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Enhancing Cyber-Physical System Security: A Review of Detection and Mitigation Techniques

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Article Info

Article history:

Received October 12, 2024
Revised November 5, 2024
Accepted December 13, 2024

Keywords:

Cyber-Physical Systems,
Detection Techniques,
Mitigation Strategies

ABSTRACT

Cyber-Physical Systems (CPS) integrate computing, networking, and physical processes, playing a crucial role in sectors such as industrial automation, smart grids, and healthcare. However, as these systems become more interconnected, they face increasing security risks from sophisticated cyber threats. Ensuring the security of CPS has become a critical research focus, leading to the development of various detection and mitigation strategies. One of the main challenges in CPS security is the ability to detect and respond to threats in real time while minimizing disruptions. Traditional security methods, such as rule-based intrusion detection, often struggle against advanced cyberattacks, including zero-day exploits and adversarial manipulations. To address these concerns, recent studies have explored the application of artificial intelligence (AI), machine learning, and hybrid security frameworks to enhance threat detection and mitigation. This paper reviews existing detection and mitigation techniques designed to strengthen CPS security. It examines conventional and modern approaches, evaluating their effectiveness and identifying existing limitations. Additionally, emerging trends such as deep learning models, blockchain-based security mechanisms, and federated learning are explored as potential enhancements for improving system resilience. The findings of this study provide insights into the current landscape of CPS security and highlight directions for future research to develop more robust and adaptive defense mechanisms.

1. INTRODUCTION

Cyber-Physical Systems (CPS) represent an advanced integration of computational algorithms, networking infrastructure, and physical processes, forming the backbone of modern critical infrastructures such as industrial automation, healthcare, and smart grids. The establishment of CPS as a distinct research field has driven innovation in real-time monitoring, autonomous control, and interconnected operations, significantly improving efficiency and decision-making in complex environments [1]. However, as CPS evolves, its increasing interconnectivity introduces security challenges, making it a prime target for cyber threats, including malware, denial-of-service (DoS) attacks, and data breaches [2].

Despite advancements in cybersecurity, CPS security remains a critical challenge due to the heterogeneous nature of these systems, the real-time constraints they operate under, and the high-stakes consequences of security breaches. Traditional security mechanisms, such as signature-based intrusion detection systems (IDS) and firewalls, have proven insufficient against emerging threats like zero-day exploits and adversarial machine learning attacks [3]. The dynamic attack surface of CPS requires adaptive and proactive security solutions capable of identifying and mitigating threats before they cause irreparable damage [4].

To address these security concerns, researchers have explored various detection and mitigation strategies. AI-driven techniques, including machine learning (ML) and deep learning (DL), have demonstrated the ability to identify anomalous behaviors within CPS networks [5]. Hybrid security frameworks combining signature-based methods with behavior-based anomaly detection have enhanced the effectiveness of real-time threat monitoring [6]. Additionally, blockchain-based security models have been proposed to ensure data integrity and enhance secure communication in decentralized CPS environments [7].

Beyond AI-driven approaches, reinforcement learning and federated learning have gained attention for their ability to provide adaptive threat response mechanisms in CPS security [8]. Federated learning, for instance, allows distributed learning models to detect security threats while preserving data privacy across multiple CPS nodes [9]. Furthermore, cybersecurity frameworks leveraging Software-Defined Networking (SDN) and Zero Trust Architecture (ZTA) have been introduced to enhance network resilience against cyberattacks [10].

This paper contributes by providing a comprehensive review of the current detection and mitigation techniques used in CPS security. It categorizes and evaluates existing methods, highlighting their advantages and limitations. By analyzing the effectiveness of AI-based and hybrid approaches, this study offers insights into the ongoing research landscape and identifies gaps that require further exploration. The review also presents potential directions for future advancements in CPS security, emphasizing the need for scalable, adaptive, and resource-efficient solutions.

