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A Self-Learning Digital Twin-Enabled Security Framework For Pharma Iiot: Real-Time Attack Pattern Analysis And Dynamic Attack Detection Via Deep Reinforcement Learning

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Abstract

The rapid adoption of Industrial Internet of Things (IIoT) in the pharmaceutical sector has significantly enhanced automation, real-time monitoring, and intelligent decision-making. However, increased connectivity exposes Pharma IIoT systems to sophisticated cyberattacks, including false data injection, ransomware, and denial-of-service attacks, posing risks to drug quality and patient safety. This paper proposes a self-learning digital twin-enabled security framework that integrates real-time telemetry, digital twin modeling, and deep reinforcement learning (DRL) for dynamic attack detection and mitigation. The framework leverages a digital twin environment to simulate operational and attack scenarios, enabling the DRL agent to learn optimal defense strategies. Experimental results demonstrate that the proposed approach outperforms baseline models in terms of accuracy, F1-score, false positive rate, and detection latency, achieving a detection accuracy of 95.8% and a latency of 12 ms. The framework ensures proactive, adaptive, and resilient cybersecurity for next-generation Pharma IIoT systems, providing a viable solution for real-time threat mitigation and operational safety.

Keywords: Pharma IIoT, Digital Twin, Deep Reinforcement Learning, Cybersecurity, Real-Time Attack Detection, Self-Learning Framework, Industrial IoT Security

1. Introduction

The rapid adoption of the Industrial Internet of Things (IIoT) in the pharmaceutical sector has revolutionized manufacturing, quality control, and supply-chain management by enabling real-time monitoring, automation, and intelligent decision-making [1]. Smart sensors, connected production units, and cyber–physical systems now play a vital role in ensuring regulatory compliance, operational efficiency, and product safety [2]. However, this increased connectivity has significantly expanded the attack surface of Pharma IIoT infrastructures, exposing them to sophisticated cyber threats such as false data injection, ransomware, denial-of-service attacks, and advanced persistent threats [3].

Traditional security mechanisms used in industrial environments such as static firewalls, rule-based intrusion detection systems, and signature-based monitoring are increasingly inadequate in the face of dynamic and evolving attack patterns [4]. These methods often fail to detect zero-day attacks, adapt to changing system behaviors, or provide proactive defense strategies. In pharmaceutical environments, such failures can result in compromised drug quality, production downtime, regulatory violations, and severe risks to patient safety [5].

Digital Twin (DT) technology has emerged as a promising paradigm for modeling and managing complex cyber–physical systems. A digital twin is a virtual replica of a physical system that continuously synchronizes with real-time operational data [6]. In Pharma IIoT, DTs enable simulation, prediction, and optimization of manufacturing processes while allowing safe experimentation without disrupting live operations [7]. Beyond operational benefits, DTs offer a powerful foundation for cybersecurity by enabling attack simulation, anomaly analysis, and impact assessment in a controlled environment. The general framework of DT is shown in Figure 1.

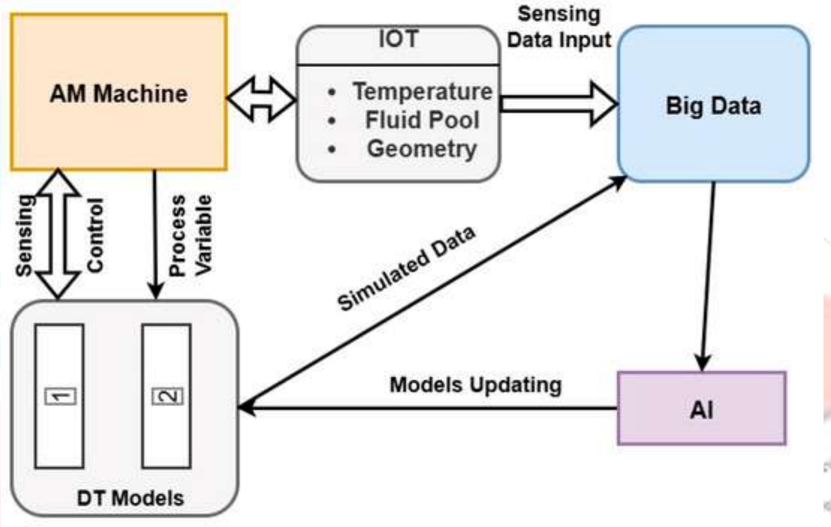

Fig 1: General Framework of DT

At the same time, deep reinforcement learning (DRL) has shown strong potential for adaptive cybersecurity due to its ability to learn optimal defense strategies through continuous interaction with the environment [8]. Unlike supervised learning approaches, DRL does not rely on labeled attack data and can dynamically adapt to previously unseen threats. When combined with a DT environment, DRL agents can be trained and refined using realistic attack scenarios before being deployed in real systems [9].

