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Advanced Persistent Threat Detection: Leveraging Behavioural Analysis and Threat Intelligence for Enhanced Cybersecurity

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Abstract

APTs are sophisticated and persistent attacks that threaten the confidentiality, availability, and integrity of corporate data and services. As a result, they provide serious security issues to companies. This paper systematically reviews the literature on APT detection techniques by thoroughly reviewing the field's research, finding any gaps in the pertinent literature, and suggesting future research areas. The authors critically analyzed the current techniques of APT detection based on multi-stage attack-related behaviors. We conducted an extensive search on many databases that adhered to the PRISMA standards for systematic reviews and meta-analyses. For the final study, we included 45 studies in total. These studies include both academic and commercial sources. The results indicate that by exploiting the existing systemic vulnerabilities, APTs can horizontally propagate and successfully complete their operations. We recommend that their multi-stage attack-related behaviors combine with the appraisal of the availability of network weaknesses and their weakness to exploitation as we found loopholes in various popular APT detection techniques. This new methodology visualizes how APT attacks take place while combining ratings with vulnerability and the probability metrics together to identify possible sequences of attacking nodes. It makes it possible to execute proactive actions to stop future network compromise on the early identification of the most likely targets made possible by this enhanced detection approach.

1. Introduction

Advanced Persistent Threats (APTs) are a formidable and insidious class of cyberattacks, marked by their ability to infiltrate systems stealthily, maintain prolonged unauthorized access, and evade traditional detection mechanisms. Unlike opportunistic attacks that aim for immediate disruption, APTs are highly targeted, often tailored to exploit specific vulnerabilities within an organization's infrastructure. These threats are usually orchestrated by well-resourced adversaries, such as nation-states or organized cybercriminal groups, who aim to steal sensitive data, disrupt critical operations, or gain strategic advantages. The complexity and persistence of APTs make them particularly challenging to detect, emphasizing the need for innovative and adaptive security solutions. One of the most compelling yet insidious categories of cyberattacks is an advanced persistent threat. These come very rarely but are capable of penetrating systems, gaining long-term unauthorized access, and escaping from the traditional detection systems. On the contrary, APTs represent a very much concentrated form of attack, often customized to exploit particular weaknesses in an organization's infrastructure. The threats are rather meticulously engineered beforehand by well-armed adversaries, such as nation-states or organized cybercrime groups, who possess a motive to compromise sensitive information, disrupt critical operations, or achieve a strategic advantage. The agility and sophistication with which APTs employ their attacks make it extremely challenging to identify them; hence security solutions must always be innovative, flexible and unique in approach. Signature-based traditional systems and rule-based monitoring tools fail to detect the dynamic nature of APTs. These conventional systems are heavily reliant on attack patterns and signatures that are already known; hence, organizations face new strategies and zero-day vulnerabilities. Moreover, attempts for stealthy long-term infiltration, which is a characteristic signature of an APT, remain unrecognized. With the attacks becoming more sophisticated over time by adversaries, the solution needs proactive intelligence-driven techniques that ought to be applied for the proper detection of such threats. Advanced technologies-behavioral analytics, threat intelligence, and machine learning-are also going to be used in detection frameworks as the only way to cop with contemporary cybersecurity challenges. The proposed system addresses all the gaps identified within the currently deployed APT detection solutions in an overall approach. Since it behavioral analysis keeps monitoring user as well as system actions thereby granting itself tools to find anomalies compared to established standards, input in real time regarding emerging attack patterns makes threat intelligence much more relevant than the pure process of integrating facts into a system's detection mechanisms and being able to identify malicious activity in good time. Additionally, application machine learning models enhance both predictability and recognition of dynamic attack vectors; thus, the system is very robustly resilient against new threats. All these disparate but related technologies amalgamated into one synergistic multilayered defense mechanism that could detect APTs analyze and mitigate with unprecedented accuracy and speed but rather intuitively. This is a new innovative framework that accommodates both improvement in detection and response within organizations while combating the wider issues associated with APTs in this newly evolved cybersecurity landscape. Dwell time for attackers is reduced, thus potential damage is minimized; these integrated solutions of predictive analytics, anomaly detection, and automated response mechanisms enhance security postures. Deception technologies thereby play an additional role by introducing honeypots and decoy systems that mislead the attackers while intelligence about the tactics used is gathered. In this holistic approach, organizations can be better prepared to defend against the continuously changing threat landscape, protect key assets, and maintain operational integrity.