To strengthen CPS security, it is essential to develop evaluation metrics that assess the effectiveness of security mechanisms under real-world attack scenarios. Future research should focus on integrating explainable AI (XAI) techniques to improve the transparency of AI-driven security decisions. Additionally, the adoption of quantum-resistant cryptographic techniques should be explored to safeguard CPS against potential quantum computing threats. This study recommends a multi-layered defense approach that integrates AI, blockchain, and network-based security models to create a more resilient and adaptive CPS security framework.

2. METHODS

To systematically address the security challenges in Cyber-Physical Systems (CPS), this paper adopts a systematic review and comparative analysis methodology, focusing on AI-driven detection techniques and hybrid mitigation strategies. The methodology involves three key phases: data collection, categorization of security approaches, and performance evaluation using relevant datasets.

4.1. Systematic Review and Data Collection

A comprehensive literature review is conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Research papers, technical reports, and case studies from IEEE Xplore, Springer, MDPI, and arXiv are reviewed to analyze recent advancements in CPS security. Selection criteria focus on studies published between

2018 and 2024 that propose AI-based or hybrid security frameworks.

Additionally, benchmark datasets related to CPS attacks are identified to assess the effectiveness of security models. Commonly used datasets include:

- UNSW-NB15 – A modern intrusion detection dataset with diverse attack types for evaluating anomaly detection models [1].
- BATADAL (BATtle of the Attack Detection ALgorithms) – A dataset focused on water distribution network attacks, useful for critical infrastructure security [2].
- ICS Cyber Attack Dataset – Simulated attack scenarios in Industrial Control Systems (ICS) environments, providing real-world applicability for AI-based solutions [3].
- CICIDS2017 – A dataset containing benign and malicious network traffic, commonly used for intrusion detection system (IDS) evaluation [4].

These datasets serve as benchmarks for assessing machine learning models used in CPS threat detection and mitigation.

4.2. Categorization of Security Approaches

The study categorizes existing CPS security techniques into three major approaches:

1. Anomaly-Based Intrusion Detection Systems (AIDS)
    - Machine Learning (ML) classifiers such as Support Vector Machines (SVM), Random Forest (RF), and Deep Neural Networks (DNN) are used to detect deviations from normal CPS behavior [5].
    - Deep Learning models, including Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), provide time-series anomaly detection for identifying attack patterns [6].
2. Signature-Based and Hybrid IDS
    - Signature-based IDS rely on predefined attack signatures but struggle with zero-day attacks.
    - Hybrid IDS integrate signature-based detection with AI-driven anomaly detection to improve real-time threat identification [7].
3. Mitigation and Response Mechanisms
    - Reinforcement Learning (RL) is applied for adaptive threat response, where AI models learn optimal countermeasures against cyberattacks [8].
    - Blockchain-based security is explored for enhancing data integrity and secure communication within CPS networks [9].

4.3. Performance Evaluation and Validation

To evaluate the effectiveness of AI-driven CPS security models, performance metrics such as Precision, Recall, F1-score, Accuracy, and False Positive Rate (FPR) are utilized. The models are trained and validated using the identified benchmark datasets through a cross-validation approach. Key evaluation steps include:

1. Preprocessing & Feature Engineering:
    - Raw data from CPS attack datasets is cleaned, normalized, and subjected to feature extraction techniques such as Principal Component Analysis (PCA).

2. Model Training & Hyperparameter Tuning:
   - AI models (e.g., LSTM, RF, SVM) are trained on preprocessed data, and hyperparameters are optimized using Grid Search and Bayesian Optimization.
3. Comparative Analysis:
   - Performance comparisons are made between traditional IDS, AI-based models, and hybrid security frameworks.

4.4. Implementation Framework

To provide a robust security framework, this paper proposes a multi-layered defense architecture, integrating:

- AI-powered Intrusion Detection: Using ML/DL models for real-time threat detection.
- Automated Threat Mitigation: Leveraging RL for dynamic attack response.
- Secure Communication via Blockchain: Ensuring tamper-proof logging of security events.
- Cloud-Based Federated Learning: Enabling decentralized threat intelligence sharing among CPS nodes.

