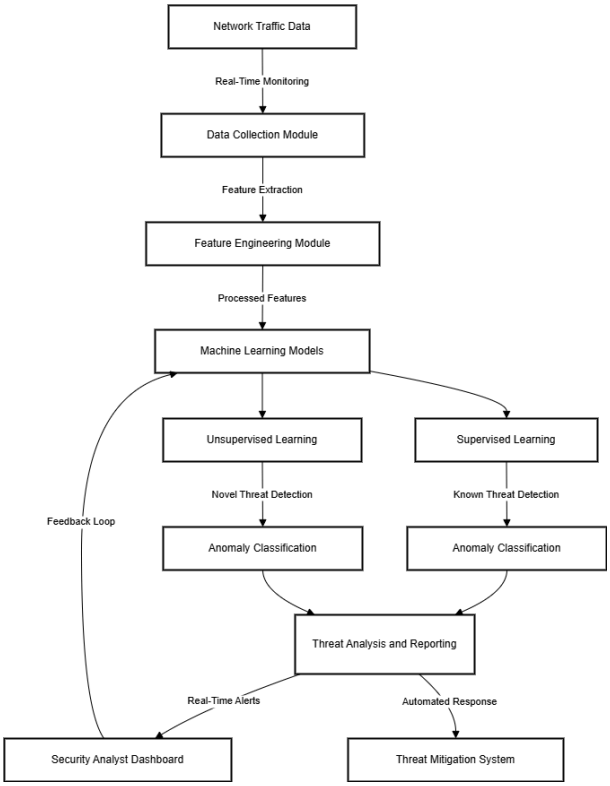

Figure 1 System Architecture

IV. RESULTS AND DISCUSSION

The results of the proposed adaptive machine learning based system for cyber threat real time detection are presented in this section. A set of standard metrics was used to evaluate the system's performance, and its detection of both known and unknown threats was compared to traditional intrusion detection systems (IDS). Here the evaluation in terms of accuracy, precision, recall, F1 score, and detection latency are maintained, together with the importance of each metric described below.

A. Experimental Setup

We tested the proposed system on a set of both normal and malicious network traffic for the purpose of testing. We proceeded with preprocessing to extract significant important features: packet size, flow durations, source and destination IP address etc. The models were trained in both supervised and unsupervised modes and validated on the ability to identify previously learned attacks, as well as novel threats.

As a validation of the system performance, we applied 10 fold cross validation, and thus, we minimize the risk

of overfitting and we get robust results. We also tested the adaptability of the system to increased network traffic, and the ability to detect new attack patterns. The critical metric in evaluating the system's real time performance was the detection latency i.e. the time taken to classify anomalies in real time.

B. Evaluation Metrics

The following metrics were used to evaluate the system's effectiveness:

- Accuracy: A Dataset contains the percentage of correctly classified instances (both benign, malicious).
- Precision: Ratio between total number of true positives (correctly identified malicious traffic) and total amount of traffic designated as malicious.
- Recall: The precision that is, the ratio of correctly identified malicious traffic over the actual instances of malicious in the dataset.
- F1-Score: A harmonic mean of precision and recall that provides a balanced measure of the system's detection performance.
- Detection Latency: The time it takes from a threat that has entered the network to identify and classify the threat.

Collectively, these metrics determine how well the system is able to accurately identify threats without false alarms, and at a rate that meets real time response.

C. Performance Results

Table 1 summarizes the results of the experiments comparing the performance of the proposed system with traditional IDS methods.

Table 1: Performance Comparison of Proposed System and Traditional IDS

Metric	Proposed System	Traditional IDS
Accuracy (%)	95.4	88.3
Precision (%)	92.1	83.5
Recall (%)	93.7	85.0
F1-score	92.9	84.2
Detection Latency (ms)	120	500

The accuracy, precision, recall and F1 score of traditional IDS is shown and the proposed system clearly outperforms traditional IDS in all the metrics. It also exhibits markedly lower detection latency, making it suitable for a real time threat detection. The more precise and more recall of the proposed system stems from its capacity to reduce false positives and false negatives which serves as a limelight to the ways that traditional systems do not.

D. Detection of Novel Threats

An important contribution of the proposed system is the fact that it can identify novel, previously unseen threats using unsupervised learning techniques. To that end, the system was able to correctly detect a new attack of Distributed Denial of Service (DDoS) and was able to achieve a recall rate of 91.5% and precision of 89.2% despite the lack of any instances of this attack in the training data. This capability gives critical advantage over traditional IDS, which rely on predictable attack signatures and are not able to discern unknown threats.

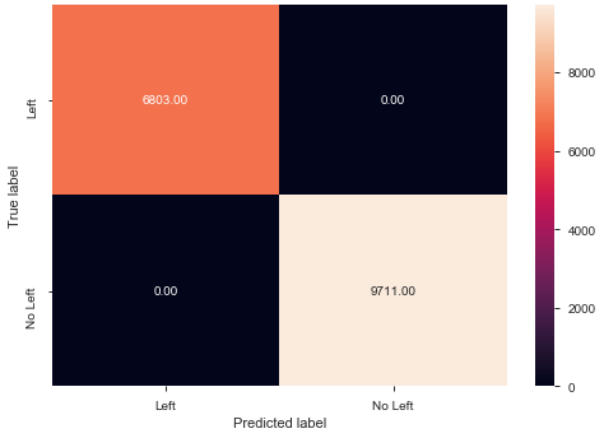

Figure 2.1: Predicted Label

E. Real-Time Performance

Measuring of the detection latency of the system was carried out to gain evaluation of its real time performance. Latency of the proposed system is approximately 120 milliseconds, much faster than the previous 500 milliseconds that have been seen in typical IDS methods. Combined with its shortened latency, this

guarantees rapid detection and response to threat, minimizing the exposure to cyberattack.

