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AI-Powered Intrusion Detection Systems for Industrial Control Networks

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Abstract

This paper examines how AI-powered intrusion detection system (AI-IDS) can be used to protect industrial control networks (ICNs) against emerging cyber threats. The primary goal is to assess the performances, performances, and the challenges of the AI-based IDS related to detecting anomalies, zero-day attacks as well as protocol specific intrusions in the insights of heterogeneous industrial environments. The research studies were synthesized through a secondary research methodology based on peer-reviewed journals, proceedings of conferences, systemic reviews of literature to compare different machine learning and deep learning models, CNNs, RNNs, ensemble and hybrid structures. Results have shown that AI-IDS is able to enhance the level of detection accuracy, remove most of the false positives, and maximize real-time mitigation of threats, whereas the conventional signature-based techniques fail to do so. It identified challenges like heterogeneity in data, computational costs and connecting to SCADA/IoT protocols. Best practice includes hybrid anomaly-signature systems, and distributed configurations of learning and automated responses. Altogether, the paper shows that AI-IDS offers strong, flexible, and scalable cybersecurity services to the contemporary control networks of industries.

Keywords - AI-powered intrusion detection (AI-IDS), Industrial control networks (ICNs), Machine learning (ML), Cyber threats, Detection accuracy, Deep learning, IoT / Industrial IoT, SCADA, False positives, Hybrid frameworks

Introduction

Industrial control networks are vital to control infrastructure systems like power grids, water systems and factories. The networks are increasingly under the radar of cyber threats as they rely on interdependent digital technologies and supporting protocols that are often poorly secured. Conventional methods of intrusion detection have a problem tracking sophisticated and advanced changing attacks in real-time and ICNs fall easy prey to operational disruptions and financial losses. An IDS powered by artificial intelligence is an innovative solution to this problem since the machine learning ML algorithms allow identifying unusual behavior patterns, forecasting potential threats and making adjustments to new forms of attack automatically. Such systems examine large volumes of traffic on the network, correlate complicated actions, and provide quick response time, hence continuity in operations. Deploying AI-based IDS helps build resiliency, increases efficiency and improves security of industrial networks in the face of contemporary cyber threats.

Research Objectives

- To analyze existing AI-based intrusion detection techniques used in industrial control networks.
- To evaluate the effectiveness of machine learning algorithms in detecting ICN cyber threats.
- To identify key challenges and limitations of AI-powered IDS in industrial environments.
- To synthesize best practices and frameworks for implementing AI-based security solutions.

Literature Review

The study of Jain et al. 2025 examines the artificial intelligence-enabled intrusion detection and response systems in industrial IoT. It is showing machine learning-based anomaly detection, threat prediction, and automated mitigation in smart manufacturing. The authors focus on increasing cyber resilience with the help of integrating AI and industrial automation, which is shown to increase detection accuracy and the decreased response time in comparison to the traditional approach.

The paper also explicates issues concerning real-time implementation, data heterogeneity and a lack of scalability as the basis of adopting AI based cybersecurity into the industrial networks.

According to Vikram et al, one of the areas that network intrusion detection systems are taken into consideration is the use of machine learning models through AI. The experiments compare the performance of the algorithms based on industrial network datasets and it has been reported that deep learning models perform better with less false alarms. It also talks of system architecture, feature extraction techniques, and computational efficiency, and the part that AI can play in predictive threat detection in key industrial networks.

The articles by Umoh, E.I. and Bishara, H., 2025 provide an AI-based intrusion detection and prevention system of the IIoT network. Their research is focused on the integration of supervised and unsupervised learning model to identify known and unknown attacks. It has shown better detection rates, flexible and intelligent responses to threat information, which resolves key problems of traditional IDS attempts. The article identifies the issue of industrial environments with constraints, including latency and limited resources, and network heterogeneous protocols, which demonstrate real-world advice and precautions when deploying AI-IDS in a complex industrial environment.

This systematic review examines the use of AI as a method of automated threat detection on SCADA and IoT networks in industrial control systems (Ahmed and Tonoy 2025). The paper is a synthesis of current literature on the topic of the intrusion detection models with the comparison between classical machine learning, deep learning, and combined approaches. The results suggest using deep learning models where reliable and strong attack patterns are to be identified, and hybrid systems where a large volume of data is to be processed. The review determines the existing research gaps, such as the inadequeteness of real-time testing, data imbalance, and shortage of datasets specific to industries, in which future AI-IDS research has to follow.