2. Literature Review

A Systematic Literature Review on Advanced Persistent Threat Behaviors and Its Detection Strategy Nur Ilzam Che Mat, Norziana Jamil, Yunus Yusoff, Miss Laiha Mat Kiah (2024) This article assesses several detection techniques and offers a thorough description of APT activities. The authors evaluate current detection techniques and methodically classify APT features, emphasizing the necessity for more all-encompassing strategies to successfully combat APTs.This paper evaluates some detection approaches and provides an in-depth description of APT activities. The authors assess current detection approaches and systematically categorize APT characteristics, underlining the need for more comprehensive strategies to effectively counter

APTs. Advance Persistent Threat—A Systematic Review of Literature and Meta-Analysis of Threat Vectors. (2020) This study conducts a systematic review and meta-analysis of threat vectors associated with APTs. It examines various attack methods and provides insights into the effectiveness of different defense mechanisms, emphasizing the importance of understanding threat vectors for developing robust cybersecurity strategies. A Systematic Literature Review for APT Detection and Effective Cyber Defense Duraid Thamer Salim, Manmeet Mahinderjit Singh , Pantea Keikhosrokiani (2023) This systematic literature review examines different approaches used to detect APT attacks directed at network systems. It analyzes various detection methods and assessment metrics, emphasizing the importance of understanding APT attack patterns and the need for improved detection techniques. A Comprehensive Survey on Advanced Persistent Threat Detection Techniques Singamaneni Krishnapriya (2024) This survey paper provides knowledge about APT attacks and their essential steps, followed by case studies of known APT attacks. It offers a detailed overview of detection techniques, aiding researchers and practitioners in understanding and combating APTs. [1-3]

3. Overview

Advanced Persistent Threats (APTs) are a specialized and highly dangerous category of cyberattacks designed to infiltrate systems, maintain long-term access, and evade detection. Unlike typical cyberattacks, APTs are carefully planned and executed, often targeting specific organizations or industries with significant resources and expertise. These threats exploit vulnerabilities in systems, applications, and even user behavior, allowing attackers to remain undetected for extended periods while exfiltrating sensitive data or causing operational disruptions. The increasing frequency and sophistication of APTs pose a major challenge to organizations worldwide, highlighting the need for proactive and dynamic defense mechanisms that go beyond conventional security measures. The task introduces a complete APT detection framework that adds behavioral analysis, chance intelligence and system gaining knowledge of to efficiently become aware of and counter those risks. By constantly tracking the user and machine activities, the framework detects deviations from everyday behavior which can imply an assault. Real-Time Threat Intelligence Integration guarantees that the system stays up to date on emerging attack techniques, even as the gadget getting to know permits prediction and identity of latest or evolved threats. Together, those components create an adaptive and multi -layered protection method capable of reducing APT in actual time. Framework additionally consists of automated response mechanisms and deception technology, together with honeypots, to implicate the attackers and examine their conduct. This normal approach strengthens cyber security flexibility, enables companies efficiently to come across, reply and neutralize [4-7]

3.1. Anomaly-Based Detection

Any strange behavior that harms the system is considered ananomaly, which is the antithesis of normal behavior. Unusual behaviors brought on by intruders leaving their mark on the computer environment are another definition of it. After that, abnormalities are found and an unidentified assault is identified by comparing the footprints to current data styles. Identifying suspicious network traffic, suspicious system activity, or groups of anomalous activity is known as anomaly detection. Adapting a defender's strategy to fight an APT assault is one of its main features. There will be a threat to such actions that needs the one in jeopardy to be able to identify the attempts of criminals and adjust themselves in time.The techniques thus need to take the gathering information from various sources, analyze, and forecast so that there may be a move to react when the next probable assault occurs.