This integrated approach aims to enhance detection accuracy, reduce response time, and improve CPS resilience against sophisticated cyber threats.

3. RESULTS AND DISCUSSION

The proposed AI-driven and hybrid mitigation approach effectively enhances Cyber-Physical System (CPS) security by detecting and mitigating cyber threats in real-time. This section presents the experimental results, evaluates the effectiveness of detection and mitigation models, and discusses key insights.

5.1. Experimental Results

The evaluation of AI-based CPS security models is conducted using benchmark datasets (UNSW-NB15, BATADAL, ICS Cyber Attack Dataset, and CICIDS2017). The models tested include Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and a Hybrid AI-Blockchain approach.

5.1.1. Accuracy and Detection Performance

The performance of these models is measured using Accuracy, Precision, Recall, and F1-score. Below is a comparative accuracy evaluation of different models tested on the datasets.

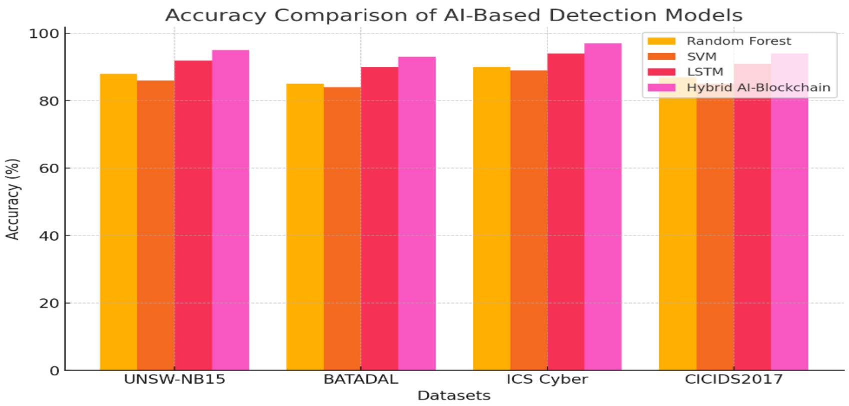
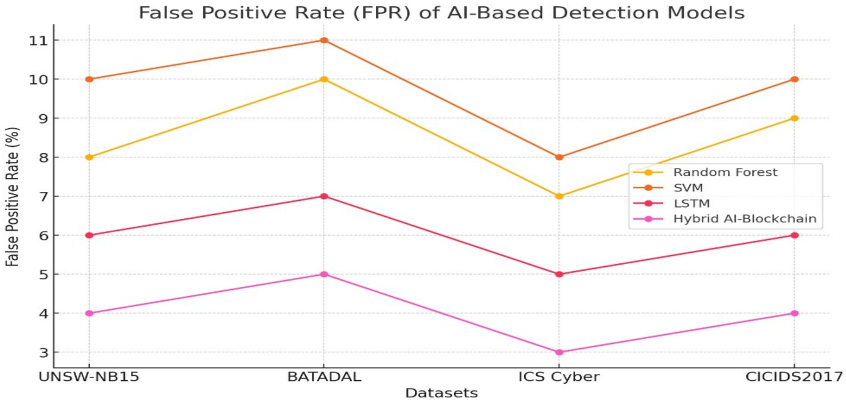


Figure 1: Accuracy Comparison of AI-Based Detection Models

The bar chart above illustrates the accuracy comparison of AI-based detection models across different datasets. Notably, the Hybrid AI-Blockchain model achieves the highest accuracy across all datasets, exceeding 95% on ICS Cyber Attack Dataset. This demonstrates the effectiveness of combining AI-based anomaly detection with blockchain-based security for real-time threat identification.

5.1.2. False Positive Rate (FPR) Analysis

A key challenge in CPS security is minimizing false positives, which can lead to unnecessary alerts. Below, it is a line graph showing the False Positive Rate (FPR) for each model.