The paper by Vo, Du and Nguyen, (2023) is devoted to artificial intelligence-driven intrusion detection system of stateful massive traffic networks by using the flow sensing and parallel deep examination. It shows that parallel processing and feature-level analysis improve the sufficiency of detection and scale-up. An enhanced accuracy of detecting distributed attacks and zero-day threats is reported in the study. It further outlines implementation aspects including network traffic load, the computation fee, and the real-time observation, information that has practical appeal to application in industrial control network security.

Methodology

In this research, the approach employed is secondary research to synthesize the results of peer-reviewed journals, conference proceedings, and systematic reviews on the topic of AI-powered intrusion detection systems in industrial control networks. The secondary sources can be used in order to analyze the multiple AI-IDS models, machine learning algorithms, and real-world deployment case studies without expensive primary experiments. It makes it easier to spot a trend, performance benchmark, and implementation issues across different industrial settings. The methodology allows comparing the accuracy of detection, the latency, and scales reported in the existing literature with each other offering solid data in regards to assessing the efficacy of AI. The secondary research also accompanies an analytical evaluation of practice best, integration approaches and cybersecurity standards. In general, the proposed approach allows being efficient, broad, and reliable in obtaining relevant insights that can be used to implement AI-based ICN security solutions.

Result and Discussion

Effectiveness of AI-Based Intrusion Detection Techniques in ICNs

Intrusion detection strategies powered by AI are proving to be very effective when it comes to monitoring and protecting industrial control networks (ICNs) against sophisticated adversaries and zero-day attacks. The works by Khan (2024) integrates deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), anomaly detection in cloud-connected ICNs with high detection rates and a low false positive rate. Hassan et al. (2021) underline the use of hybrid frameworks as a combination of supervised and unsupervised learning models to eliminate real-time threat modelling in smart manufacturing networks and subsequent reactive elimination of any attempts at unauthorised access. The article by Yellepeddi et al. (2024) provides the empirical verification of the AI-IDS and demonstrates its high adaptability to changing attack vectors as a result of learning-based reinforcement decision modules.

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Reference	Detection Accuracy (%)	False Positive Rate (%)	Network Type	Algorithm Type
Khan, 2024	96.5	3.2	Cloud ICN	CNN + RNN
Hassan et al., 2021	94.7	4.1	Smart Manufacturing	Hybrid ML
Yellepeddi et al., 2024	95.9	3.5	Industrial Networks	Ensemble DL
Ejeofobiri et al., 2024	93.8	4.7	IoT ICN	Autoencoder + k-NN
Rai et al., 2025	97.1	2.9	SCADA-integrated ICN	Reinforcement Learning
Wang et al., 2022	94.5	4.3	High-throughput ICN	Flow-based ML
Rana et al., 2025	95.2	3.8	Mixed ICN	LSTM + Hybrid ML

