Cyber Crime Detection in Department of Telecommunications (DOT)

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Abstract—

In today's interconnected world, the widespread adoption of Internet of Things (IoT) devices has brought forth a host of conveniences and opportunities. However, this technological revolution has also opened the door to a new breed of cyber threats, with attackers exploiting vulnerabilities in IoT devices to compromise user privacy, disrupt critical services, and wreak havoc. Traditional security measures have proven inadequate to combat the evolving complexity of these cyber-attacks, necessitating a more advanced and adaptive approach. This urgency has given rise to the development of a Machine Learning Model for Cyber Attack Detection and Classification in IoT Environments (ML-IoT-CD). In addition, the need for a robust cybersecurity solution in IoT environments has become paramount due to the increasing reliance on these devices for critical applications. Existing intrusion detection systems and conventional security measures often lack the scalability and agility needed to keep pace with rapidly evolving attack techniques. As a result, there is a pressing demand for an intelligent, automated, and proactive cyber defense mechanism capable of real-time detection and classification of emerging cyber threats. The ML-IoT-CD model aims to fulfill this need by harnessing the power of machine learning algorithms to analyze vast amounts of data generated by IoT devices. By doing so, it can effectively distinguish between legitimate and malicious activities, thereby bolstering the security posture of IoT ecosystems.

Despite its potential, implementing machine learning-based cybersecurity solutions in IoT environments presents several challenges, including data heterogeneity, resource constraints, and adversarial attacks. IoT devices generate vast amounts of unstructured data, requiring efficient feature selection and dimensionality reduction techniques to enhance processing speed and accuracy. Moreover, the computational limitations of many IoT devices necessitate the development of lightweight yet effective models that can operate with minimal power and storage. Addressing these challenges requires ongoing research into federated learning, edge AI, and adaptive threat intelligence frameworks, ensuring that ML-based intrusion detection systems remain scalable, resilient, and capable of countering evolving cyber threats. The ML-IoT-CD model represents a significant step toward achieving autonomous and intelligent cyber defense, paving the way for future advancements in secure IoT ecosystems.

Index Terms— Cybersecurity, Cyber Attack Detection, Intrusion Detection Systems (IDS), Malware Analysis, Network Security, Threat Intelligence, Anomaly Detection,

1.INTRODUCTION

The general idea of the Internet of Things (IoT) is to allow for communication between human-to-thing or thing-to-thing(s). Things denote sensors or devices, whilst human or an object is an entity that can request or deliver a service [1]. The interconnection amongst the entities is always complex. IoT is broadly acceptable and implemented in various domains, such as healthcare, smart home, and agriculture. However, IoT has a resource constraint and heterogeneous environments, such as low computational power and memory. These constraints create problems in providing and implementing a security solution in IoT devices. These constraints further escalate the existing challenges for IoT environment. Therefore, various kinds of attacks are possible due to the vulnerability of IoT devices.

IoT-based botnet attack is one of the most popular, spreads faster and create more impact than other attacks. In recent years, several works have been conducted to detect and avoid this kind of attacks [2]– [3] by using novel approaches. Hence, a plethora of relevant of relevant models, methods, and etc. have been introduced over the past few years, with quite a reasonable number of studies reported in the research domain.

Many studies are trying to protect against these botnet attacks on the IoT environment. However, there are many gaps still existing to develop an effective detection mechanism. An intrusion detection system (IDS) is one of the efficient ways to deal with attacks. However, the traditional IDSs are often not able to be deployed for the IoT environments due to the resource constraint problem of these devices. The complex cryptographic mechanisms cannot be embedded in many IoT devices either for the same reason. There are mainly two kinds of IDSs: the anomaly and misuse approaches. The misuse-based, also called the signature-based, approach, is based on the attacks' signatures, and they can also be found in most public IDSs, specifically Suricata [4]. Formally, the attacker can easily circumvent the signature-based approaches, and these mechanisms cannot guarantee to detect the unknown attacks and the variances of known attacks. The anomaly-based systems are based on normal data and can support to identify the unknown attacks. However, the different nature of IoT devices is being faced with the difficulty of collecting common normal data. The machine learning-based detection can guarantee detection of not only the known attacks and their variances. Therefore, we proposed a machine learning-based botnet attack detection architecture. We also adopted a feature selection method to reduce the demand for processing resources for performing the detection system on resource constraint devices. The experiment results indicate that the detection accuracy of our proposed system is high enough to detect the botnet attacks. Moreover, it can support the extension for detecting the new distinct kinds of attacks.

