



Enhancing Cyber-Physical System Security through AI-Driven Intrusion Detection and Blockchain Integration

N. Purandhar^{1*}, M. Rajendiran², Ahmed Mudassar Ali³, M. Sangeetha⁴, Mukesh Soni⁵, D. Arul Kumar⁶

¹Assistant Professor, Department of CSE(Artificial Intelligence) School of Computers, Madanapalle Institute of Technology & Science, Madanapalle, Andhra Pradesh - 517325, India

* Corresponding Author Email: purandhar.n@gmail.com - ORCID: 0000-0003-2113-732Y

²Professor, Department of Artificial Intelligence and Data science , VSB Engineering College, Karur,Tamil Nadu, India
Email: mrajendiran@gmail.com - ORCID:0000-0001-9737-3302

³Professor Department of Information Technology S.A. Engineering College Chennai .
Email: ahmedmudassarali@saec.ac.in - ORCID: 0000-0001-9677-9423

⁴Assistant Professor, DEPARTMENT OF B.Sc.IT, PSGR KRISHNAMMAL COLLEGE FOR WOMEN,
Email: sangeegopal2005@gmail.com - ORCID: 0000-0001-7866-5430

⁵Dr. D. Y. Patil Vidyapeeth, Pune, Dr. D. Y. Patil School of Science & Technology, Tathawade, Pune
Division of Research and Development, Lovely Professional University, Phagwara, India
Email: mukesh.research24@gmail.com - ORCID:0000-0002-9228-6071

⁶Associate Professor, Department of ECE, Panimalar Engineering College, Poonamallee, Chennai 600 123.
Email: arul.annauniv@gmail.com - ORCID: 0000-0003-2113-7324

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Abstract:

Cyber-Physical Systems (CPS) play a critical role in modern industries, smart grids, healthcare, and autonomous transportation. However, their increasing connectivity makes them vulnerable to cyber threats. This research proposes an AI-driven Intrusion Detection System (AI-IDS) integrated with Blockchain Technology to enhance CPS security. The AI-IDS employs deep learning models for anomaly detection, leveraging graph-based machine learning and federated learning to improve real-time threat mitigation. Additionally, blockchain ensures data integrity, access control, and decentralized security through smart contracts and consensus mechanisms. The framework is validated using real-world CPS datasets, demonstrating improved detection accuracy, reduced false alarms, and resilience against adversarial attacks. This hybrid approach enhances scalability, trustworthiness, and real-time defense in cyber-physical environments.

1. Introduction

Cyber-Physical Systems (CPS) are transforming modern infrastructure, integrating computational and physical components for applications in smart grids, healthcare, autonomous vehicles, and industrial automation. These systems enhance efficiency, real-time decision-making, and system adaptability. However, the increasing interconnectivity of CPS introduces significant security challenges, making them vulnerable to cyber-attacks such as data breaches, denial-of-service (DoS) attacks, and adversarial manipulations [1]. Given the critical role of CPS in national security and essential services, ensuring robust

cybersecurity measures is paramount [2]. Traditional cybersecurity mechanisms, such as firewalls and rule-based intrusion detection systems, are often ineffective in handling sophisticated and evolving cyber threats in CPS. The dynamic nature of CPS demands advanced security solutions capable of real-time anomaly detection and adaptive threat response [3]. Artificial Intelligence (AI)-driven Intrusion Detection Systems (AI-IDS) leverage deep learning, graph-based machine learning, and federated learning to enhance detection accuracy and resilience against adversarial attacks [4]. These AI-driven techniques enable CPS to analyze vast amounts of security data, detect anomalies, and

