A Survey of Security Frameworks for Industrial Internet of Things Using Artificial Intelligence: Detection and Prevention Approaches

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***Abstract*—Industrial systems have changed significantly with the arrival of connected devices and sensors. These Industrial Internet of Things (IIoT) setups allow factories, power plants, and hospitals to monitor operations in real time and make automatic decisions. However, connecting physical equipment to digital networks brings serious security risks. Old security methods often do not work well in these industrial settings because they have special needs like fast response times, old equipment still in use, and limited computing power.**

This paper looks at how artificial intelligence methods are being used to make IIoT systems more secure. We examine different AI approaches for finding intrusions, spotting unusual activities, and gathering threat information. The paper compares various AI methods and analyzes how well they work in real industrial situations. We also discuss problems in implementing these solutions and suggest ways to make them better in the future.

***Index Terms*—Industrial IoT, Security, Artificial Intelligence, Intrusion Detection, Anomaly Prevention, Simulation, Test-beds**

I. Introduction

Industrial operations have entered a new phase with connected devices and sensors. Manufacturing plants, energy systems, and healthcare facilities now use networks of smart devices that share information and control physical processes. This Industrial Internet of Things makes operations more efficient but also creates new security problems.

Security in industrial settings is especially challenging. Old industrial control systems were kept separate from other networks, but IIoT connections have opened them to attacks. Hackers can now try to stop production, change sensor readings, or damage equipment remotely. Real attacks on power systems and factories show these dangers are real and serious.

Traditional security tools have limitations in industrial environments. Methods that look for known attack patterns may miss new types of attacks. Systems that follow fixed rules need constant updating. The mix of different devices, communication methods, and the need for instant responses makes security difficult to implement properly.

Artificial intelligence provides new possibilities for industrial security. AI methods can learn what normal operations look like and notice when something unusual happens. They can adapt to new threats without needing complete reprogramming. This flexibility is valuable in industrial settings where threats keep changing and old security approaches may not be sufficient.

This paper reviews AI-based security methods for industrial IoT systems. Section II explains different AI approaches. Section III looks at intrusion detection systems. Section IV examines methods for finding unusual activities. Section V discusses threat information systems. Section VI reviews evaluation methodologies. Section VII compares different approaches. Section VIII shows real examples. Section IX discusses problems and future work. Section X concludes [1], [2], [3], [4], [5].

II. AI Methods for Industrial Security

A. Learning with Labeled Data

Some AI methods work with data that has been marked as normal or suspicious. Support Vector Machines create boundaries to separate safe from unsafe activities in network data. These work well for finding subtle attack patterns in industrial networks.

Random Forest methods use multiple decision trees together. This approach gives reliable results for classifying attacks and helps security staff understand which system measurements best indicate problems. Gradient Boosting methods keep improving by focusing on examples that were previously identified incorrectly, making them good for finding complex multi-step attacks [6], [7], [8].

B. Learning Without Labels

Other methods work with data that hasn't been labeled. K-Means grouping finds similar patterns in network behavior and helps identify unusual activities. This is useful in industrial settings where normal operations are consistent but attack methods may be unknown.

Autoencoders are neural networks that learn compressed versions of normal system behavior. When they cannot properly reconstruct input data, it suggests something unusual might be happening. Isolation Forest methods efficiently find unusual data points by randomly selecting features, requiring less calculation than other methods and working well in industrial settings with limited computing resources [9], [10], [11].

C. Deep Learning Methods

Deep learning handles complex data common in industrial systems. Convolutional Neural Networks find patterns in network traffic or sensor readings. Recurrent Neural Networks and Long Short-Term Memory networks work with data over time, making them suitable for detecting attack sequences that develop gradually.

Generative Adversarial Networks have two parts that work against each other. They can create synthetic attack data for training when real attack examples are scarce. They also help train systems to resist manipulated inputs designed to avoid detection [12], [13], [14].

D. Learning Through Interaction

Reinforcement learning helps systems learn security policies by trying different approaches. Q-learning and Deep Q-Networks have been used to create response strategies that balance detection accuracy with keeping operations running. Multi-agent approaches coordinate security actions across different parts of industrial systems without needing central control [15], [16].

