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ADVANCED PERSISTENT THREATS IN IOT AND SMART INFRASTRUCTURE: A SURVEY OF DETECTION FRAMEWORKS AND CHALLENGES

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Abstract: Advanced Persistent Threats (APTs) represent a sophisticated and prolonged cyberattack strategy that poses a critical risk to the increasingly pervasive Internet of Things (IoT) and smart infrastructure systems. These environments, characterized by high interconnectivity, heterogeneous device configurations, and limited security capabilities, offer fertile ground for APT actors to infiltrate, persist, and exfiltrate sensitive data with minimal detection. This paper surveys the APT lifecycle within IoT and smart environments, highlighting phases that include data exfiltration, lateral movement, compromise, and reconnaissance, and investigates cutting-edge detection frameworks like hybrid, AI-driven, anomaly-based, and signature-based techniques. In addition, it provides an in-depth analysis of the core challenges impeding effective APT detection in IoT systems, such as device heterogeneity, resource constraints, encryption, lack of labeled datasets, privacy concerns, and legacy infrastructure integration. The study emphasizes the urgent need for lightweight, adaptive, and privacy-preserving detection systems designed to meet the particular limitations of IoT networks.

Keywords: Advanced Persistent Threats (APTs); Internet of Things (IoT); Smart Infrastructure; Cybersecurity; Intrusion Detection Systems (IDS); Anomaly Detection; AI in Security; Deep Learning; Edge AI; IoT Vulnerabilities; Network Security; Threat Lifecycle; Privacy; Legacy Systems; Secure IoT Frameworks.

1 INTRODUCTION

The Industrial Internet of Things (IIoT) represents a transformative convergence of unified sensors, computing systems, and networked realms that are connected through industrial enterprise apps [1]. IIoT is a development of the Distributed Control System that facilitates advanced automation by leveraging cloud computing for the optimization of industrial process controls. Modern industrial environments now process terabytes of telemetry data daily, underscoring the critical importance of accuracy, security, and real-time monitoring to reduce safety risks and improve operational efficiency.

With this proliferation of I-IoT systems, a new class of cyber threats, APTs has emerged as a formidable challenge [2]. Unlike conventional cyber threats, APTs are stealthy, targeted attacks that aim to establish and maintain unauthorized access over extended periods, often orchestrated by nation-states or organized threat actors [3]. APTs are motivated by espionage, sabotage, or data theft, and have the technical sophistication to cause real-world hazards, including physical damage and threats to human life. Traditional security mechanisms, primarily relying on cryptographic methods, often struggle to operate effectively in IIoT environments due to the high volume and velocity of generated data, making real-time threat detection increasingly difficult.

To protect mission-critical assets, cyber-resiliency engineering, as emphasized by the NIST institute, highlights the need for robust attack detection mechanisms. These include IDS, security information and event management (SIEM) programs, and ongoing network traffic and log monitoring [4]. Because of their extended dormant periods and clandestine nature, APTs are especially difficult to detect, during which they quietly exfiltrate sensitive information or manipulate industrial control systems.

The integration of IoT technologies into Critical Infrastructure (CI), including electricity networks, intelligent city systems, and manufacturing plants, has further expanded the attack surface [5]. For instance, in smart city applications, IoT sensors are deployed to optimize energy use, transportation, and service delivery. However, these systems are also susceptible to attacks such port scanning, reconnaissance, and Denial-of-Service (DoS), which provide attackers the opportunity to take advantage of weaknesses and get vital network data such as IP and MAC addresses [6].

Once a foothold is established, attackers set up Command and Control (C&C), (C2) channels to maintain persistent access. Sensitive data are often compressed, encrypted, and stealthily exfiltrated to avoid detection, presenting significant challenges to existing defence mechanisms [7][8]. These sophisticated attacks exploit not only technological vulnerabilities but also human and organizational weaknesses, making them a multifaceted threat that calls for integrated and intelligent defence strategies [9].

1.1 Structure of the Paper

The following is the outline of the paper: Section 2, overview of APT Lifecycle and Smart Environments. Section 3: Detection Frameworks of APTs. Section 4: Challenges in Detecting APT and Smart Systems. Section 5: Literature Review of Case Studies. Section 6, Conclusions.