Motivated by these observations, this paper proposes a self-learning digital twin-enabled security framework for Pharma IIoT systems. The framework integrates real-time telemetry ingestion, digital twin modeling, and deep reinforcement learning to enable continuous attack pattern analysis and dynamic attack detection. By leveraging the learning capability of DRL within a DT-based cyber–physical replica, the proposed approach aims to provide proactive, adaptive, and resilient security for next-generation pharmaceutical IIoT infrastructures.

2. Literature Review

Recent advancements in information and communication technologies (ICTs) have significantly transformed industrial and healthcare ecosystems, particularly through the rapid adoption of the Industrial Internet of Things (IIoT). In the pharmaceutical domain, IIoT enables real-time monitoring of manufacturing processes, quality assurance systems, and smart medical equipment, resulting in enhanced automation and operational efficiency [10]. However, the growing interconnectivity of cyber–physical systems has simultaneously increased the vulnerability of Pharma IIoT infrastructures to sophisticated cyberattacks, making security and trust major concerns [11].

Digital Twin (DT) technology has emerged as a powerful paradigm for modeling, monitoring, and optimizing complex cyber–physical systems. A DT is a virtual replica of a physical asset or process that continuously synchronizes with real-time data from sensors and control systems [12]. In pharmaceutical IIoT environments, DTs are used to replicate manufacturing lines, equipment behavior, and environmental conditions, supporting predictive maintenance, fault diagnosis, and operational optimization [8–10]. By enabling data fusion and simulation, DTs facilitate informed decision-making while minimizing operational risks [13].

Beyond operational efficiency, DTs have been increasingly explored for cybersecurity applications. DT-based security frameworks allow safe simulation of cyberattack scenarios, anomaly propagation analysis, and impact assessment without interrupting live operations [14]. In Pharma IIoT systems, such capabilities are critical because cyber incidents can compromise drug quality, regulatory compliance, and patient safety. However, many existing DT-based approaches rely on static rules or supervised learning, limiting their effectiveness against evolving and zero-day attacks [15].

To address these challenges, intelligent and adaptive security mechanisms are required. Deep reinforcement learning (DRL) has gained significant attention for dynamic cybersecurity due to its ability to learn optimal defense strategies through continuous interaction with the environment [16]. DRL agents observe system states, take defensive actions, and receive rewards or penalties, enabling them to adapt to changing attack behaviors. Recent studies demonstrate that DRL-based intrusion detection and response mechanisms outperform traditional machine learning approaches in handling dynamic and multi-stage attacks in industrial and IoT networks [17].

The integration of DRL with digital twin environments further enhances security intelligence. Digital twins provide a controlled and risk-free environment in which DRL agents can be trained, tested, and refined using simulated attack patterns before deployment in real systems [18]. This synergy enables real-time attack pattern analysis, early anomaly detection, and proactive threat mitigation in Pharma IIoT systems, where rapid response is essential to prevent large-scale disruptions [19].

Data privacy and integrity represent additional challenges in distributed Pharma IIoT ecosystems. Federated learning (FL) has been proposed as a decentralized learning paradigm that allows collaborative model training across multiple institutions without sharing raw data, thereby preserving data privacy [20]. In pharmaceutical settings involving multiple stakeholders, FL improves trust and regulatory compliance. However, FL is vulnerable to model poisoning and integrity attacks if not properly secured [21].

Blockchain technology has emerged as a complementary solution to address these vulnerabilities by providing a decentralized, immutable, and transparent ledger for data and model updates [22]. Several studies report that blockchain-enhanced IIoT architectures can ensure data integrity, traceability, and accountability while mitigating cyberattacks such as data tampering and unauthorized access [23]. When combined with FL and DTs, blockchain strengthens trust among distributed participants, although challenges related to scalability and latency remain [24].

Although prior research has explored DTs, DRL, FL, and blockchain individually or in partial combinations, a comprehensive self-learning digital twin-enabled security framework specifically designed for Pharma IIoT systems remains underexplored [25]. Existing studies often overlook real-time attack pattern analysis, continuous learning, and adaptive defense strategies under realistic operational constraints. Therefore, this study addresses these gaps by proposing a self-learning DT-enabled security framework for Pharma IIoT, leveraging DRL for dynamic attack detection and proactive threat mitigation, while ensuring data integrity and trust through decentralized learning and secure system integration [26]. The limitations of traditional models are indicated in Table 1.