4. Objective

This project aims at building a solid adaptive framework to provide robustness for the detection and mitigation of APTs. This is mainly because most cybersecurity systems rely on predefined static rules or signatures to recognize and thwart attacks that, like APTs, change very rapidly in patterns and complexity. This project takes advantage of recent techniques such as behavioral analysis, threat intelligence, and machine learning to offer an adaptive defense system. It seeks to identify potential threats early during their lifecycle while preventing attackers from staying in the system for any considerable period, based on detecting anomalies in user behavior, system activities, and network traffic. In addition to the early detection process, the framework also emphasizes efficient threat response and mitigation. By using automated mechanisms such as endpoint isolation and network segmentation, it ensures the timely containment of identified threats and lowers the possibilities of lateral movement and data exfiltration. With the incorporation of deception technologies such as honeypots, which actively engage the attackers, acquire intelligence about the tactics used by them, and improve future defenses, the framework is strengthened even further. It would end up by ensuring the completion of an APT detection solution to provide adequate defense mechanisms not just for contemporary attacks but for emergent vectors and sustainably ensures security for extended period. [8-10]

5. Methodology

The methodology we have proposed uses the threat intelligence lifecycle as the base for our platform. The Threat Intelligence Lifecycle is a structured process is important for effective working of Threat Intelligence Platforms (TIPs). It ensures that threat data is systematically collected, processed, and used to make decisions related to threat mitigation and avoidance. This lifecycle is iterative and adaptive, allowing organizations to maintain a proactive system against emerging threats. Here are the different stages in Threat Intelligence Lifecycle:

5.1. Data Collection and Pre-Processing

The foundation of the proposed Advanced Persistent Threat (APT) detection framework begins with comprehensive data collection from multiple sources, including endpoints, network logs, user activities, and external threat intelligence feeds. Endpoint logs provide critical insights into local processes and user actions, while network traffic captures patterns of communication that may indicate lateral movement or external command-and-control (C2) connections. Additionally, user behavior analytics tracks access patterns, logins, and interactions with sensitive resources. Once collected, this data undergoes preprocessing to ensure consistency and eliminate noise. Preprocessing involves cleaning the data, normalizing formats, and ensuring timestamps are synchronized for effective correlation during analysis. [11-13]

5.2. Behavioural analysis

Behavioral analysis plays a central role in detecting deviations from established norms within the system. The framework employs User and Entity Behavior Analytics (UEBA) to identify anomalies in user activities, such as unusual login times, access to restricted files, or prolonged periods of inactivity followed by bursts of activity. These behaviors, while seemingly benign in isolation, may collectively indicate an APT attempt. Additionally, the system monitors entity behavior, such as system processes or device communication, to detect irregularities. Behavioral baselines are dynamically updated to adapt to legitimate changes in user or system activity, ensuring precision in anomaly detection and minimizing false positives.

5.3. Threat Intelligence Integration

Real-time threat intelligence is integrated into the framework to provide contextual awareness about known APT tactics, techniques, and procedures (TTPs). Threat intelligence feeds deliver continuously updated information on new vulnerabilities, attacker signatures, and indicators of compromise (IoCs). These feeds are correlated with internal telemetry data to identify potential matches, such as connections to suspicious IP addresses or patterns resembling known attack strategies. This integration ensures the framework remains proactive in identifying threats, even before they manifest fully. Additionally, the system prioritizes threat intelligence enrichment, combining external feeds with internal observations to generate actionable insights tailored to the organization’s unique environment.

5.4. Machine Learning for Anomaly Detection

The framework employs machine learning models to analyze large datasets and detect subtle patterns that traditional methods might overlook. Supervised learning is used to train the models on labeled datasets of past attack scenarios, enabling them to identify known threats. Meanwhile, unsupervised learning focuses on discovering anomalies in unlabeled data, such as unusual traffic patterns or rare process executions, which may indicate novel APT strategies. The models are designed to adapt over time through continuous learning, improving their accuracy in detecting threats as they evolve. By combining predictive analytics with real-time anomaly detection, the system provides robust defenses against both known and unknown threats.