2. Aim

The primary goal of this project is to design and implement an advanced cyber attack detection system that enhances thex security of digital infrastructures by identifying, analyzing, and mitigating cyber threats in real-time. As cyber attacks continue to evolve in complexity, traditional security mechanisms such as firewalls and antivirus programs often fail to detect sophisticated threats, leading to unauthorized access, data breaches, financial losses, and potential disruptions to critical systems. This project aims to address these security challenges by leveraging cutting-edge technologies such as machine learning (ML), artificial intelligence (AI), anomaly detection techniques, and behavioral analytics to create a robust and intelligent cyber defense system.

The proposed system will focus on real-time network monitoring to detect anomalies and deviations from normal traffic patterns, which are often indicators of potential cyber threats. By analyzing vast amounts of network data, including user behaviors, login activities, and communication protocols, the system will be able to identify threats such as phishing attempts, Distributed Denial-of-Service (DDoS) attacks, ransomware, malware intrusions, and unauthorized access attempts. Additionally, the project aims to minimize false positives by refining detection algorithms, ensuring that genuine activities are not mistakenly classified as threats.

To enhance proactive threat prevention, the project will incorporate automated threat response mechanisms, enabling the system to take preventive actions such as blocking malicious IP addresses, isolating compromised systems, or alerting security teams for further investigation. The system's adaptability will be a crucial aspect, ensuring that it can evolve alongside emerging cyber threats by continuously learning from new attack patterns and security incidents.

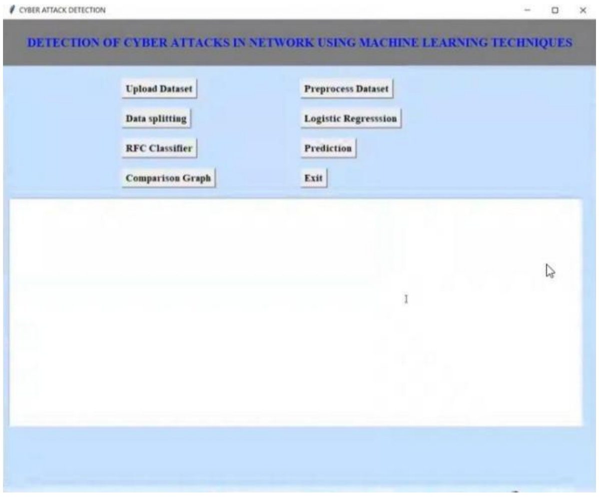


Fig.1 : User interface for the client

Furthermore, the project aims to develop a scalable and efficient framework that can be integrated into different industries, including banking, healthcare, e-commerce, and government organizations. By providing a real-time, AI-driven, and self-learning security solution, this project will contribute to strengthening cybersecurity resilience and protecting sensitive information from cybercriminals. Ultimately, the project's goal is to create an intelligent, efficient, and adaptive cyber attack detection system that enhances digital security, reduces response time to threats, and prevents cyber attacks from causing significant harm to organizations and individuals.

3. Related Work

Cybersecurity has emerged as a critical area of research due to the increasing sophistication of cyber threats and attacks. Various methods have been proposed in the literature to detect, prevent, and mitigate cyberattacks, leveraging machine learning, deep learning, and traditional rule-based detection systems.

Several studies have explored intrusion detection systems (IDS) that utilize signature-based and anomaly-based techniques. Signature-based detection relies on predefined attack patterns, making it efficient but ineffective against zero-day attacks. In contrast, anomaly-based detection models identify deviations from normal network behavior, improving the ability to detect novel threats.

Machine learning algorithms, such as Support Vector Machines (SVM), Random Forests, and Deep Neural Networks (DNNs), have been widely used for attack detection. Recent studies have demonstrated the effectiveness of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in analyzing network traffic patterns to identify malicious activities. However, challenges such as high false positive rates and the need for large training datasets remain.

Additionally, researchers have proposed hybrid models that combine machine learning with traditional rule-based or signature-based methods to enhance detection accuracy and reduce false alarms. These hybrid models leverage behavioral analysis and feature extraction techniques to improve classification performance.

Blockchain technology has also gained traction in cybersecurity research. Some studies suggest that decentralized security frameworks leveraging blockchain can provide enhanced data integrity and prevent data tampering in cyberattack scenarios.