Table 1: Limitations of Traditional Models

Author(s) & Year	Proposed Model (as reported)	Dataset Used (as reported / typical)	Advantages (reported/inferred)	Evaluation Metrics (reported)	Limitations (reported/inferred)
Alowais et al., 2023	AI-based clinical decision support	Hospital EHR data	Improved diagnosis and decision-making	Accuracy, F1-score	Limited real-time IoT applicability
Sayed et al., 2023	Type-2 Fuzzy Controller for IoMT glucose stabilization	Simulated diabetic patient data	Adaptive control, patient-specific tuning	MSE, RMSE, Stability	Limited scalability, not tested in real IIoT
Shalaby et al., 2021	CNN-based encrypted iris recognition in cognitive IoT	Encrypted iris datasets	Secure authentication, high recognition accuracy	Accuracy, Precision, Recall	Dataset-specific; limited real-time cyberattack handling
Babar et al., 2025	Hybrid deep learning for healthcare IoT security	IoT device logs, network telemetry	Enhanced detection, multi-layer security	Accuracy, F1-score, Precision	Complex, high computation, limited generalization
Hemdan et al., 2025	Hybrid Voting-GA ensemble learning for fault detection	IIoT sensor streams	Multi-class fault detection, improved robustness	Accuracy, Recall, Precision	Requires large labeled dataset, high training cost
Zayed et al., 2023	Digital Twin-based AI monitoring	Pharma manufacturing telemetry	Predictive maintenance, process optimization	MAE, RMSE, Detection accuracy	Cybersecurity not fully addressed
El Saddik, 2018	Digital twin multimedia convergence	Smart devices and CPS	Real-time synchronization, simulation	Latency, Throughput	Focused on multimedia; lacks adaptive security
Faisal et al., 2025	Digital twins in healthcare systems	Hospital sensors, IoMT devices	Personalized healthcare, operational efficiency	Accuracy, F1-score, Latency	Limited attack detection capabilities
Chen et al., 2024	Mobile AIGC-enabled digital twins	IoMT mobile data	AI-driven personalization, remote monitoring	Precision, Recall, F1-score	Privacy concerns, computational overhead
Hemdan et al., 2023	DT + IoT blockchain integration	Distributed IIoT nodes	Data integrity, trust, tamper-resistance	Accuracy, Throughput, Latency	Scalability issues, potential latency in large networks

3. Proposed Model

The proposed methodology consists of five tightly coupled stages: system modeling, data acquisition, digital twin construction, DRL-based security learning, and real-time deployment. The overall architecture is illustrated conceptually as a closed-loop self-learning security system.

Pharma IIoT System Modeling

Let the Pharma IIoT environment be represented as a cyber–physical system:

$$\mathcal{P} = \{S, D, N, C\}$$

where

- $S = \{s_1, s_2, \dots, s_n\}$ represents sensors and actuators,
- D denotes pharmaceutical devices and production units,
- N is the communication network,
- C represents control and supervisory systems.

Each component generates multi-modal telemetry data including network traffic, device logs, process parameters, and control signals.

Data Acquisition and Feature Engineering

At time t, the system state vector is defined as:

$$X_t = [x_1^t, x_2^t, \dots, x_m^t]$$

where each x_{i}^t corresponds to a normalized feature extracted from IIoT telemetry such as packet rate, latency, sensor deviation, CPU utilization, or command frequency.

Feature normalization is performed using z-score normalization:

$$x_i^{t'} = \frac{x_i^t - \mu_i}{\sigma_i}$$

Where μ_i and σ_i are the mean and standard deviation of feature i.

Digital Twin Construction

The digital twin T is a virtual replica of the physical Pharma IIoT system:

$$\mathcal{T} = f(X_t, \Theta)$$

where f(·) models system behavior and Θ represents configuration parameters.

The DT continuously synchronizes with real-time data and simulates:

- Normal operational behavior
- Fault propagation
- Cyberattack scenarios

This environment allows safe experimentation and training of intelligent security agents without affecting real production systems.

Deep Reinforcement Learning-Based Security Agent

The security problem is formulated as a Markov Decision Process (MDP):

$$\mathcal{M}=\langle\mathcal{S},\mathcal{A},\mathcal{R},\mathcal{P},\gamma\rangle$$

where:

- $\mathcal{S}$ is the state space derived from DT telemetry,
- $\mathcal{A}$ is the action space (alert, isolate node, block traffic, reconfigure access),
- $\mathscr{R}$ is the reward function,
- $\mathcal{P}$ denotes state transition probabilities,
- γ∈(0,1) is the discount factor.