2 APT LIFECYCLE IN IOT AND SMART ENVIRONMENTS

The APT lifecycle in IoT and Smart Environments refers to the stages through which sophisticated attackers operate to infiltrate, persist within, and exploit such systems over extended periods [10]. Due to the highly interconnected, heterogeneous, and often poorly secured nature of IoT devices and smart infrastructure, APTs pose a significant threat in Figure 1 [11]

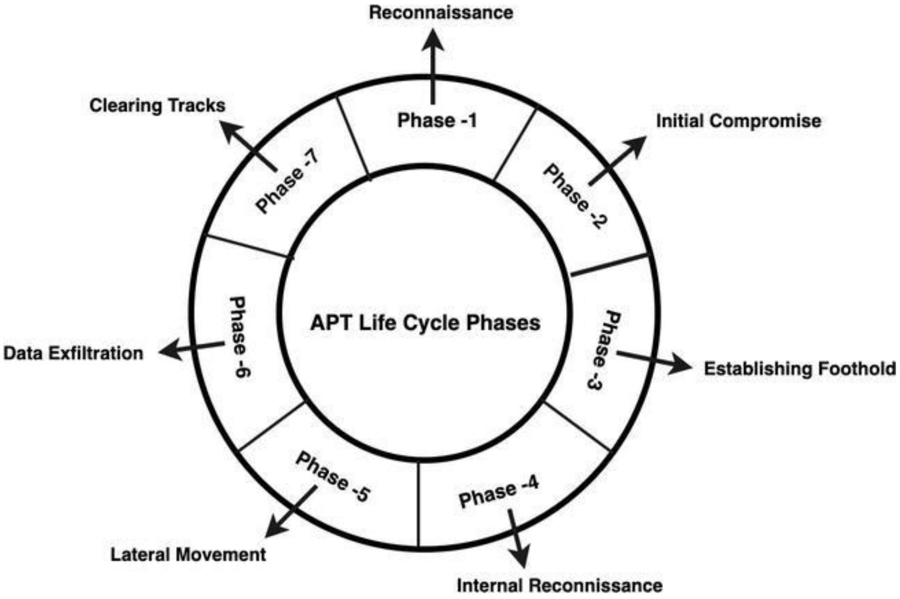

Figure 1: Overview of APT Life Cycle Phases

3.1 Reconnaissance

Attackers gather intelligence on the target IoT ecosystem, identifying devices (e.g., smart cameras, thermostats, or industrial sensors), their firmware versions, network configurations, and vulnerabilities. They may scan for open ports, weak authentication, or unpatched devices using tools like Shodan or by monitoring network traffic. Social engineering or supply chain analysis can reveal entry points, such as poorly secured vendor systems shown in Figure 2

Figure 2: Reconnaissance

3.2 Initial Compromise

Attackers gain entry into the network. Common techniques include phishing campaigns aimed at users with privileged access, exploiting firmware vulnerabilities in outdated IoT devices, or injecting malicious components during the supply chain process. Due to the limited security controls on many IoT devices, such as hardcoded credentials or default settings, attackers often find it easier to compromise them than traditional systems shown in Figure 3.

Figure 3: Initial Compromise

3.3 Establishing Foothold

This is typically done by deploying malware droppers, Remote Access Trojans (RATs), or lightweight botnet clients that enable long-term control and communication with the C2 server. The goal is to maintain access without raising suspicion, often using encrypted communication and stealth techniques to hide the malware's presence and function shown Figure 4

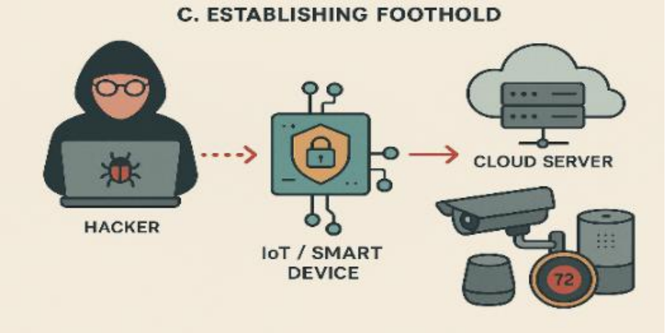

Figure 4: Establishing Foothold

3.4 Internal Reconnaissance

Internal reconnaissance involves mapping the internal structure of the IoT ecosystem, identifying high-value targets, and discovering vulnerabilities or misconfigurations within the network. Attackers leverage their initial access (e.g., a compromised smart device or hub) to explore the environment discreetly.