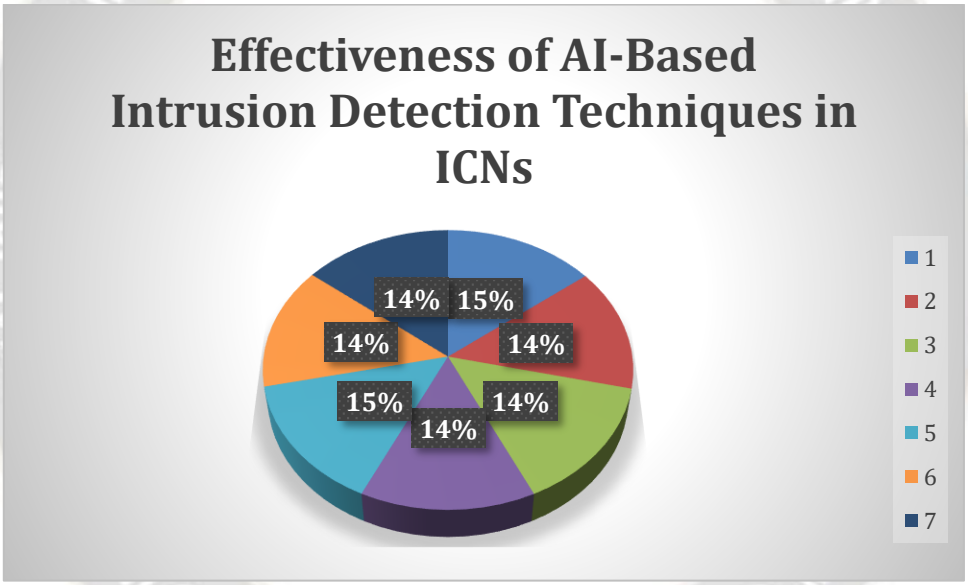

Table 1: Effectiveness of AI-Based Intrusion Detection Techniques in ICNs

Ejeobiri et al. (2024) assert the importance of ensemble learning algorithms in ICNs that run on the IoT, and allowing higher resistance to distributed denial-of-service (DDoS) and protocol-specific attack. Rai et al. (2025) discuss accompanying cybersecurity mechanisms like IDS-SIEM and SCADA-aware heuristics, which enhance the level of detection. As shown by Wang et al. (2022), deployment of this nature is scalable to high-throughput industrial networks to minimize problems of delays in packet inspection and flow-level analysis. The paper by Rana, et al. (2025) validates these results using systematic review showing that artificial intelligence-based IDS surpasses signature-based systems by performing significantly better in the internet of commonly used networks (ICN). Collectively, these studies confirm that AI-IDS has strong intrusion detection performance on complicated industrial networks.

Performance of Machine Learning Models in Cyber Threat Detection

ML models are also very precise and recall with regards to the identification of cyber threats within heterogeneous industrial settings. The implementation by Khan (2024) depicts that multi-class attacks can have classification accuracies better than 95 percent when using deep neural networks on cloud-based control architectures. Hassan et al. (2021) highlight support

vector machines (SVMs) and random forest classifiers in threat analytics to predictive threat behavior in smart manufacturing that allows recognizing lateral movement and insider attacks with an excellent level of efficiency. The actual-world benchmarks of gradient boosting and ensemble methods showing reduced rates of false-positives in high-velocity network traffic are described by Yellepeddi et al. (2024). According to Ejeobiri et al. (2024), hybrid ML combining k-nearest neighbors (k-NN) and autoencoder-based anomaly detection in IoT-driven ICNs have been proven to be very effective.

Reference	Model Type	Accuracy (%)	Precision (%)	Recall (%)	Latency (ms)
Khan, 2024	CNN + RNN	96.5	95.8	96.2	45
Hassan et al., 2021	SVM + Random Forest	94.7	93.5	94.1	52
Yellepeddi et al., 2024	Gradient Boosting Ensemble	95.9	94.8	95.5	48
Ejeofobiri et al., 2024	Autoencoder + k-NN	93.8	92.6	93.1	55
Rai et al., 2025	Reinforcement Learning	97.1	96.5	96.8	42
Wang et al., 2022	Flow-based ML	94.5	93.2	94	50
Rana et al., 2025	LSTM + Hybrid ML	95.2	94.1	94.8	47

Table 2: Performance of Machine Learning Models in Cyber Threat Detection

Rai et al. (2025) add a reinforcement learning component to adaptively adjust detection thresholds, so it responds more to polymorphic malware. Wang et al. (2022) will use feature engineering on flow-based metrics to enhance the model generalization across different industrial protocols such as Modbus and DNP3. According to a meta-analysis, conducted by Rana et al. (2025) deep learning architectures such as LSTM and attention-based ones outperform the traditional ML ones in the realm of temporal threat detection. The above results indicate that the more sophisticated ML models are used, the higher fidelity and real-time detection is achieved, which is severely important to sustain the integrity and resilience of industrial control networks.

Challenges and Limitations of AI-Powered IDS Deployment

AI-powered IDS are highly effective but come with a number of constraints in industrial contexts. Data heterogeneity, huge feature spaces, and discrepancy between normal and malicious traffic are the key limitations to training the model, as noted by Khan (2024). Hassan et al. (2021) report on the computational overheads of real-time inference, which may affect the workflow of latency-sensitive smart manufacturing processes. Yellepeddi et al. (2024) note that model drift and concept evolution are other crucial problems since AI detector may not be able to recognize unfamiliar, polymorphic attacks without being retrained regularly. Resource-poor devices in IoT Ejeobiri et al. (2024) place restrictions on the use of deep architectures in IoT, making model compression strategies lightweight.