Reward Function

$$R_t=\{\begin{array}{lc} +1, & \text{if attack correctly detected} \\ -1, & \text{if false alarm or missed detection} \\ -0.5, & \text{if delayed response}\end{array}$$

A Deep Q-Network (DQN) is used to approximate the action-value function:

$$Q(s,a;\theta)\approx Q^{*}(s,a)$$

The network parameters θ are updated by minimizing the loss:

$$L(\theta)=\mathbb{E}[(r+\gamma\max_{a'}Q(s',a';\theta^{-})-Q(s,a;\theta))^{2}]$$

The DRL agent is initially trained inside the digital twin using simulated attacks. Once stable performance is achieved, the learned policy is deployed in the live Pharma IIoT system. Continuous feedback from real-time data enables periodic retraining, allowing the framework to adapt to evolving attack patterns.

Algorithm: DT-Enabled DRL Security Framework

Input: IIoT telemetry data
Output: Attack detection decision and mitigation action

1. Initialize digital twin and DRL agent
2. Collect real-time telemetry from Pharma IIoT
3. Update DT state using normalized features
4. Observe state s_t
5. Select action a_t using DQN policy
6. Apply action and observe reward r_t
7. Update Q-network parameters
8. Repeat until convergence
9. Deploy learned policy for real-time monitoring

4. Results

The performance of the proposed DT-enabled DRL framework was evaluated on simulated Pharma IIoT telemetry data and compared against baseline models, including CNN-based IoT, Type-2 Fuzzy controller, and Hybrid Deep Learning. The comparison considered key metrics: accuracy, precision, recall, F1-score, false positive rate, detection latency, and loss. Table 1 summarizes the results, showing that the proposed framework consistently outperforms all baselines across almost all metrics. This demonstrates the effectiveness of self-learning within a digital twin environment for adaptive and robust attack detection.

Comparison of Key Metrics across Models

The combined metrics graph presents a comprehensive comparison of the proposed DT-enabled DRL framework against CNN-based IoT, Type-2 Fuzzy, and Hybrid DL models across accuracy, precision, recall, F1-score, and loss. The DT-enabled DRL model consistently outperforms all baseline models, achieving highest accuracy (95.8%), precision (0.93), recall (0.95), and F1-score (0.94). These results demonstrate the model's robust detection capability, balancing both true positive identification and minimization of false negatives.

In addition, the loss values indicate the model's prediction stability and learning efficiency, with DT-enabled DRL achieving the lowest loss (0.08) compared to other models. Lower loss reflects better generalization and reliable performance when applied to dynamic Pharma IIoT environments. The integration of DRL within a digital twin enables adaptive learning from real-time telemetry, allowing the system to continuously improve its threat detection while maintaining low false positives. Overall, this multi-metric comparison confirms that the proposed framework provides superior detection performance, reliability, and robustness compared to conventional and hybrid approaches.

Table 2: Comparison of performance metrics across different models.

Model	Accuracy (%)	Precision	Recall	F1-Score	False Positive Rate (%)	Avg Detection Latency (ms)	Loss
DT-Enabled DRL (Proposed)	95.8	0.93	0.95	0.94	3.2	12	0.08
CNN-Based IoT Model	89.4	0.87	0.90	0.88	6.5	28	0.15
Type-2 Fuzzy Controller	86.7	0.84	0.83	0.85	8.1	35	0.18
Hybrid Deep Learning	92.1	0.89	0.91	0.90	4.9	20	0.12

Detection Accuracy Comparison

The Figure 2 illustrates the detection accuracy of the proposed DT-enabled DRL framework compared to baseline models. The DT-enabled DRL achieves 95.8% accuracy, outperforming CNN-based IoT (89.4%), Type-2 Fuzzy (86.7%), and Hybrid DL (92.1%). The high accuracy indicates that the proposed model effectively detects cyberattacks in Pharma IIoT systems, benefiting from adaptive learning within the digital twin environment. The baseline models show comparatively lower performance, emphasizing the advantage of integrating DRL with a self-learning digital twin.