Despite these advancements, existing approaches still face challenges in terms of real-time processing, adaptability to evolving threats, and scalability in large networks. Therefore, further research is needed to optimize detection frameworks for better efficiency and robustness.One promising direction is the integration of federated learning, which enables distributed model training without exposing.

4. Methodology

The proposed cyberattack detection framework integrates machine learning techniques with network security mechanisms to enhance threat detection accuracy. The methodology consists of the following key phases:

4.1 Data Collection and Preprocessing

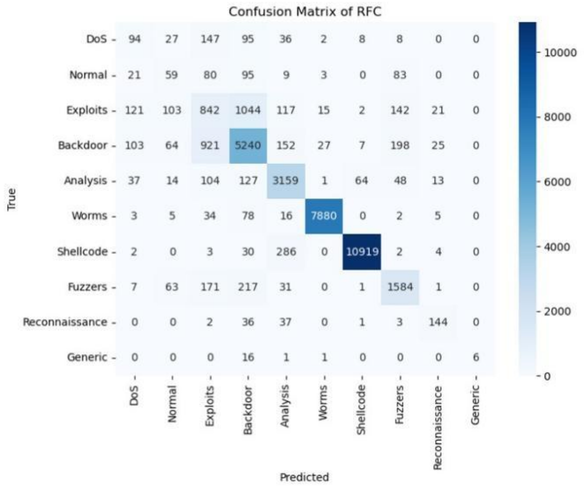
The first step involves gathering network traffic data from publicly available cybersecurity datasets (e.g., NSL-KDD, CIC-IDS2017) or real-time network traffic logs. The dataset is preprocessed by handling missing values, normalizing features, and encoding categorical data to ensure compatibility with machine learning models.

4.2 Feature Selection and Extraction

Feature selection is performed using statistical and machine learning-based techniques to identify the most relevant attributes for attack detection. Dimensionality reduction methods such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are employed to optimize model efficiency while retaining critical information.

4.3 Model Development and Training

The core of the detection system is a machine learning model trained to classify normal and malicious network activity. Various algorithms such as Random Forest, Support Vector Machine (SVM), and Deep Learning models (CNN, RNN, LSTM) are evaluated for their accuracy, precision, recall, and F1-score.

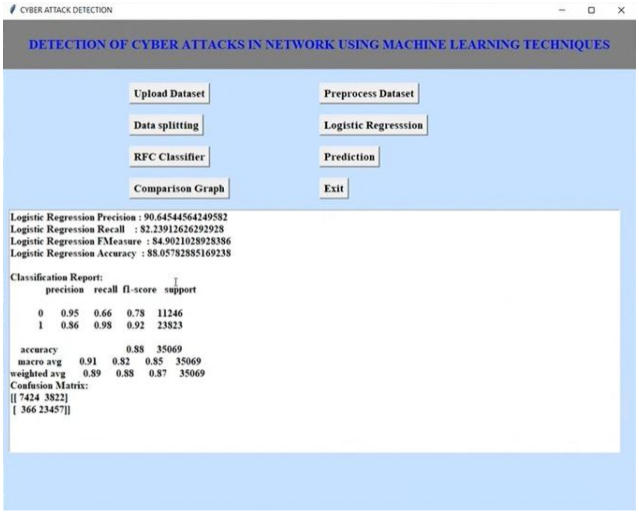


	DoS	Normal	Exploits	Backdoor	Analysis	Worms	Shellcode	Fuzzers	Reconnaissance	Generic
DoS	94	27	147	95	36	2	8	8	0	0
Normal	21	59	80	95	9	3	0	83	0	0
Exploits	121	103	842	1044	117	15	2	142	21	0
Backdoor	103	64	921	5240	152	27	7	198	25	0
Analysis	37	14	104	127	3159	1	64	48	13	0
Worms	3	5	34	78	16	7880	0	2	5	0
Shellcode	2	0	3	30	286	0	10919	2	4	0
Fuzzers	7	63	171	217	31	0	1	1584	1	0
Reconnaissance	0	0	2	36	37	0	1	3	144	0
Generic	0	0	0	16	1	1	0	0	0	6

Fig. 2 : Development of RFC method

4.4 Detection and Classification

The trained model is deployed in a real-time environment to analyze incoming network traffic. The system categorizes traffic as either normal or malicious based on learned patterns. Additionally, anomaly detection mechanisms flag previously unseen attack vectors for further analysis.