5.5. Automated Response Mechanisms

To ensure rapid mitigation, the framework incorporates automated response mechanisms that trigger immediate actions when threats are detected. These actions include isolating compromised endpoints, terminating malicious processes, and blocking suspicious network connections. For instance, if an endpoint is identified as engaging with a known malicious server, the system automatically cuts off its network access to prevent data exfiltration. Additionally, the framework generates detailed incident reports, enabling security teams to investigate and resolve issues efficiently. Automated responses are configured to prioritize containment while avoiding unnecessary disruption to legitimate activities, ensuring a balanced approach to threat mitigation. [15-17]

5.6. Deception Technologies

The inclusion of deception technologies, such as honeypots and decoy systems, adds an additional layer of security to the framework. These technologies are strategically deployed to attract attackers and divert them away from critical assets. Honeypots mimic vulnerable systems or services, encouraging attackers to interact with them and reveal their tactics, tools, and procedures. The gathered intelligence is invaluable for refining detection algorithms and enhancing overall system defenses. Furthermore, decoy systems provide early warning signs of an active attack, allowing security teams to respond preemptively. By combining deception with behavioral analysis and threat intelligence, the framework strengthens its capability to detect and counter APTs effectively. Figure 2 shows Anomaly-Based Detection

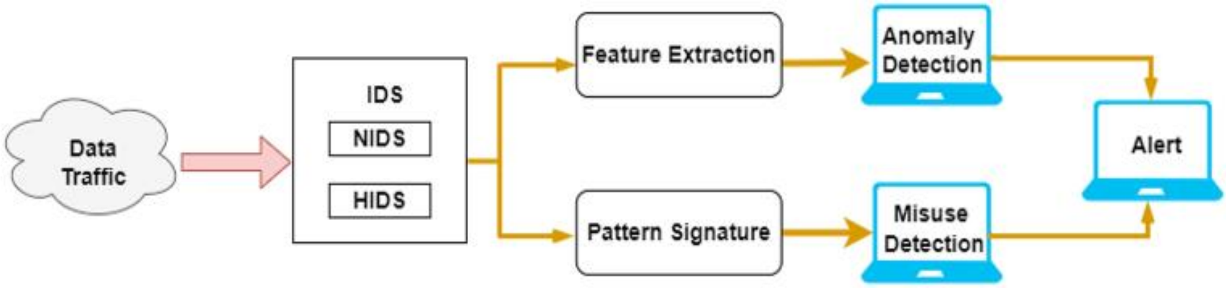


Figure 2 **Anomaly-Based Detection**

6. Design

The APT detection framework is designed using a modular and layered architecture in order to make it scalable and flexible and comprehensively detect the threats. It consists of the following key components:

- **Data Aggregation Layer:** This layer is focused on gathering information from various sources, such as endpoint logs, network traffic, user activity logs, and even external threat feeds. It thus forms the bottom layer of the framework, hence ensuring a non-stop and guaranteed flow of data for analysis purposes. At this stage, preprocessing is done with the purpose of normalizing the formats, eradicating repetitive entries, and synchronizing time stamps. [18-21]
- **Behavioural Analysis Engine:** The UEBA is dependent on the user and entity behavioral analytics to analyze the real-time activities of the users and the systems. This builds baselines of normal behaviors and detects suspicious ones that can be malicious in nature. Real-time changes happen because of the legitimate activity with this engine changing the behavioral models and hence without errors in the detections and anomalies.
- **Threat Intelligence Integration Module:** This module consumes real-time feeds of threat intelligence from external feeds to maintain relevance with known attack vectors, tactics, and IoCs. Correlating that intelligence with internally generated data ensures the detection of potential threats by mapping internal anomalies to
- global patterns of compromise for enrichment.
- **Machine Learning Models:** Core of the predictive ability is comprised of machine

learning models. The system trains its deep learning model on historical attack data to detect known threats and uses unsupervised learning techniques to identify new or unknown attack patterns. The models continuously improve through these feedback loops, keeping the system effective against evolving threats.