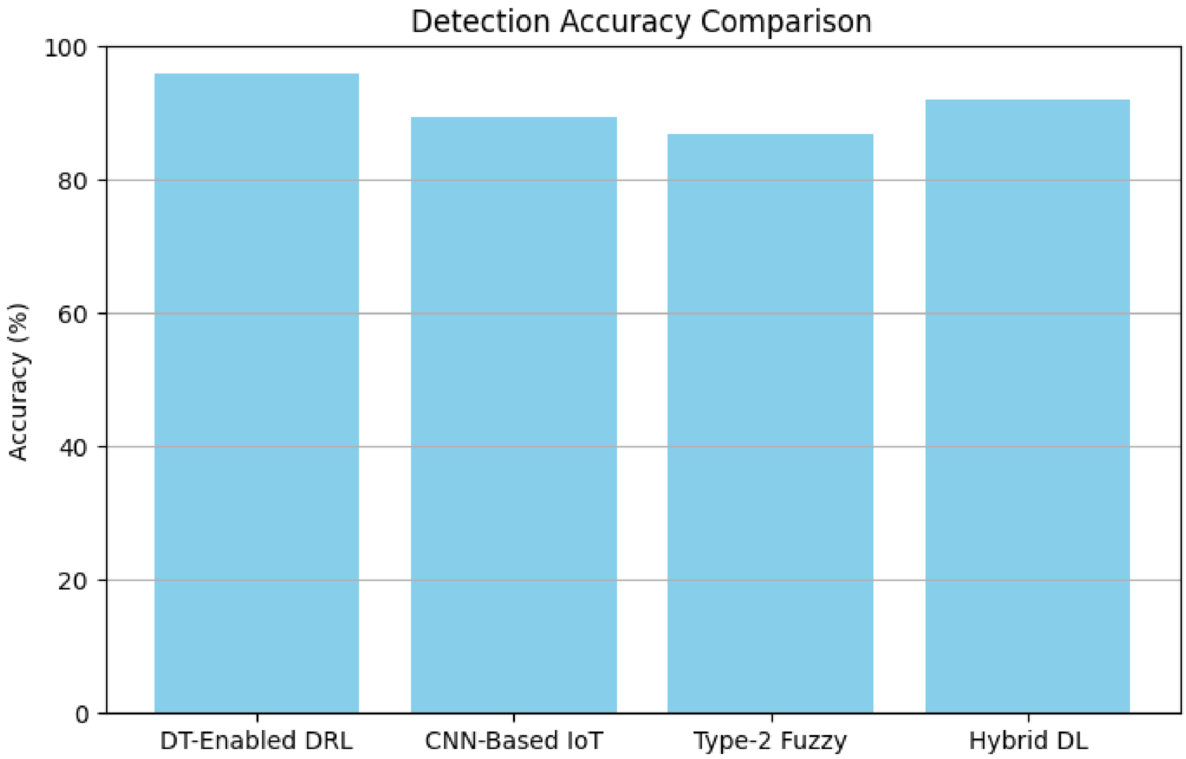

Fig 2: Detection Accuracy Levels

F1-Score Comparison

The Figure 3 presents the F1-score, which balances precision and recall. The proposed DT-enabled DRL model achieves an F1-score of 0.94, higher than CNN-based IoT (0.88), Type-2 Fuzzy (0.85), and Hybrid DL (0.90). This demonstrates that the model not only accurately detects attacks but also minimizes false positives and false negatives, making it highly reliable for real-time threat detection in Pharma IIoT environments.