3.5 Lateral Movement

Lateral movement within the network. This involves probing the internal system to find additional vulnerable devices or higher-value targets, such as control systems, data storage servers, or cloud interfaces [12]. They use methods like credential harvesting, protocol abuse, or exploiting trusted communication paths between devices to expand their reach across the infrastructure shown in Figure 5

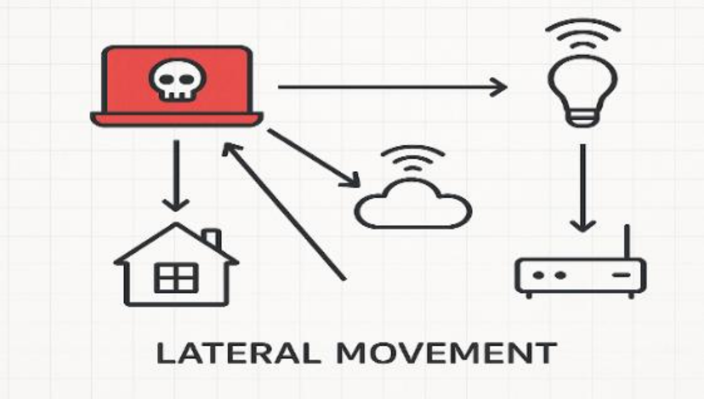

Figure 5: Lateral Movement

3.6 Data Exfiltration

In IoT environments, this can mean stealing sensitive personal data, operational logs, video surveillance, or intellectual property related to critical infrastructure [13]. Attackers may compress, encrypt, and stealthily transmit this data to external servers, often disguising the traffic as legitimate device communication to avoid triggering alarms.

3.7 Clearing Tracks

In IoT and smart environments, attackers may engage in several track-clearing techniques. These include log tampering, where system and device logs are deleted, altered, or overwritten to hide unauthorized access, file transfers, or command execution. Timestamp manipulation is another method, where attackers modify file creation or access times to make malicious activity blend in with legitimate operations.

4 DETECTION FRAMEWORKS FOR APTS

Detection frameworks for APTs are essential for safeguarding IoT systems from stealthy and persistent cyberattacks [14]. These frameworks are generally categorized into four major approaches [15].

4.1 Signature-Based Detection

Security systems that use signatures to identify threats often look for certain behaviour, such as specific byte sequences in network traffic or behaviour patterns of malware. Tools like antivirus software, IDS, and rule-based engines use pre-defined signatures to identify threats [16]. While efficient in detecting well-known dangers, they fail miserably when faced with unique assaults and zero-day vulnerabilities. In IoT, where devices may be constrained in processing power and updated infrequently, signature-based methods face additional limitations in scalability, update distribution, and memory use Figure 6.