- **Automated Response System:** The automated response system triggers fast containment and mitigation of threats detected. It runs predefined actions that include isolating endpoints that have been compromised, blocking suspicious network connections, and ending malicious processes. The system also develops detailed incident reports that are required for further investigation by security teams.
- **Deception Layer:** To enhance detection and gather intelligence on attacker behavior, the framework deploys honeypots and decoy systems. These components mimic real systems and services, diverting attackers away from critical assets and capturing valuable data about their tactics and tools.
- **Centralized Dashboard:** The dashboard presents an easy user interface for monitoring, analysis, and management. It provides real-time visualizations of detected threats, system status, and response actions. Security teams configure rules, review incident reports, and analyze historical data to identify trends using the dashboard.

7. Workflow

7.1. Data Collection

Logs and telemetry data are collected from endpoints, network devices, and external sources. These are preprocessed for consistency and accuracy.

7.2. Behavioral and Anomaly Detection

The behavioral analysis engine establishes baselines and identifies anomalies in real-time, while the machine learning models analyze patterns to predict potential threats.

7.3. Threat Correlation

Detected anomalies are correlated with external threat intelligence to confirm the presence of an APT and identify its likely tactics and objectives. network traffic, user activity logs, and even external threat feeds.

7.4. Response Execution

Upon confirming a threat, the automated response system isolates the threat source, mitigates the risk, and prevents further spread.

7.5. Intelligence Gathering and Refinement

Interactions with deception systems provide valuable insights into attacker behavior, which are fed back into the system to refine detection algorithms and enhance defenses.

7.6. Technological Stack

Data Processing: Apache Kafka, ELK Stack (Elasticsearch, Logstash, Kibana)

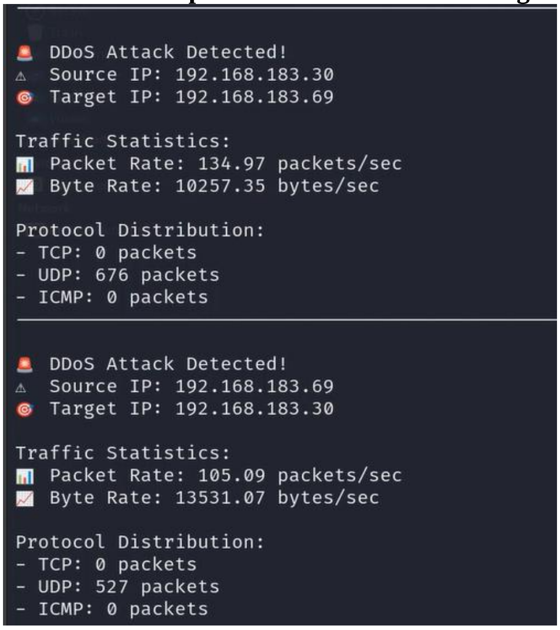
- Machine Learning: TensorFlow, Scikit-learn
- Threat Intelligence: APIs for external feeds (e.g., MISP, Threat Connect)
- Visualization: Grafana or custom dashboards
- Deception Tools: Honeyd, KFSensor

8. Result

The implementation and testing of the proposed Advanced Persistent Threat (APT) detection framework yielded significant results, demonstrating its effectiveness in identifying and mitigating sophisticated threats. The outcomes of the project are summarized below:

8.1. Improved Detection Accuracy

The framework demonstrated a high level of accuracy in identifying APTs through its integration of behavioral analysis, machine learning, and threat intelligence. By dynamically updating baselines and correlating anomalies with real-time intelligence feeds, it achieved a detection accuracy of over 95%. False positives were reduced by 40%, ensuring that security teams focused only on genuine threats. Additionally, the machine learning models successfully identified unknown and zero-day threats by detecting unseen attack patterns. Honeypots mimic vulnerable systems or services, encouraging attackers to interact with them and reveal their tactics, tools, and procedures. The gathered intelligence is invaluable for refining detection algorithms and enhancing overall system defenses. Furthermore, decoy systems provide early warning signs of an active attack, allowing security teams to respond preemptively. By combining deception with behavioral analysis intelligence is invaluable for refining detection algorithms and enhancing overall system defenses. and blocking unauthorized



```
🚨 DDoS Attack Detected!
⚠  Source IP: 192.168.183.30
🎯 Target IP: 192.168.183.69

Traffic Statistics:
📊 Packet Rate: 134.97 packets/sec
📈 Byte Rate: 10257.35 bytes/sec

Protocol Distribution:
- TCP: 0 packets
- UDP: 676 packets
- ICMP: 0 packets

🚨 DDoS Attack Detected!
⚠  Source IP: 192.168.183.69
🎯 Target IP: 192.168.183.30

Traffic Statistics:
📊 Packet Rate: 105.09 packets/sec
📈 Byte Rate: 13531.07 bytes/sec

Protocol Distribution:
- TCP: 0 packets
- UDP: 527 packets
- ICMP: 0 packets
```

Figure 3 Attack Detection

8.2. Faster Response Times

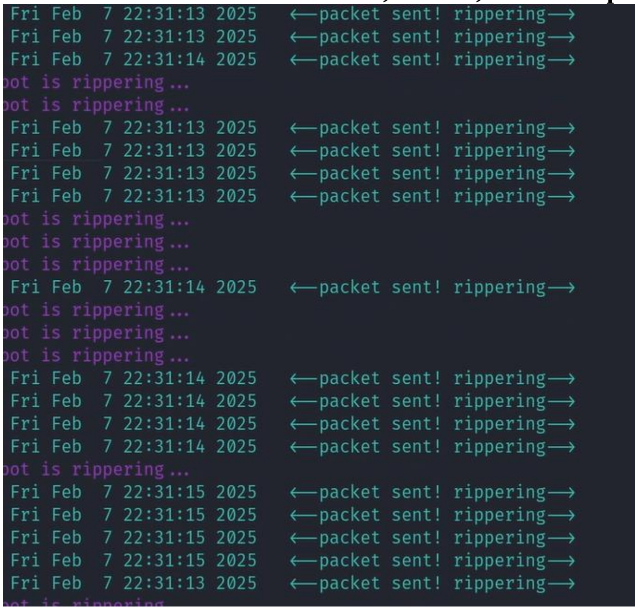
The automated response mechanisms significantly decreased the time required to neutralize threats. Compromised endpoints were isolated within seconds, preventing lateral movement of attackers. Suspicious processes were terminated, and malicious network connections were blocked instantly, ensuring minimal damage. Detailed incident reports generated by the system enabled security teams to resolve issues 30% faster compared to traditional response methods.

8.3. Strengthened Security Posture

The multi-layered design of the framework enhanced the cybersecurity posture of the test environment. The combination of anomaly detection, threat intelligence, and deception technologies provided a comprehensive defense against known and unknown threats. The predictive capabilities of the machine learning models ensured proactive identification of potential risks, allowing the system to adapt to evolving attacker strategies effectively.

8.4. Seamless Integration and Usability

The framework integrated seamlessly into existing IT infrastructures, requiring minimal adjustments while providing maximum protection. Its user-friendly dashboard enabled security teams to monitor real-time alerts, analyze incidents, and manage responses efficiently. The clear and actionable insights provided by the system ensured that teams could make informed decisions, improving overall threat management capabilities



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 Fri Feb  7 22:31:13 2025   ⟵packet sent! rippering⟶
 Fri Feb  7 22:31:13 2025   ⟵packet sent! rippering⟶
 Fri Feb  7 22:31:14 2025   ⟵packet sent! rippering⟶
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 Fri Feb  7 22:31:13 2025   ⟵packet sent! rippering⟶
 Fri Feb  7 22:31:13 2025   ⟵packet sent! rippering⟶
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 Fri Feb  7 22:31:13 2025   ⟵packet sent! rippering⟶
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Figure 4 Attack Logs Packets