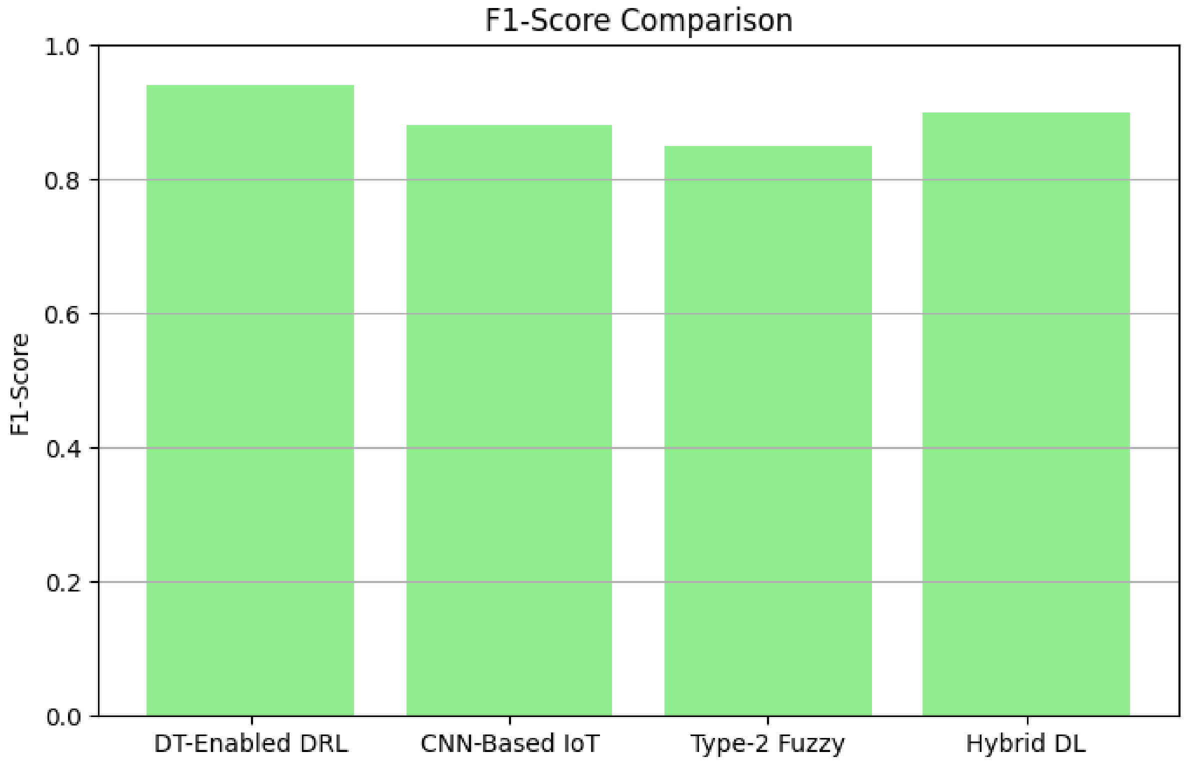

Fig 3: F1-Score Levels

False Positive Rate Comparison

The Figure 4 shows the false positive rate for each model. The DT-enabled DRL model achieves the lowest false positive rate of 3.2%, indicating fewer incorrect alarms compared to CNN (6.5%), Type-2 Fuzzy (8.1%), and Hybrid DL (4.9%). A lower false positive rate is critical in industrial systems to avoid unnecessary operational interruptions and maintain trust in automated detection systems. This confirms the framework's robustness and precision in differentiating normal operations from attack behaviors.