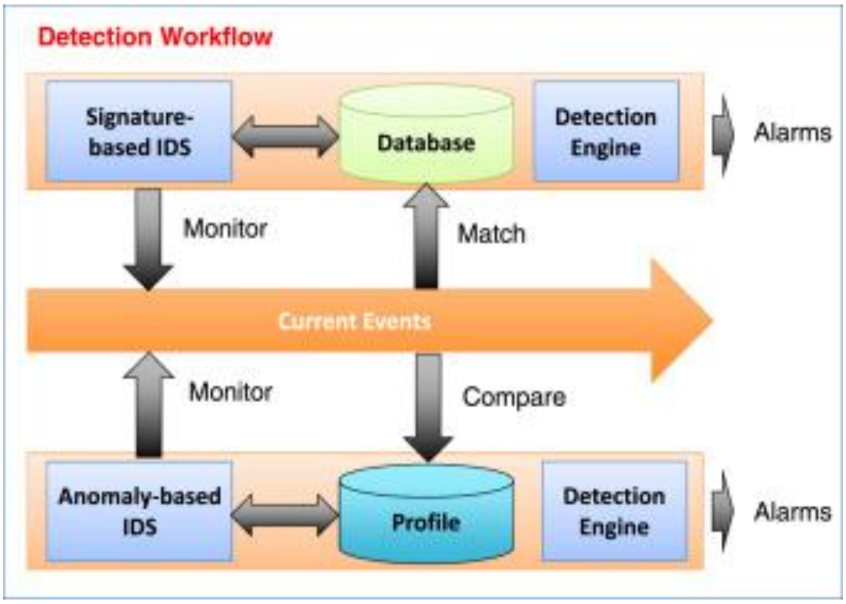

Figure 6: Signature Detection Workflow

4.2 Anomaly-Based Detection

This method identifies possible dangers by establishing a baseline of "normal" behaviour using statistical analysis or machine learning. Unusual device behaviour in IoT contexts may be captured using anomaly-based detection, unexpected traffic spikes, or protocol misuse. Techniques include supervised and unsupervised ML models like Isolation Forests, One-Class SVMs, and K-means clustering. Behavioral modelling plays a critical role by continuously analyzing the typical usage patterns of devices and users to detect intrusions that signature-based systems may miss. However, tuning these systems is complex, and they can suffer from high false-positive rates shown in Figure 7.

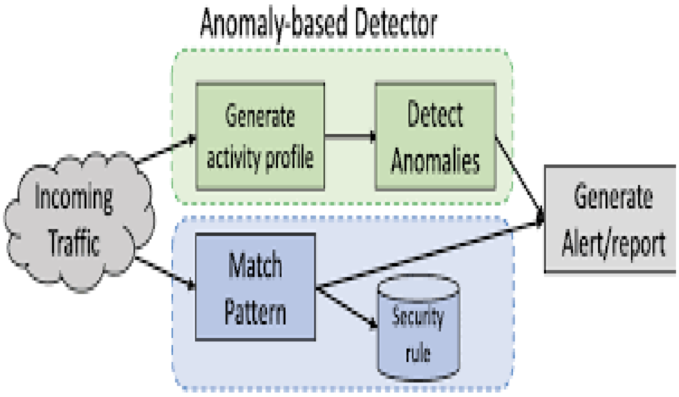

Figure 7: Anomaly-Based-Detection

4.3 Hybrid Detection Techniques

Hybrid systems aim to strike a compromise between detection accuracy and coverage by combining signature-based and anomaly-based approaches. These frameworks leverage the rapid detection capabilities of signature-based methods while also incorporating the adaptability of anomaly-based systems in Figure 8. Ensemble models such as Random Forests and correlation engines (which aggregate alerts from multiple sources and analyze contextual relationships) are used to improve detection precision. This layered approach is especially beneficial in IoT settings where both known malware and unknown anomalous behavior must be identified quickly and accurately.

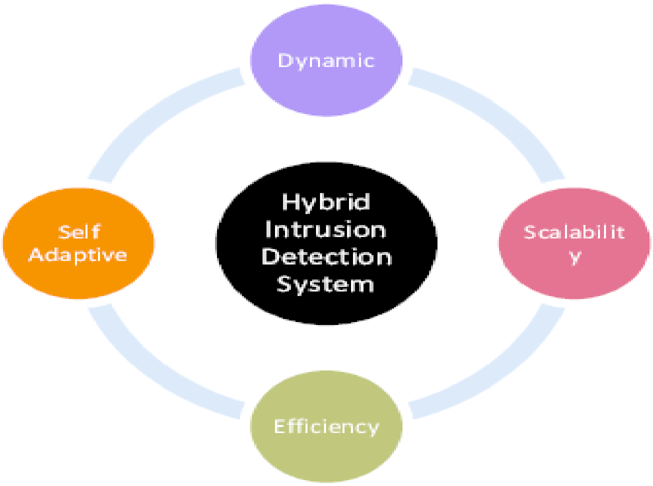

Figure 8: Hybrid Intrusion Detection

4.4 AI and Deep Learning-Based Detection

AI and DL frameworks have become effective methods for identifying intricate, elusive APTs. Convolutional Neural Networks (CNNs) are applied to network traffic images, Recurrent Neural Networks (RNNs) analyze temporal sequences of behavior, and Autoencoders are used for unsupervised anomaly detection [17][18]. These models excel at identifying subtle and evolving threats that evade traditional detection techniques [19]. Moreover, **Edge AI** deployment enables real-time detection directly on IoT devices or gateways, reducing latency and bandwidth consumption. This is critical in smart environments requiring fast, autonomous threat responses. Challenges in Detecting APTs in IoT/Smart Systems.