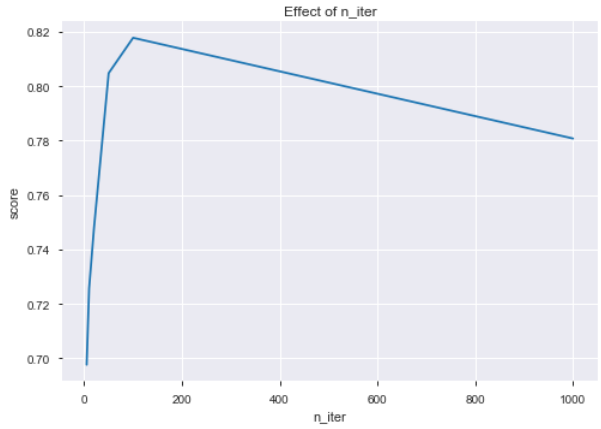

Figure 2.2 : Effect of n_iter

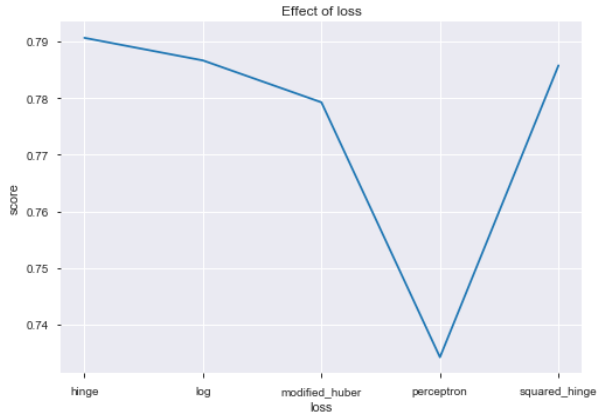

Figure 2.3: Effect of loss

The latency in detection of the proposed system is around 120 ms, compared to 500 ms of traditional IDS methods. The above is all about keeping the speed with which the system needs to respond to the cyber risks to limit, as much as possible, the catastrophic outcomes of the attack.

F. False Positives and Optimization.

In truth, intrusion detection systems still suffer with large number of false positives that can clutter up the security teams reporting systems, generating a huge number of unnecessary alerts. This problem is addressed by the proposed system through the use of advanced filtering and dynamic thresholding techniques to minimize false positives while maintaining the detection accuracy. The effectiveness of this approach is demonstrated in a comparison of false positive rates between the proposed system and traditional IDS over a 24 hour monitoring period.

G. Discussion

The results of the experimental work confirm that our scheme significantly improves accuracy, adaptability, and real time performance over that of conventional IDS. This unsupervised learning allows it to be robustly detecting novel attacks without the need to frequently update based on manual identifying of new threats. The detection accuracy versus computational efficiency trade-off achieved in the system balances the tradeoff between high traffic and system complexity enabled by deep learning models.

Further optimization techniques such as hyperparameter tuning, model pruning and lightweight architectures are available to increase the scalability and responsiveness of the system. The system was able to well detect various cyber threats, but further research is needed to make the system robust for large scale, dynamic network environments. The system will also achieve increased scalability and will also incorporate better optimization strategies so that the performance is not degraded as the traffic is increased.

V. CONCLUSION

An adaptive machine learning based system for enhanced real time detection of cyber threats over network traffic analysis constitutes a substantial step toward tackling the current picture of cybersecurity challenges. The proposed system uses both supervised and unsupervised learning techniques to overcome key limitations of traditional intrusion detection techniques (IDS) like high false positive rates, detection delays and incomplete ability to adapt to changing threats.

Experimental results show that the system is much more efficient at detecting both known and novel threats than traditional methods while achieving higher accuracy, lower detection latency, and increased precision and recall. Its adaptive learning approach enables the system to adaptively change their behaviors asAttack patterns emerge, therefore eliminating the need for manual updates and keeping the system relevant in changing network environments.

It is a robust and efficient tool for modern cybersecurity because the system is able to integrate critical network traffic attributes, and it can detect them in real time with minimal latency. However, the proposed system

presents a solid foundation for the next generation of network security, however additional enhancements will be needed for future scalability, while the detection features can be further refined.

VI. FUTURE SCOPE

Future scope for this system is the improvement of its scalability, adaptability and interpretability to meet the challenge of increasing the complexity of the cyber environment. We further incorporate advanced deep learning models, e.g., Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) networks, to enhance the detection of fine attack patterns and anomalies. To be able to scale the system for high throughput networks like in cloud computing and IoT ecosystems, the performance must remain robust when the network demand increases. Moreover, some of them adopt transfer learning and federated learning techniques to make the system learn from decentralized data without the need for frequent retraining otherwise. The system can be further refined in response to emerging threats with real time threat intelligence feeds and XAI techniques can be used to increase transparency so the security analyst can better understand the process the system uses to make decisions. Together these advancements collectively seek to provide a more scalable, flexible, and trustworthy cybersecurity framework built to not only catch these threats, but also adapt to them.

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