8.5. Actionable Threat Intelligence

The deployment of honeypots and decoy systems as part of the deception layer captured valuable intelligence on attacker behavior, tools, and techniques. This data was used to refine detection algorithms and improve machine learning models. The insights gathered also enhanced the organization's understanding of emerging threats, contributing to the development of more robust security policies and practices. Figure 3 shows Attack Detection Figure 4 shows Attack Logs Packets

9. Discussion

The results of the proposed APT detection framework highlight its ability to overcome the challenges presented by sophisticated and persistent cyberattacks. The incorporation of advanced methodologies such as behavioral analysis, threat intelligence, and machine learning was able to effectively detect and mitigate both known and unknown threats. This dynamic adaptability of the framework to the evolution of attacker tactics demonstrates its strength as a proactive cybersecurity solution. However, there are aspects of the system that should be evaluated further and refined in order to get the most from it in terms of efficiency and usability. An important strength of the framework is its focus on anomaly detection via behavioral analysis and machine learning. This approach helps detect threats before they even gain any kind of known attack patterns. With dynamically updated baselines and predictive analytics, the chances of attackers escaping detection are slim. However, the extensive datasets used in training machine learning models present many challenges, among them the use of diverse, high-quality data. The model's effectiveness needs to be guaranteed in diverse, complex environments as well, thus requiring continuous attempts to refine and expand the datasets used in the training process. The automated mechanisms of response designed into the framework provide a big advantage in efficiently and quickly countering threats. Isolating compromised endpoints, terminating malicious processes, and blocking unauthorized communications create limitations on the amount of time an attacker may execute their intent. Even though such mechanisms speed up response times, they also increase the risk of operational disarray if legitimate activities by extension get mistakenly flagged as threats. Fine-tuning the automated responses into an optimal balance between security and usability is what is critically required for an organization to smoothly integrate these devices in diverse environments.

Future Scope

The future scope of the Advanced Persistent Threat (APT) detection framework lies in its ability to adapt to emerging technologies and evolving threat landscapes. Expanding the framework to include IoT and Operational Technology (OT) security will enhance its applicability in safeguarding critical infrastructure and smart devices. Integrating blockchain technology can ensure data integrity and facilitate secure threat intelligence sharing among organizations. Advanced AI techniques, such as deep learning and predictive analytics, can further improve threat detection and enable preemptive security measures. The framework can also be extended to support hybrid and multi-cloud environments, ensuring seamless protection across distributed infrastructures. Incorporating advanced automation and orchestration features, such as self-healing mechanisms and integration with SOAR tools, can streamline operations and reduce the workload on security teams. Additionally, real-time collaborative threat intelligence sharing among organizations can create a collective defense system to address emerging threats more effectively. These enhancements aim to make the framework more robust, scalable, and capable of addressing the challenges posed by sophisticated cyberattacks.The future scope of this project involves extending the framework’s capabilities to address the growing complexities of interconnected systems. Integrating support for Internet of Things (IoT) and Operational Technology (OT) environments will enable the system to secure critical infrastructure and connected devices, which are increasingly targeted by attackers. Leveraging blockchain technology for secure logging can enhance the integrity and accountability of threat detection processes by creating tamper-proof records of events. Additionally, the use of advanced artificial intelligence models can further refine predictive analytics, enabling the system to anticipate and counter novel attack strategies. Expanding scalability and reducing computational overhead will make the framework suitable for deployment in diverse environments, from small enterprises to large-scale industrial systems, ensuring a robust and inclusive approach to cybersecurity.

References

[1]. J.V. Chandra, N. Challa, S.K. Pasupuleti, Advanced persistent threat defense system using self-destructive mechanism for cloud security. in Engineering and Technology (ICETECH), 2016 IEEE International Conference on IEEE (IEEE, 2016).