The key challenges in detecting APTs in IoT and Smart Systems, explained in detail: Figure 9 [20]

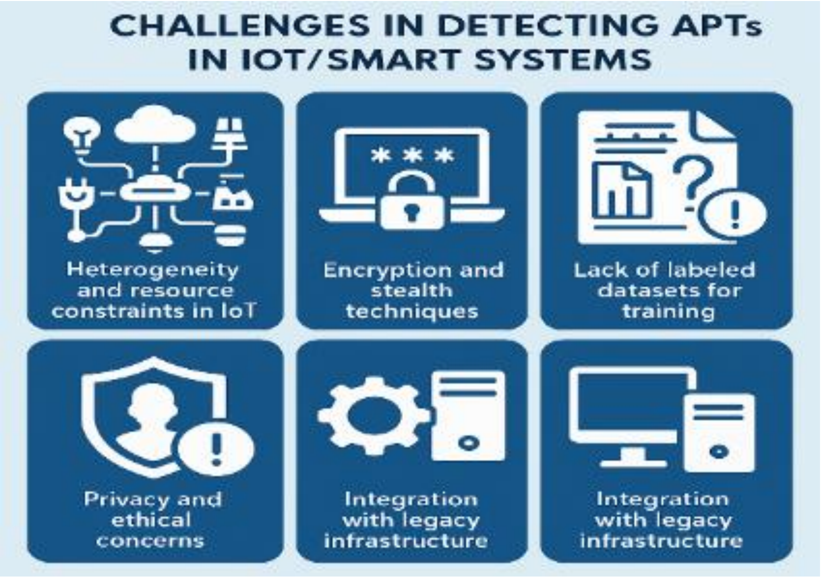
CHALLENGES IN DETECTING APTs IN IOT/SMART SYSTEMS
Heterogeneity and resource constraints in IoT
Encryption and stealth techniques
Lack of labeled datasets for training
Privacy and ethical concerns
Integration with legacy infrastructure
Integration with legacy infrastructure

Figure 9: Challenges in Detection

4.5 Heterogeneity and Resource Constraints in IoT

One of the most significant challenges in detecting APTs within IoT and smart systems lies in their highly heterogeneous environment. IoT devices vary widely in hardware, operating systems, communication protocols, and security capabilities. This diversity creates a fragmented ecosystem where standard detection mechanisms cannot be universally applied. Additionally, many IoT devices are designed to be lightweight and cost-effective, which results in limited computational power, memory, and energy resources. These constraints hinder the deployment of traditional or complex security solutions such as IDS, real-time behavioral analytics, or machine learning models directly on the device shows in Figure 10.

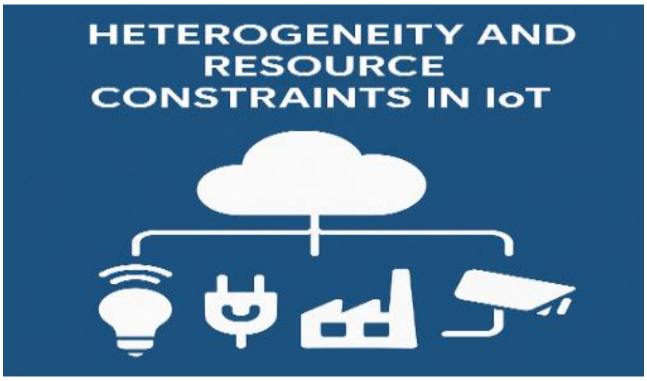

Figure 10: Heterogeneity and Resource

4.6 Encryption and Stealth Techniques

APTs are known for their stealthy and persistent nature, often employing advanced evasion techniques, including encryption and polymorphic malware in Figure 11. In IoT systems, attackers might conceal their identity and conduct via the use of encrypted communications or obfuscation techniques, making it difficult for monitoring systems to inspect traffic and identify malicious behavior. Moreover, these threats can remain dormant for extended periods, further complicating timely detection. The encrypted payloads and covert command-and-control (C2) communications challenge even advanced detection models that rely on traffic patterns or content inspection.