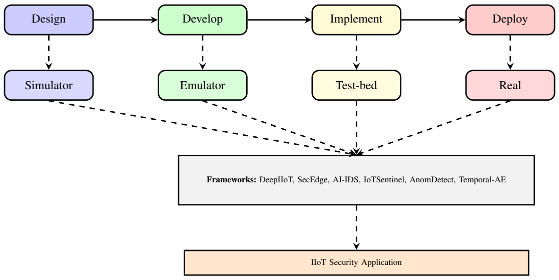
Design
Develop
Implement
Deploy
Simulator
Emulator
Test-bed
Real
Frameworks: DeepIIoT, SecEdge, AI-IDS, IoTSentinel, AnomDetect, Temporal-AE
IIoT Security Application

Fig. 1: AI Security Framework Development Methodology

III. Intrusion Detection for Industrial Systems

Intrusion Detection Systems watch network traffic and system activities for signs of attacks. AI-enhanced systems offer better detection for industrial environments.

A. Network-Based Detection

Network-based systems analyze communication between industrial devices. One approach uses combined neural network designs to find multiple attack types in industrial control networks. This system achieves high accuracy while keeping response times fast enough for industrial operations.

Another method uses federated learning with classification algorithms for distributed detection at network edges. This design protects privacy by allowing different industrial sites to improve detection models without sharing sensitive operational data. It works with industrial communication protocols commonly used in automation [17], [18].

B. Device-Based Detection

Device-based systems monitor activities on individual industrial controllers. One system uses Random Forest methods to analyze system activities, process behaviors, and resource usage. It achieves good accuracy with few false alarms, reducing unnecessary production stops in manufacturing.

Another approach uses autoencoder designs for lightweight detection on industrial devices with limited capabilities. The method compresses normal behavior patterns and notices deviations, requiring little computing power. This works well for older industrial equipment still in use [19], [20].

C. Protocol-Specific Detection

Industrial networks use special protocols needing tailored approaches. One system uses gradient boosting to detect manipulation of industrial communication commands and values. It finds both obvious attack commands and subtle data changes that might bypass simpler checks.

Another method uses LSTM networks to analyze patterns in power grid communications. It learns normal interaction patterns between control systems and detects deviations that might indicate scanning, command injection, or denial attempts [21], [22].

TABLE I: Network Intrusion Detection Frameworks

Framework	AI Technique	Acc (%)	Lat (ms)	Protocol
DeepIIoT	CNN-LSTM	98.7	15	Modbus/TCP
SecEdge	Fed. SVM	96.2	25	OPC UA
AI-IDS	Random Forest	95.8	10	Multiple
IoTSentinel	Autoencoder	96.8	20	Multiple

IV. Finding Unusual Activities

Anomaly detection identifies deviations from normal operations that might indicate security problems or system faults.

A. Behavior-Based Detection

One framework uses Isolation Forest methods to find unusual behaviors in manufacturing systems. It analyzes sensor readings, control commands, and production measurements to detect subtle manipulations that might indicate insider threats or compromised devices. Implementation in car factories reduced false alarms significantly compared to older methods.

Another approach uses temporal autoencoders for finding unusual patterns in power grid data. The method learns normal patterns in grid measurements and detects false data injections meant to mislead operators. Testing showed high accuracy while maintaining grid stability during simulated attacks [23], [24].

B. Resource Monitoring

One system uses Light Gradient Boosting Machine algorithms to monitor resource usage in medical devices. It analyzes processor use, memory allocation, network activity, and power consumption to identify compromised devices or unauthorized data transfers. The method's efficiency allows use on devices with limited capabilities [25].

C. Process Monitoring

Another approach uses convolutional neural networks to analyze equipment vibrations, temperatures, and pressures. By learning normal operational signatures, the system detects subtle changes that might indicate attacks manipulating sensor readings or control signals. Early detection helps with preventive maintenance and reduces equipment damage risks [26].

TABLE II: Anomaly Detection Framework Comparison

Framework	AI Method	Acc (%)	FP (%)	Application
AnomDetect	Iso. Forest	97.3	2.1	Manufacturing
Temporal-AE	Autoencoder	99.1	0.8	Power Grid
EdgeAnomaly	LightGBM	97.5	2.3	Healthcare
ProcessGuardian	CNN	98.2	1.1	Industrial

V. Threat Information Systems

Threat intelligence systems collect, analyze, and share information about current and emerging threats to industrial environments.