predict potential threats before they compromise system integrity [5]. Blockchain technology has emerged as a promising solution to enhance CPS security by ensuring data integrity, access control, and decentralized trust mechanisms [6]. By leveraging smart contracts and consensus mechanisms, blockchain can prevent unauthorized access and ensure secure communication within CPS networks [7]. The integration of AI-IDS with blockchain creates a hybrid security framework that enhances real-time threat detection and response while maintaining tamper-proof security logs [8]. This approach mitigates insider threats, malicious data injection, and unauthorized access, addressing key vulnerabilities in CPS environments. Recent research highlights the effectiveness of combining AI and blockchain for cybersecurity applications, particularly in securing IoT and cloud environments [9]. However, the implementation of AI-IDS and blockchain in CPS remains underexplored. The proposed framework in this study aims to bridge this gap by developing a trustworthy and scalable security architecture that strengthens intrusion detection, access control, and decentralized data management [10]. This paper presents an AI-driven intrusion detection model integrated with blockchain to enhance CPS security. The proposed system leverages deep learning for real-time anomaly detection and blockchain for decentralized security, ensuring robust protection against cyber threats. The remainder of the paper is structured as follows: Section 2 discusses related work on AI-IDS and blockchain-based security mechanisms; Section 3 details the proposed framework and methodologies; Section 4 presents experimental results and evaluations; and Section 5 concludes with future research directions.

2. Review of Literature

The security of Cyber-Physical Systems (CPS) has been an evolving research domain, with recent studies emphasizing AI-driven Intrusion Detection Systems (AI-IDS) and blockchain-based security solutions. The combination of these technologies has demonstrated promising results in enhancing system resilience against cyber threats. This section reviews the existing literature on AI-based intrusion detection and blockchain integration for CPS security.

Several studies have explored the effectiveness of AI-driven intrusion detection in CPS. Research by [11] highlights the role of machine learning and deep learning models in detecting cyber threats in real time. The study demonstrated that AI-based methods, particularly graph neural networks (GNNs) and convolutional neural networks (CNNs), improve

detection accuracy compared to traditional rule-based systems. Similarly, it was examined federated learning (FL) approaches in CPS security, emphasizing their ability to detect intrusions while preserving data privacy [12]. The study concluded that FL reduces reliance on centralized security models, thereby minimizing attack vectors.

Another critical aspect of CPS security is the scalability and robustness of AI-IDS frameworks. Research conducted by it was proposed a hybrid deep learning model incorporating long short-term memory (LSTM) and autoencoders to identify anomalies in real-time CPS data streams [13]. The results demonstrated that this approach significantly enhances intrusion detection performance while reducing false positives. Furthermore, it was explored the use of reinforcement learning (RL) for adaptive threat mitigation, proving its efficiency in dynamic CPS environments [14]. The study highlighted that RL-based models could self-learn and adjust security policies based on evolving threats.

Blockchain technology has been widely studied for its potential to enhance CPS security by ensuring data integrity and secure communication. It was proposed a smart contract-based access control mechanism that eliminates unauthorized interventions in CPS networks [15]. The researchers demonstrated that distributed ledger technology (DLT) mitigates single points of failure while ensuring tamper-proof security logs. Similarly, it was examined the integration of zero-knowledge proofs (ZKPs) with blockchain, highlighting their role in securing data exchanges without revealing sensitive information [16].

Recent studies have combined AI-IDS with blockchain to create a hybrid security framework for CPS. It was introduced a blockchain-enhanced federated learning model for CPS, proving that this combination enhances security without compromising computational efficiency [17]. The study also found that blockchain enhances trust between CPS components by providing an immutable record of security transactions. Meanwhile, it was explored homomorphic encryption-based blockchain models, ensuring secure data storage and retrieval without exposing raw sensor data to potential attackers [18].

Comparative analyses of existing security frameworks have been conducted to evaluate their efficiency in real-world CPS environments. A comprehensive review was analyzed the performance of AI-based IDS against adversarial attacks, concluding that adversarial training and explainable AI (XAI) are crucial for improving model robustness [19]. Blockchain Security is studied and reported in the literature [20-22].