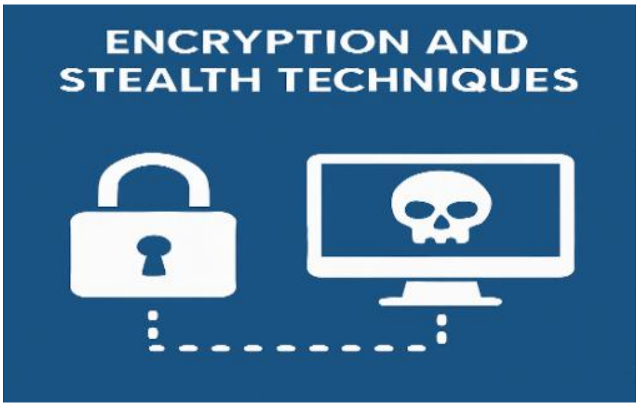

Figure 11: Encryption and Stealth

4.7 Lack of Labeled Datasets for Training

Effective detection of APTs using machine learning or AI-based models requires access to high-quality, labelled datasets that represent both normal and malicious behaviors. Figure 12 However, in the context of IoT and smart environments, there is a severe scarcity of such datasets. This lack of comprehensive and annotated data limits the ability to train, validate, and benchmark intelligent detection systems. Furthermore, due to the evolving nature of APT tactics, existing datasets quickly become outdated, reducing their effectiveness for real-world applications.

Figure 12: Lack of Labeled

4.8 Privacy, Security and Ethical Concerns

Monitoring IoT devices and smart infrastructure often involves collecting and analyzing sensitive data, which raises substantial privacy and ethical issues in Figure 13 [21][22][23]. Deploying deep packet inspection, behaviour tracking, or anomaly detection may conflict with users' rights to privacy, especially in environments like smart homes or healthcare. Balancing the need for security with respect for individual privacy is a delicate task and may impose legal or regulatory limitations on the kind of data that can be collected, stored, or analyzed for APT detection.

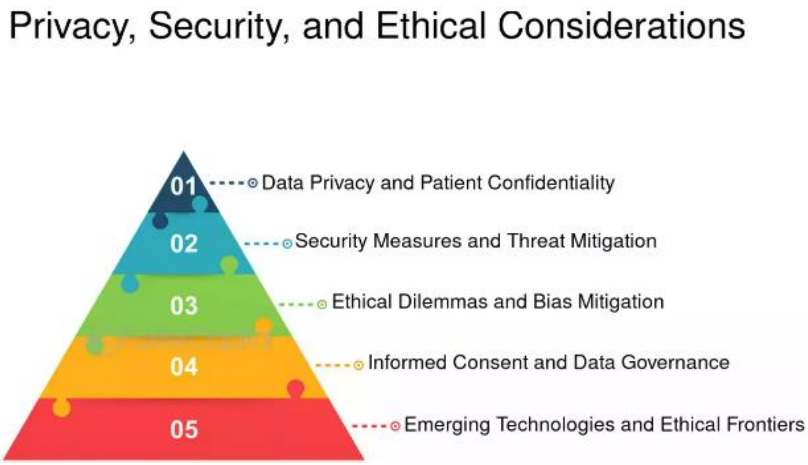
Privacy, Security, and Ethical Considerations
01
Data Privacy and Patient Confidentiality
02
Security Measures and Threat Mitigation
03
Ethical Dilemmas and Bias Mitigation
04
Informed Consent and Data Governance
05
Emerging Technologies and Ethical Frontiers

Figure 13: Privacy Security and Ethical

4.9 Integration with Legacy Infrastructure

Many IoT and smart systems are deployed in environments that include older, legacy infrastructure, which was not originally crafted to meet the strictest security standards of today Picture Figure 14. It is typically difficult to upgrade these systems, and they often lack fundamental security safeguards and may be incompatible with current security solutions [24]. Integrating APT detection frameworks in such environments poses technical challenges, including interoperability issues, insufficient logging capabilities, and the risk of disrupting critical operations during integration. This creates vulnerabilities that sophisticated APT actors can exploit with minimal resistance.