A. Knowledge-Based Systems

One system combines natural language processing with knowledge structures to extract threat information from security reports, vulnerability databases, and monitoring sources. It identifies attack patterns targeting specific industrial areas and suggests protective measures. Cloud-based operation allows timely updates as new threat information appears.

Another platform uses reinforcement learning for proactive threat searching in industrial control systems. It simulates possible attack situations, evaluates system weaknesses, and recommends security improvements before exploitation happens. Hybrid deployment balances computing needs with response time requirements [27], [28].

B. Collaborative Information Sharing

One system uses deep learning for security information management in industrial settings. It connects alerts from different detection sources, reduces false alarms through context analysis, and provides useful insights to security staff. Local installation addresses data privacy concerns common in industrial organizations.

Another approach enables privacy-protecting threat information sharing among industrial companies. Participating organizations train local detection models using their operational data, then share model improvements rather than raw data. This cooperative method improves detection while protecting sensitive industrial information [29], [30].

TABLE III: Threat Intelligence Features

Framework	AI Technique	Functionality	Deployment
ThreatIntel-IIoT	NLP+KG	Pattern Recog.	Cloud
CPS-Guardian	RL	Proactive	Hybrid
IIoT-SIEM	DL	Event Mgmt.	On-premise
Fed. Exchange	FL	Sharing	Distributed

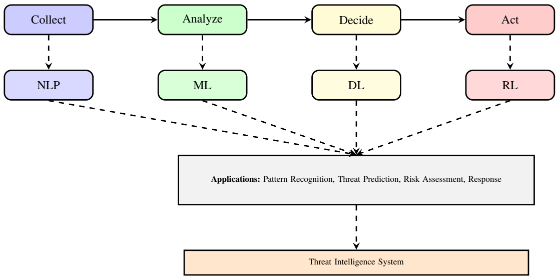
Collect
Analyze
Decide
Act
NLP
ML
DL
RL
Applications: Pattern Recognition, Threat Prediction, Risk Assessment, Response
Threat Intelligence System

Fig. 2: Threat Intelligence System Architecture

VI. Simulation, Emulation and Test-beds for IIoT Security Evaluation

A. Evaluation Methodologies

AI-driven IIoT security frameworks require rigorous testing before industrial deployment. Three primary methodologies exist: simulation, emulation, and test-bed implementation. Each approach offers distinct advantages for different development stages [41].

B. Simulation Tools

Simulators provide high-level abstraction for early-stage testing. Table IV compares simulators relevant to IIoT security.

TABLE IV: Simulation Tools for IIoT Security

Simulator	Focus	Scale	Security Use
OMNeT++	Network Protocols	Large	Protocol attacks
NS-3	Network Security	Large	DDoS, MITM testing
iFogSim	Edge Computing	Medium	Edge attacks
IOTSim	Cloud IoT	Large	Cloud analysis
Cooja	WSN Security	Small	Sensor detection
IoTIFY	IoT Devices	Large	Device attacks

C. Emulation Platforms

Emulation bridges simulation and real implementation. Key platforms include Cooja for testing intrusion detection on constrained IIoT nodes, NetSim for simulating protocol-specific industrial network attacks, and MAMMotH for large-scale device emulation for stress testing [42].

D. Test-bed Implementations

Test-beds provide realistic environments for comprehensive evaluation. Table V compares relevant test-beds.

TABLE V: Test-beds for IIoT Security Validation

Test-bed	Focus Area	Scale	Security Testing
FIT IoT-LAB	WSN/IoT Devices	Large	Physical attacks [44]
FIESTA-IoT	Federated IoT	Large	Cross-domain [45]
Smart Santander	Smart City IoT	Large	Infrastructure
MBTAAS	Model-based Testing	Variable	Automated testing

E. Comparative Analysis

Simulators offer maximum configurability but limited realism. Emulators provide better accuracy by executing real code. Test-beds offer highest realism with actual/virtualized hardware [43].