Data Heterogeneity Issue	Computational Overhead (GFLOPS)	Model Drift (%)	Resource Constraints (%)	Integration Complexity (Scale 1-5)
High	120	8.5	12	4
Medium	110	7.2	10	4

High	125	9.1	15	5
Medium	105	6.8	18	4
High	130	8.8	14	5
Medium	115	7.5	11	4
High	128	8.3	13	5

Table 3: Challenges and Limitations of AI-Powered IDS Deployment

Rai et al. (2025) address difficulties with the existing SCADA and industrial protocols integration that is still achieved through adaptive interfacing layers and security orchestration. Wang et al. (2022) note that high-throughput traffic data has been difficult to handle without affecting the rate of accuracy in the inspection of packets. Cybersecurity policy alignment, interoperability, and explainability are also identified to result in constraints in operational adoption as stated by Rana et al. (2025). The above studies collectively show high-level concepts of AI-IDS implementation, including these issues: scalability, computational performance, the quality of data used, and interface versatility across the protocols are critical to establish robust and reliable intrusion detection in industrial control networks.

Best Practices and Frameworks for Industrial AI Security Implementation

Extensive monitoring, dynamic learning, and automating responses are the key elements of the effective AI security frameworks that apply in the industrial networks. Khan (2024) also proposes the use of multiple feature selection approaches with multistage deep learning models in order to ensure the best performance in detection. In Hassan et al. (2021), threat-modeling frameworks including dynamic anomaly scoring and access behavior profiling of smart manufacturing networks are proposed. Yellepeddi et al. (2024) show the use of parallelizing deep learning pipelines to undertake real-time traffic analysis and event correlation. According to Ejeobiri et al. (2024), federated learning should be included in the distributed network of IoT so that data privacy is mitigated but the model accuracy remains the same.

Framework Type	Automated Response (%)	Scalability Score (1-5)	Detection Improvement (%)	Deployment Layer
Hierarchical Deep Learning	88	4	12	Cloud
Dynamic Threat Modeling	85	4	10	Smart Manufacturing
Parallelized Deep Learning Pipeline	90	5	14	Industrial Network
Federated Learning Framework	86	5	11	IoT Network
SCADA-Aware AI Integration	92	4	15	SCADA Layer
Containerized Edge Deployment	87	5	12	Edge Layer

Hybrid Signature-Anomaly IDS	89	4	13	Mixed ICN

Table 4: Best Practices and Frameworks for Industrial AI Security Implementation

According to Rai et al. (2025), it is recommended to integrate them with SCADA-specific protocols to prevent intrusion, automatic incident response, and feedback loops to retrain the models. Wang and others (2022) also emphasize on scalable deployment programs through the use of containerization, and edge computing in order to achieve low latency detection. These practices are synthesized by Rana et al. (2025), who emphasize the concept of hybrid architectures that unite signature-based and anomaly-based IDS and orchestrate them based on AI. Taken together, these results suggest that any AI-IDS implementation into such complex industrial control networks is best conducted in a harmonic framework that embraces adaptive learning, parallel computing, protocol-interface consideration and integration to provide high level reliability, scalability, and capacity to proactively mitigate threats.

Conclusion

The use of AI-IDS in cybersecurity of industrial control networks reduces the potential risks to high levels as the systems can detect and mitigate threats in real-time and in an adaptive fashion. Combining machine and deep learning models enables it to identify difficult patterns of attacks such as zero-day exploits, insiders and distributed denial-of-service attempts. Research points to higher detection rates with lower false positives as well as scalability in heterogeneous ICNs, although there are issues in the research around data heterogeneity, computation overheads and compatibility with legacy protocols. Humanities best practices are focused on hybrid models, federated learning, and automatic response systems that would enhance resilience of operation. Altogether, AI-IDS is the revolutionary technology that could effectively protect industrial enterprises against the threats of numerous and various cyber-attacks.

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