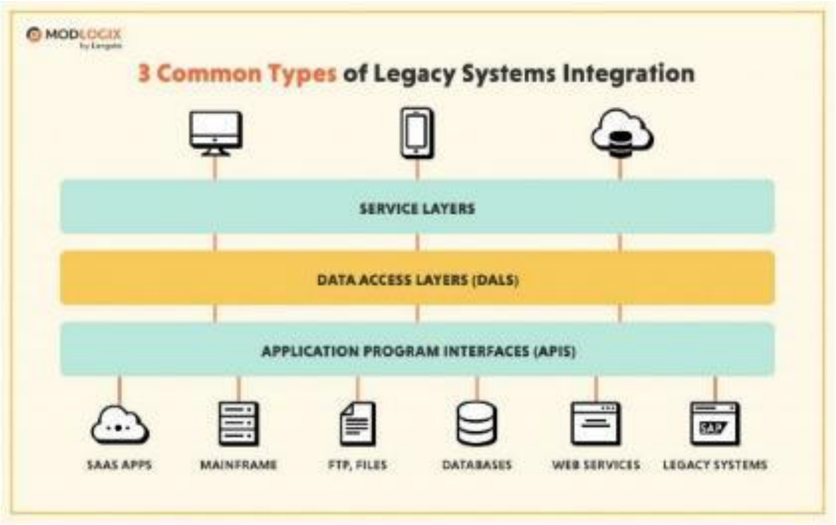
MODLOGIX
3 Common Types of Legacy Systems Integration
SERVICE LAYERS
DATA ACCESS LAYERS (DALS)
APPLICATION PROGRAM INTERFACES (APIS)
SAAS APPS
MAINFRAME
FTP, FILES
DATABASES
WEB SERVICES
LEGACY SYSTEMS

Figure 14: Integration with Legacy

5 LITERATURE OF REVIEW

Table 1 Comparative Analysis of Recent Research on APTs Focus Areas, Findings, Challenges, and Contributions.

Muniyappan, M and Pavithra (2025) the strategy of using AI and XAI to enhance cybersecurity in DT systems is analyzed. Some of the AI techniques are Anomaly detection, analysis that predicts and Automated response facilities to provide Security precautionary measures. Such methods are improved by XAI through the addition of the process by which the decisions were made and the trust with the parties involved. Mirroring literature review, deficits of existing DT cybersecurity frameworks, analyzed, include overall issues of scalability, insufficient new threat integration, and increased opacity. For such reasons, the current paper offers a detailed cybersecurity framework that adopts both AI and XAI to fill the existing research gaps [25].

Krishnapriya and Singh (2024) The likelihood of cyberattacks is directly proportional to the number of people using the Internet. Attacks that persist online for a long period are called APTs. APTs deploy a plethora of complex tactics and technologies to accomplish their goals. Even the most advanced countries, including the US, Russia, UK, and India, might be the targets of this kind of targeted attack. The term "APT attack" refers to a multi-tactical assault that is carried out in stages. A key hallmark of APTscis the use of unique attack tools, techniques, and procedures developed by the perpetrator to evade the security system [26].

Rani, Saha and Shukla (2024) Accurately identifying the individuals responsible for complex assaults is known as APT attribution, and it is a major obstacle in the field of cybersecurity. It has the potential to greatly improve defensive mechanisms and guide strategic reactions. Instead of relying on time-consuming and error-prone human processes, researchers are putting more emphasis on creating automated solutions that can identify cyber threats and their perpetrators, thanks to the proliferation of AI and ML approaches. Notably absent from the existing literature on automated threat attribution is a comprehensive analysis of key artefacts and automated approaches that might facilitate the attribution process. In addition, they point towards unanswered research questions, address difficulties in automatic attribution, and provide critical remarks on existing literature techniques. To fill in the gaps and overcome the obstacles, this study suggests that there are a lot of chances for future research on APT attribution. This study lays the groundwork for future research and development in automated, reliable, and actionable APT attribution methodologies by highlighting strengths and limits in present approaches [27].

Mat et at. (2024) The sophisticated and persistent nature of APTs makes them a major security threat to organizations; these threats also threaten the availability, integrity, and confidentiality of the information and services that organizations rely on. This paper surveys the important research in the field, finds gaps in it, and suggests options for future work in a systematic way to evaluate the literature on ways of detecting APTs. Existing APT detection approaches based on behaviors linked to multi-stage attacks are thoroughly examined by the authors. They searched several databases thoroughly while following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [28].

Mutalib et al. (2024) The use of complex deception techniques by APT assaults on computer networks has grown in frequency and sophistication over the last several years. Low detection accuracy, high false-positive rates, and difficulties distinguishing new assaults like remote-to-local (R2L) and user-to-root (U2R) are problems with traditional IDSs. This study delves into the basics of APTs and the shortcomings of current detection approaches to tackle these difficulties. Later on, the focus shifts to investigating how APT detection might be enhanced via the innovative use of DL methods and Explainable Artificial Intelligence (XAI). More effective and dependable cybersecurity solutions will be possible thanks to the recommendations for future study in this article, which aim to address increasing threats. When it comes to improving the efficiency and reliability of cybersecurity systems, this research stresses the significance of explain ability [29].