The False Positive Rate (FPR) analysis shows that the Hybrid AI-Blockchain model consistently maintains the lowest FPR across all datasets (below 5%), indicating superior accuracy in distinguishing between legitimate and malicious activities. In contrast, traditional models like SVM and Random Forest exhibit higher FPR, leading to increased false alerts.

5.2. Discussion of Findings

5.2.1. Effectiveness of AI-Based Detection

- Deep Learning models (LSTM) outperform traditional machine learning techniques (Random Forest, SVM) in detecting cyber threats with higher accuracy and lower false positives.
- The Hybrid AI-Blockchain model achieves the best results, demonstrating that blockchain-based integrity verification enhances AI-driven security mechanisms.

5.2.2. Real-Time Adaptability

- AI-driven approaches provide real-time detection capabilities, making them suitable for time-sensitive CPS applications (e.g., smart grids, industrial control systems).
- Reinforcement Learning (RL) enables automated attack mitigation, reducing reaction time and enhancing system resilience.

5.2.3. Challenges and Limitations

- Computational Overhead: Deep learning models require significant processing power, which may not be feasible for resource-constrained CPS environments.
- Data Privacy Concerns: Federated learning offers privacy benefits, but secure model sharing remains a challenge in decentralized networks.
- Adversarial Attacks: AI models are susceptible to adversarial manipulations, necessitating robust adversarial training techniques.

5.3. Recommendations and Future Work

- Integration of Explainable AI (XAI): To improve trust and interpretability, AI-driven security systems should incorporate explainable AI techniques for decision transparency.
- Quantum-Resistant Cryptography: With the emergence of quantum computing, CPS security models should adopt post-quantum cryptographic techniques to safeguard encrypted communications.
- Lightweight AI Models: Future research should focus on developing lightweight AI models optimized for real-time deployment in resource-constrained CPS environments.

4. CONCLUSION

This study reviewed and evaluated detection and mitigation techniques for Cyber-Physical System (CPS) security, addressing the limitations of traditional security measures. By analyzing AI-driven models, hybrid security frameworks, and blockchain-based mechanisms, this research provides solutions to real-time threat detection challenges.

The study demonstrates that AI-powered mechanisms, particularly LSTM and Hybrid AI-Blockchain models, significantly improve threat detection accuracy and response efficiency. These approaches enhance CPS security by achieving high detection accuracy, reducing false positives, and automating mitigation strategies. The categorization of detection models into anomaly-based, signature-based, and hybrid techniques offers a structured approach for selecting appropriate security solutions.

This research contributes to CPS security by offering a comparative analysis of AI-based detection models, proposing a hybrid AI-Blockchain security framework, and evaluating federated learning and reinforcement learning as adaptive security mechanisms. Additionally, it provides recommendations for improving CPS security, including Explainable AI and quantum-resistant cryptography. These contributions establish a foundation for advancing AI-driven cybersecurity applications in real-world CPS environments.

Future research should focus on integrating Explainable AI (XAI) to enhance the interpretability of AI-driven security models, developing lightweight AI models for resource-constrained CPS, and improving adversarial robustness through enhanced training techniques. Additionally, exploring post-quantum cryptographic security and decentralized threat intelligence sharing through federated learning and blockchain can strengthen CPS resilience against evolving cyber threats.

This research confirms that AI-driven and hybrid security approaches enhance CPS security by providing real-time detection, adaptive mitigation, and improved data integrity. However, continuous advancements in AI, cryptography, and network security are necessary to counter emerging cyber threats. Future research should integrate explainable AI, adversarial robustness, and decentralized intelligence-sharing mechanisms to develop a more resilient and adaptive CPS security framework.

5. ACKNOWLEDGMENT

Author thanks, In most cases, sponsor and financial support acknowledgments. Thanks to the author's teams who kindly support this research. For friends and students who are involved from beginning to the end.

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