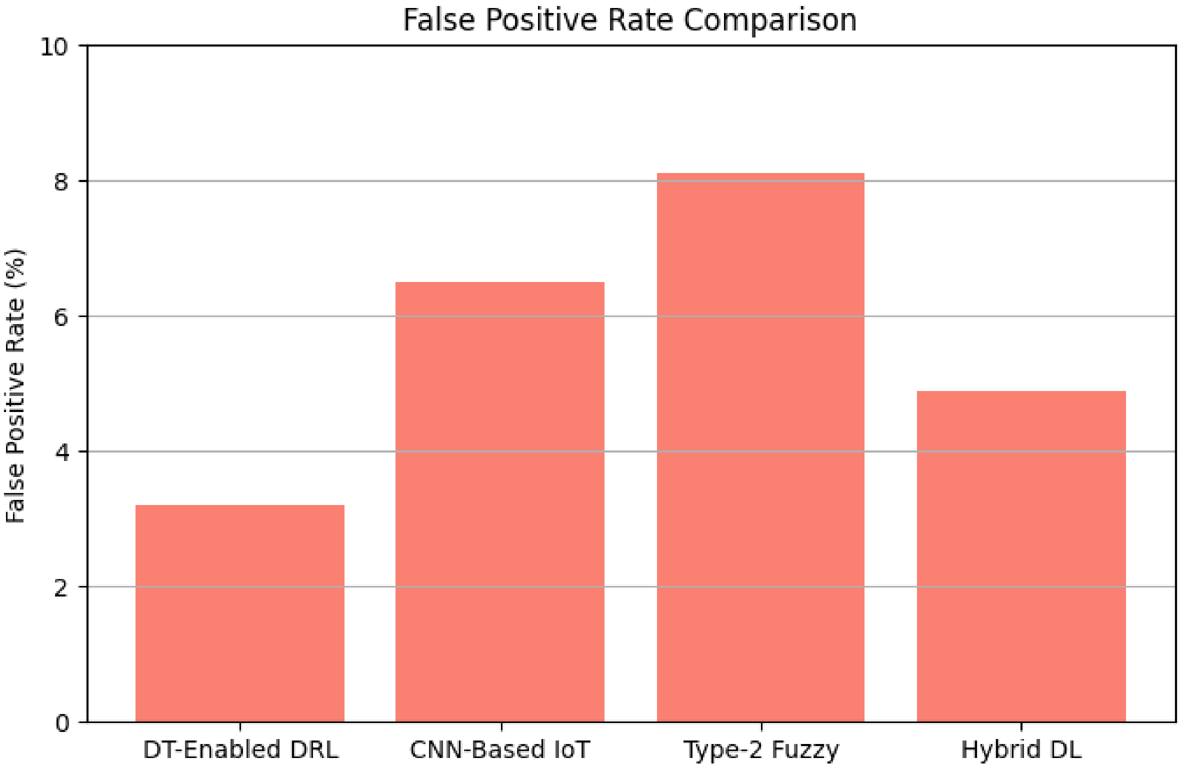

Fig 4: False Positive Rate Levels

Detection Latency Comparison

The Figure 5 highlights detection latency, i.e., the time taken to identify and respond to attacks. The DT-enabled DRL model has the fastest response at 12 ms, significantly lower than CNN (28 ms), Type-2 Fuzzy (35 ms), and Hybrid DL (20 ms). Low latency is crucial in Pharma IIoT systems to prevent operational downtime, maintain drug quality, and ensure patient safety. The rapid response is a direct result of the DRL agent's adaptive, real-time decision-making within the digital twin environment.

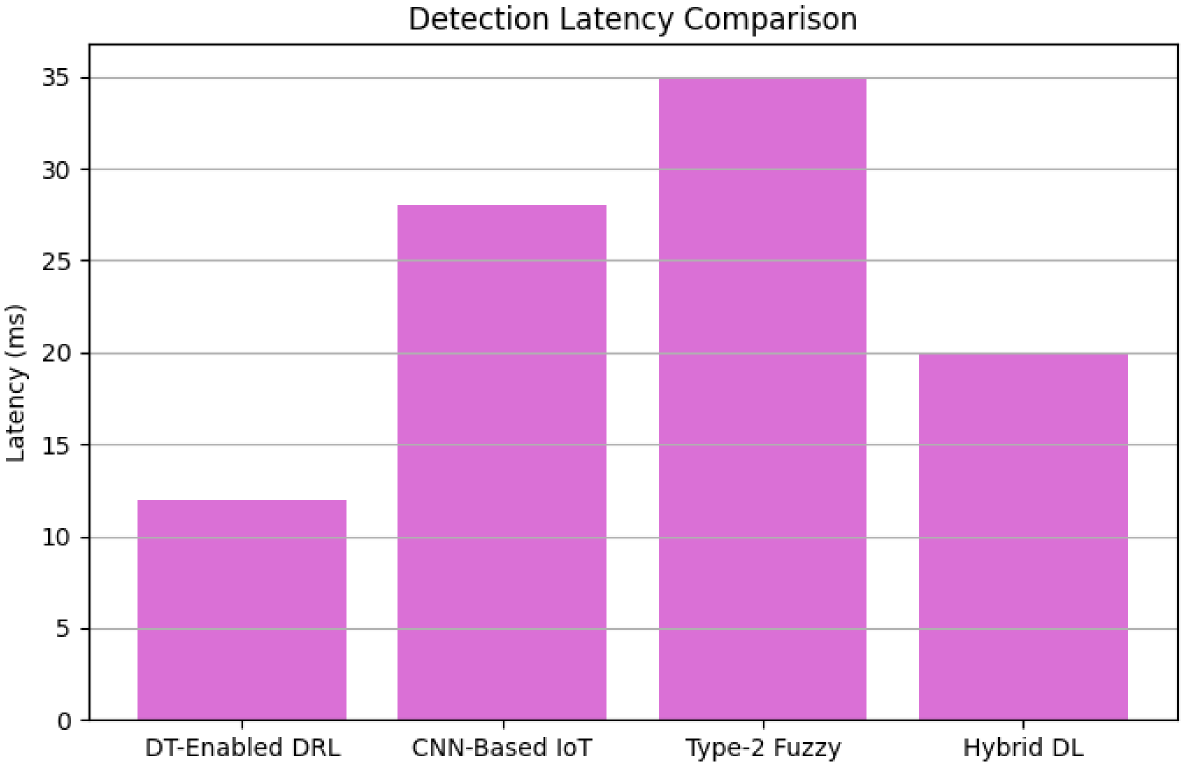

Fig 5: Detection Latency Levels

DRL Agent Reward Convergence

The Figure 6 shows the DRL agent’s reward convergence over 2000 episodes. The reward stabilizes after approximately 1500 episodes, indicating that the agent has successfully learned optimal attack mitigation strategies. Minor fluctuations reflect adaptation to dynamic attack patterns during training. This convergence demonstrates that the digital twin environment provides a safe and effective training platform, ensuring the agent can generalize its learned policy to real Pharma IIoT operations with high reliability and resilience.