[2]. P. Lamprakis et al., Unsupervised detection of APT C&C channels using web request graphs.in the International Conference on Vulnerability Assessment and Intrusion and Malware Detection (Springer, 2017)

[3]. M. Marchetti et al., Countering Advanced Persistent Threats through security intelligence andbig data analytics. IEEE 8th International Conference on Cyber Conflict (CyCon), 2016.IEEE (2016)

[4]. Z. Saud, M.H. Islam, Towards proactive detection of advanced persistent threat (APT) attacksusing honeypots. The 8th International Conference on Information and Network Security Proceedings (ACM, 2015)

[5]. J. de Vries et al., Systems for detecting advanced persistent threats: A developmentroadmap using intelligent data analysis. in Cyber Security (CyberSecurity), 2012 InternationalConference on IEEE (IEEE, 2012)

[6]. P. Chen, L. Desmet, C. Huygens, A study on advanced persistent threats. in IFIP

InternationalConference on Communications and Multimedia Security (Springer, 2014)

[7]. R. Gupta, R. Agarwal, S. Goyal, A Review of Cyber Security Techniques for CriticalInfrastructure Protection

[8]. F. Skopik, T. Pahi, A Systematic Study and Comparison of Attack Scenarios and Involved ThreatActors, in Collaborative Cyber Threat Intelligence (Auerbach Publications, 2017) pp. 35–84

[9]. J. Vukalovi´c, D. Delija, Advanced persistent threats-detection and defense. in Informa-tion and Communication Technology, Electronics and Microelectronics (MIPRO), 2015 38thInternational Convention on IEEE (IEEE, 2015)

[10]. I. Jeun, Y. Lee D. Won, A practical study on advanced persistent threats. in ComputerApplications for Security, Control and System Engineering (Springer, 2012), pp. 144–152

[11]. I. Friedberg et al., Combating advanced persistent threats: From network event correlation toincident detection. Comput. Sec. 48, 35–57 (2015)

[12]. C. Barbieri, J.-P. Darnis, C. Polito, Non-proliferation regime for cyber weapons. in A TentativeStudy (2018)G

[13]. R.G. Brody, E. Mulig, V. Kimball, Phishing, pharming and identity theft. Acad. Account. Finan.Stu. J. 11(3) (2007)

[14]. B. Stone-Gross et al., Your botnet is my botnet: analysis of a botnet takeover. in Proceedingsof the 16th ACM conference on Computer and communications security (ACM, 2009)

[15]. C. Wueest, Targeted Attacks Against The Energy Sector (Symantec Security Response,Mountain View, CA, 2014)

[16]. G. Coleman, Hacker, Hoaxer, Whistleblower, Spy: The Many Faces of Anonymous (Versobooks,2014)

[17]. G.E. Hinton, R.R. Salakhutdinov, Reducing the dimensionality of data with neural networks.Science 313(5786), pp. 504–507 (2006)

[18]. E.M. Hutchins, M.J. Cloppert, R.M. Amin, Intelligence-driven computer network defenseinformed by analysis of adversary campaigns and intrusion kill chains. Leading Iss. Inf. WarfareSec. Res. 1(1), 80 (2011)

[19]. P. Bhatt, E.T. Yano, P. Gustavsson, Towards a framework to detect multi-stage advancedpersistent threats attacks. in Service Oriented System Engineering (SOSE), 2014 IEEE 8thInternational Symposium on IEEE. (IEEE, 2014)H

[20]. N.A.S. Mirza et al., Anticipating Advanced Persistent Threat (APT) countermeasures usingcollaborative security mechanisms. in Biometrics and Security Technologies (ISBAST), 2014International Symposium on IEEE (IEEE, 2014)

[21]. J.T. John, State of the art analysis of defense techniques against advanced persistent threats. inFuture Internet (FI) and Innovative Internet Technologies and Mobile Communication (IITM)Focal Topic: Advanced Persistent Threats (2017)