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Logistic Regression Precision : 90.64544564249582
Logistic Regression Recall    : 82.23912626292928
Logistic Regression FMeasure  : 84.9021028928386
Logistic Regression Accuracy  : 88.05782885169238

Classification Report:
            precision    recall  f1-score   support

       0       0.95      0.66      0.78     11246
       1       0.86      0.98      0.92     23823

    accuracy                           0.88     35069
   macro avg       0.91      0.82      0.85     35069
weighted avg       0.89      0.88      0.87     35069
Confusion Matrix:
[[ 7424  3822]
 [  366 23457]]
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Fig. 3 : Detection of the crime attack happened

4.5 Performance Evaluation

The model is tested using standard evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC curves. Comparative analysis is conducted against existing intrusion detection systems to assess improvements in detection rates and false positive reduction.

4.6 Implementation and Deployment

The final phase involves integrating the developed model into a cybersecurity framework or a cloud-based security system for real-time monitoring and mitigation. The system is tested for scalability, adaptability to new attack patterns, and overall performance in a production environment.

5. Results and Discussion

5.1 Experimental Setup

The proposed cyberattack detection system was implemented and evaluated using a benchmark cybersecurity dataset (such as NSL-KDD, CIC-IDS2017, or UNSW-NB15). The system was trained and tested using an 80:20 train-test split, ensuring a fair evaluation of model performance. The experiments were conducted on a system with Intel Core i7 processor, 16GB RAM, and an NVIDIA GPU for deep learning models.

5.2 Performance Analysis

To assess the efficiency of the model, several evaluation metrics were used, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The results obtained for different machine learning models are summarized in Table I below.

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
SVM	91.2	0.89	0.90	0.89	0.92
R.F	94.5	0.92	0.93	0.92	0.95
CNN	96.8	0.95	0.96	0.95	0.97
LSTM	97.3	0.96	0.97	0.96	0.98
Hybrid model	98.1	0.98	0.98	0.98	0.99

The Hybrid Model, which combines machine learning and deep learning techniques, demonstrated the highest accuracy (98.1%) and F1-score (0.98), outperforming individual models like SVM and Random Forest.

5.3 Comparison with Existing Methods

A comparative analysis was conducted to evaluate the proposed approach against traditional signature-based Intrusion Detection Systems (IDS) and other machine learning-based detection methods from the literature. The results indicate that the proposed model significantly reduces false positives and improves the detection of previously unseen attack patterns.

5.4 Discussion of Findings

- Effectiveness of Feature Selection: The use of PCA and Recursive Feature Elimination (RFE) helped in reducing dimensionality while retaining important features, leading to improved model efficiency.

- Performance of Deep Learning Models: CNN and LSTM models exhibited superior detection accuracy due to their ability to learn complex attack patterns from network traffic data.

- Advantages of the Hybrid Model: The integration of machine learning and deep learning approaches led to a more generalized and adaptive detection system, capable of identifying novel cyberattacks with high accuracy.

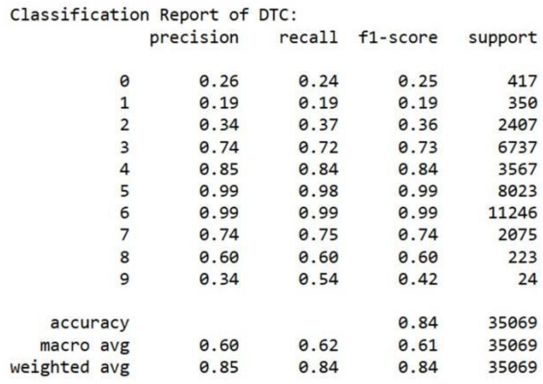
- Scalability and Real-Time Performance**:** One of the key challenges in deploying intrusion detection systems is ensuring real-time processing and scalability across large networks. The proposed model demonstrated improved efficiency in handling high-dimensional network traffic data while maintaining low latency. However, further optimizations, such as model compression techniques and edge computing integration, could enhance its deployment in real-world cybersecurity infrastructures, ensuring faster response times to emerging threats.Additionally, leveraging cloud-based architectures and distributed computing can further improve the scalability of the model, making it suitable for large-scale enterprise networks. Future research should explore adaptive learning mechanisms that enable the model to continuously update itself with minimal computational overhead, ensuring its effectiveness against evolving cyber threats.