Gan et al. (2023) The IIoT, or industrial IOT, is an essential component of the smart society because it bridges the gap between conventional manufacturing and cutting-edge IT to boost output quality and efficiency. APTs pose a significant danger to the IIoT as well. APTs are a kind of covert assault that may wreak havoc and destruction on an immense scale. they explain how APTs came to be in this work. In addition, they assess current defence strategies and analyze the kinds of APTs that each of the four layers of the IIoT reference architecture may encounter. Then, to find the patterns and traits that APT actions in IIoT have, they model and examine them using many models. Lastly, after going over IIoT security challenges in detail, suggest several areas for further study and paths to take the field [30].

Table 1: Comparative Analysis of Recent Advanced Persistent Threats (APTs)

Reference	Focus Area	Key Findings	Challenges	Key Contribution
Muniyappan and Pavithra (2025)	AI and XAI in Digital Twin (DT) Cybersecurity	AI techniques (anomaly detection, predictive analysis, automated response) enhance DT security; XAI improves trust and transparency	Scalability, threat integration, and model opacity in existing frameworks	Proposes an AI-XAI based cybersecurity framework to address existing deficits
Krishnapriya and Singh (2024)	APTs and Global Cybersecurity Threat Landscape	APTs use advanced TTPs to bypass defenses; even tech-advanced nations are vulnerable	Rapid evolution of TTPs, target-specific attack sophistication	Highlights the severity and evolving nature of APTs and the inadequacy of current defenses
Rani, Saha and Shukla (2024)	Deep Learning-Based Automated APT Attribution	Explores shift from manual to automated threat attribution using AI/ML	Lack of systematic reviews, challenges in accurate attribution	Provides a critical survey and identifies open research directions for automated APT attribution
Mat et al. (2024)	Research on Advanced Persistent Threat Detection Methods	Surveys multi-stage behavior-based APT detection approaches	Gaps in comprehensive detection techniques; evolving nature of APTs	PRISMA-based systematic literature review offering future research guidance
Mutalib et al. (2024)	IDS Limitations and DL + XAI	Traditional IDSs have high false positives, poor unknown	Accuracy, explainability,	Advocates deep learning and XAI for accurate, explainable APT detection

	for APT Detection	attack detection; DL and XAI enhance detection and trust	detection of unknowns like R2L and U2R	
Gan et al. (2023)	APT Threats in IIoT Architectures	APTs impact all layers of IIoT; existing techniques are insufficient for stealthy attacks	Multi-layer vulnerability, lack of unified models	Presents modeling of APTs in IIoT, identifies attack patterns, and proposes research directions

6 CONCLUSION AND FUTURE WORK

APTs pose a formidable challenge in the domain of IoT and smart infrastructure due to their stealthy, long-term nature and their ability to exploit the weak security posture of interconnected devices. These threats follow a multi-phase lifecycle beginning with reconnaissance and ending with data exfiltration and track clearing that allows attackers to stealthily infiltrate, maintain persistence, and exploit IoT systems over extended periods. Given the resource-constrained and heterogeneous nature of IoT environments, traditional security measures such as signature-based detection often prove inadequate. Although newer frameworks involving anomaly-based detection and AI-driven approaches have demonstrated promise, they are not without limitations. These include high false-positive rates, dependency on high-quality datasets, and computational demands that exceed the capabilities of many IoT devices. Moreover, the lack of standardized protocols and the difficulty in integrating with legacy infrastructure further complicate the deployment of effective APT defenses. In light of these factors, it is clear that while progress has been made in detecting and mitigating APTs, existing solutions often remain reactive and neglect to tackle the ever-changing and enduring character of contemporary cyber dangers.

Enhancing existing infrastructures via the construction of, scalable, and adaptive security frameworks tailored specifically to the constraints of IoT environments. One critical direction is the development of lightweight, energy-efficient detection algorithms that can operate effectively on devices that have a low amount of RAM and computational power. These types of models could benefit from edge computing and federated learning paradigms to reduce latency and preserve bandwidth. Additionally, incorporating advanced threat intelligence especially behavior-based indicators and cross-layer context can enhance situational awareness and detection precision.

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