F. Practical Applications

Surveyed frameworks can be evaluated using NS-3 for network attacks, FIT IoT-LAB for device validation, iFogSim for edge deployment scenarios, and Cooja for federated learning on constrained devices.

VII. Comparison of Approaches

TABLE VI: Performance Comparison of AI-Driven IIoT Security Frameworks

Framework	AI Method	Acc (%)	FA (%)	Time (ms)	Compute	Real-Time
DeepIIoT	Combined NN	98.7	1.2	15	High	Yes
SecEdge	Fed. SVM	96.2	2.8	25	Medium	Yes
AI-IDS	Random Forest	95.8	1.5	10	Low	Yes
AnomDetect	Iso. Forest	97.3	2.1	30	Medium	Yes
Temporal-AE	Autoencoder	99.1	0.8	45	High	Limited
ThreatIntel	NLP+Knowledge	94.5	3.5	100	High	No

Evaluation used standard network attack datasets and specialized industrial datasets including water system data and manufacturing information.

VIII. Real-World Examples

A. Manufacturing Implementation

A car manufacturer implemented detection systems across production facilities to protect connected assembly lines. The systems found unauthorized access attempts from compromised computers and identified abnormal equipment movements suggesting possible sabotage. Integration with existing security operations reduced response time from hours to minutes while keeping production running [31].

B. Power System Protection

A national power company deployed detection systems across substations to protect against false data attacks. The systems identified manipulated voltage and current measurements that could have caused incorrect grid responses. During simulated attacks, AI-based detection gave alerts much faster than traditional methods, allowing operators to maintain grid stability [32].

C. Medical Device Security

A hospital network implemented detection methods on connected medical equipment including infusion pumps, patient monitors, and imaging systems. The lightweight detection found unusual network patterns suggesting possible ransomware spread and detected unauthorized configuration changes to device settings. The privacy-protecting design followed healthcare data rules while improving security [33].

IX. Problems and Future Work

A. Technical Problems

Adversarial attacks are a concern for AI security systems. Attackers can create inputs specifically designed to avoid detection while still being malicious. Developing systems resistant to such attacks needs continued research.

Understanding why AI systems make specific decisions remains difficult, especially for complex neural networks. Industrial operators need to understand alert reasons to make good response decisions. Research in explainable AI must progress to provide clear insights without losing detection accuracy [34], [35].

B. Implementation Problems

Real-time requirements in industrial settings limit how complex AI models can be. Balancing detection accuracy with computing efficiency remains challenging, especially for devices with limited capabilities. Model simplification methods, efficient designs, and hardware acceleration offer possible solutions [36].

Lack of attack examples limits model training effectiveness. Industrial companies often hesitate to share security incident data due to competition concerns and regulations. Synthetic data creation, transfer learning, and federated approaches can help with this limitation [37].

C. Future Directions

Combined AI designs using multiple methods might offer better performance. For example, mixing supervised learning for known attacks with unsupervised approaches for new threats could provide complete protection. Reinforcement learning could dynamically adjust detection settings based on changing threat situations [38].

Blockchain technology could improve threat information sharing while keeping data integrity. Distributed records could provide tamper-proof logs of security events and enable trusted cooperation among industrial organizations [39].

Quantum-resistant security will become more important as quantum computing advances. Research should explore AI models that maintain security even when basic security methods might be broken by quantum attacks [40].

Human-AI cooperation frameworks can use human expertise to check AI findings and guide improvements. Interactive systems combining automated detection with human review might achieve the best balance between automation and human judgment.

X. Conclusion

This paper has examined how artificial intelligence methods are being applied to improve security in Industrial Internet of Things environments. AI approaches offer important advantages over traditional security methods for finding intrusions, identifying unusual activities, and developing threat information in complex industrial systems.

The reviewed methods show good results across different industrial areas, with detection accuracies above 95% in many cases. However, problems remain in areas including resistance to manipulation, understandability, real-time performance, and data availability. Future work should address these limitations while exploring combined designs, blockchain integration, quantum resistance, and human-AI cooperation.

As industrial IoT use continues to grow across important infrastructure areas, developing effective, adaptable, and trustworthy AI-based security solutions will remain essential for protecting industrial systems against evolving threats. Continued work in this area will help create safer, more reliable industrial operations in our increasingly connected world.

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