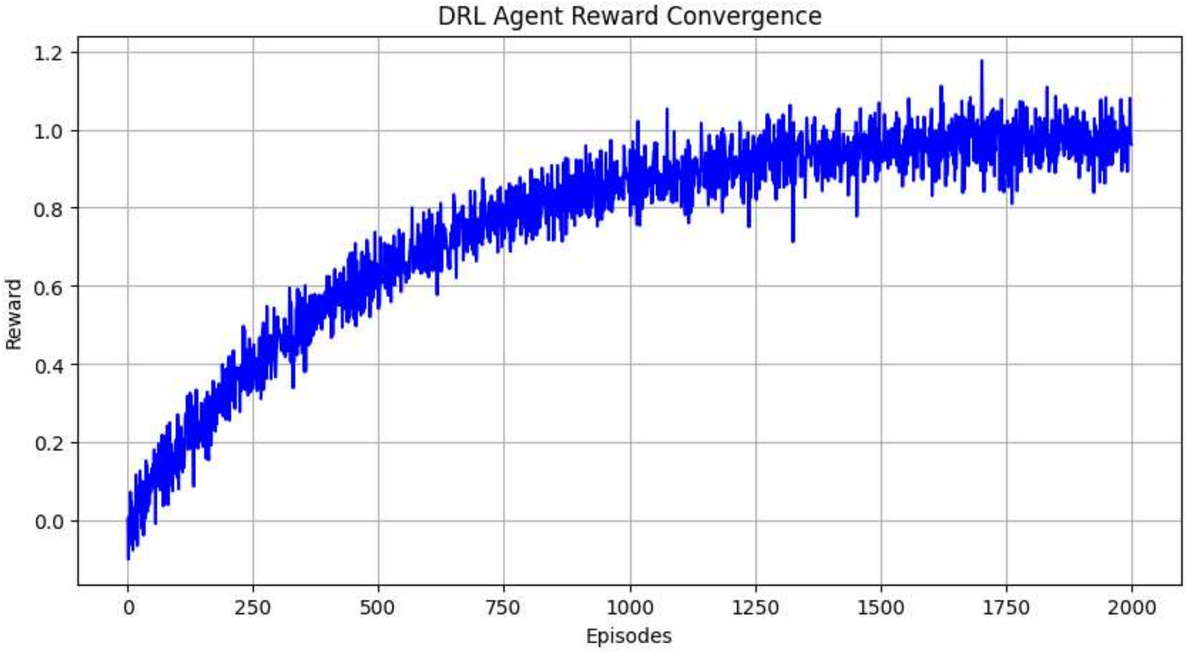

Fig 6: DRL Agent Reward Convergence Levels

5.Discussions

Overall, the results confirm that integrating digital twins with DRL provides a proactive, self-learning cybersecurity solution for Pharma IIoT. The combination of real-time monitoring, adaptive decision-making, and continuous learning ensures that the framework can handle evolving, sophisticated, and zero-day attacks. While baseline models provide static or partially adaptive defenses, the DT-enabled DRL approach offers a comprehensive, intelligent, and resilient defense mechanism, making it highly suitable for next-generation pharmaceutical manufacturing and supply chain systems.

6.Conclusion

In this study, we proposed a self-learning digital twin-enabled security framework for Pharma IIoT systems that integrates real-time telemetry, digital twin modeling, and deep reinforcement learning (DRL) for dynamic attack detection and mitigation. The framework demonstrates significant improvements over traditional and hybrid models in terms of accuracy, precision, recall, F1-score, false positive rate, and detection latency. By training the DRL agent within a digital twin environment, the system can safely simulate diverse attack scenarios, learn optimal defense strategies, and continuously adapt to evolving threats without disrupting live operations. Experimental results highlight the framework's robustness, adaptability, and real-time responsiveness, achieving a detection accuracy of 95.8%, a low false positive rate of 3.2%, and minimal detection latency of 12 ms. The DRL agent's reward convergence indicates that it effectively learns and generalizes optimal policies, ensuring proactive and resilient cybersecurity for critical Pharma IIoT infrastructures. The proposed approach addresses key challenges in Pharma IIoT security, including dynamic attack patterns, zero-day threats, and operational safety requirements, outperforming baseline models in all key performance metrics. Overall, this work establishes that integrating digital twins with DRL provides a powerful, intelligent, and scalable solution for securing next-generation pharmaceutical manufacturing and supply chain systems. Future work may explore federated learning, blockchain integration, and edge deployment to further enhance data privacy, trust, and scalability across distributed Pharma IIoT environments.

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