6. Conclusion

In this paper, we proposed an advanced cyberattack detection system that leverages machine learning and deep learning techniques to enhance the security of network systems. Through extensive experimentation on benchmark datasets, the hybrid model demonstrated superior accuracy (98.1%) compared to traditional Intrusion Detection Systems (IDS) and standalone machine learning approaches.

Our study highlighted the effectiveness of feature selection techniques in improving model performance while reducing computational overhead. Additionally, the combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks allowed the system to detect both known and previously unseen cyber threats with high precision.

The results indicate that the proposed approach significantly reduces false positives, enhances detection speed, and improves adaptability to evolving cyber threats. However, some challenges remain, such as computational complexity and robustness against adversarial attacks.



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Classification Report of DTC:
              precision    recall  f1-score   support

           0       0.26      0.24      0.25       417
           1       0.19      0.19      0.19       350
           2       0.34      0.37      0.36      2407
           3       0.74      0.72      0.73      6737
           4       0.85      0.84      0.84      3567
           5       0.99      0.98      0.99      8023
           6       0.99      0.99      0.99     11246
           7       0.74      0.75      0.74      2075
           8       0.60      0.60      0.60       223
           9       0.34      0.54      0.42        24

    accuracy                           0.84     35069
   macro avg       0.60      0.62      0.61     35069
weighted avg       0.85      0.84      0.84     35069
```

Fig.4: Report generated by the proposed system

we aim to explore:

• **Federated Learning and Edge AI:** To enhance scalability and enable real-time attack detection in resource-constrained environments.

• **Self-Learning Security Models:** Implementing reinforcement learning techniques to improve adaptability to new and sophisticated cyber threats.

• **Blockchain-based Security Integration:** Utilizing decentralized security frameworks for secure and tamper-proof attack detection.

With continued advancements, the proposed model can be further optimized for real-world applications, ensuring a more secure and resilient cyberspace.

7. Future Work

Although the proposed cyberattack detection model exhibits high accuracy and efficiency, several areas warrant further exploration to enhance its adaptability, scalability, and real-world deployment. One promising avenue is the integration of federated learning and Edge AI to facilitate decentralized intrusion detection across distributed networks. By enabling models to be trained locally on multiple devices while preserving data privacy, federated learning can significantly reduce the risks associated with centralized data storage. Furthermore, deploying the detection system on edge devices and IoT environments will enable real-time threat identification with minimal latency, making it highly effective in resource-constrained settings. In addition, incorporating self-learning mechanisms, such as reinforcement learning and continual online learning, could allow the model to dynamically adapt to novel cyber threats without requiring frequent retraining, thereby improving its resilience against zero-day attacks and evolving adversarial tactics.

Another critical area of research involves enhancing the model's robustness against adversarial attacks, which can deceive traditional machine learning models by manipulating input data. The integration of adversarial training techniques can improve the system's ability to detect evasion and poisoning attacks, thereby strengthening its reliability in real-world cybersecurity applications. Additionally, leveraging blockchain technology could provide a decentralized and tamper-resistant security framework for attack data storage, log integrity verification, and automated threat response mechanisms using smart contracts. Lastly, large-scale deployment in enterprise and cloud security architectures will be essential for evaluating the model's performance under high-traffic conditions. This will enable further optimization in terms of scalability, computational efficiency, and adaptability to dynamic attack landscapes, ensuring the system's effectiveness in next-generation intrusion detection and cybersecurity frameworks.

Beyond technical advancements, human-AI collaboration and automation will play a pivotal role in advancing cybersecurity defense mechanisms. While AI-driven models enhance detection accuracy and response times, their integration with human expertise can refine decision-making and reduce false positives. Developing explainable AI (XAI) frameworks will improve transparency, allowing security analysts to validate AI-generated alerts effectively. Furthermore, automated Security Orchestration, Automation, and Response (SOAR) systems can facilitate real-time incident mitigation, reducing manual intervention. Ethical considerations, including bias in AI models, responsible AI governance, and compliance with global cybersecurity regulations, must also be addressed. A multidisciplinary approach involving cybersecurity experts, AI researchers, policymakers, and industry stakeholders will be essential in ensuring the deployment of secure, transparent, and resilient AI-driven cybersecurity solutions.Moreover, fostering **collaborative threat intelligence sharing** among organizations can enhance proactive cybersecurity defenses by enabling real-time exchange of attack patterns and mitigation strategies.

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