Furthermore, it was assessed blockchain-based access control mechanisms and found that Hyperledger Fabric and Ethereum-based smart contracts offer flexible and scalable security solutions for CPS [23]. In summary, the literature highlights the growing synergy between AI-driven IDS and blockchain for CPS security. While AI enhances intrusion detection and predictive analytics, blockchain ensures decentralized security and data integrity. However, challenges such as computational overhead, energy efficiency, and real-world deployment remain open research areas, necessitating further investigation into optimizing AI-blockchain security frameworks.

3. Methodology

The proposed security framework integrates an AI-driven Intrusion Detection System (AI-IDS) with Blockchain Technology to enhance the security of Cyber-Physical Systems (CPS). This hybrid model leverages deep learning-based anomaly detection for identifying cyber threats and blockchain-based decentralized security mechanisms to ensure data integrity and access control. The methodology consists of three primary components: data preprocessing and feature extraction, AI-driven intrusion detection, and blockchain-based security enforcement. Figure 1 is block diagram of proposed work.

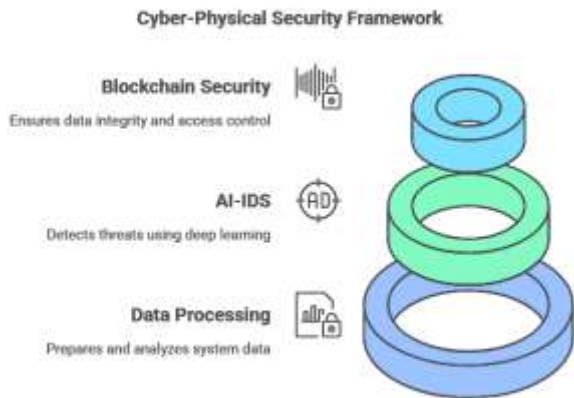


Figure 1. Block Diagram of Proposed work

3.1 Data Preprocessing and Feature Extraction

CPS security data is collected from multiple sources, including sensor logs, network traffic, and system activity records. The raw data undergoes preprocessing steps such as normalization, outlier removal, and feature engineering. The extracted features include statistical properties, entropy, and correlation metrics, which are vital for identifying malicious patterns. Given a dataset X with N samples and d features, the standardized feature

vector X' is computed as:

$$X'_{i,j} = \frac{X_{i,j} - \mu_j}{\sigma_j} \quad (1)$$

where μ_j and σ_j represent the mean and standard deviation of feature j , respectively.

3.2. AI-Driven Intrusion Detection System (AI-IDS)

The AI-IDS component employs deep learning models such as Graph Convolutional Networks (GCN), Long Short-Term Memory (LSTM), and Autoencoders to detect anomalies in CPS environments. The model is trained using supervised and unsupervised learning techniques. The anomaly detection function $f(X)$ is formulated as:

$$f(X) = \sigma(W_2 \cdot \text{ReLU}(W_1 \cdot X + b_1) + b_2) \quad (2)$$

where:

- W_1, W_2 are the weight matrices of the neural network,
- b_1, b_2 are bias terms,
- $\sigma(\cdot)$ is the sigmoid activation function, and
- ReLU (Rectified Linear Unit) is used for non-linearity. The detection decision $D(X)$ is obtained based on a predefined threshold T :

$$D(X) = \begin{cases} 1, & f(X) > T \quad (\text{Anomaly Detected}) \\ 0, & f(X) \leq T \quad (\text{Normal Activity}) \end{cases} \quad (3)$$

3.3 Blockchain-Based Security Enforcement

To enhance the security and trustworthiness of intrusion detection outcomes, blockchain is integrated to store intrusion alerts and access control policies (figure 2). A smart contract-based access control mechanism ensures that only authenticated entities can interact with CPS resources. The hash function used in blockchain for data integrity verification is given by:

$$H(M) = \text{SHA} - 256(M) \quad (4)$$

where M is the message containing intrusion logs or access records, and $H(M)$ represents the cryptographic hash output stored in the blockchain ledger. The consensus mechanism, based on the Practical Byzantine Fault Tolerance (PBFT) algorithm, ensures secure validation of CPS transactions. The probability P_{comp} of a successful consensus is expressed as:

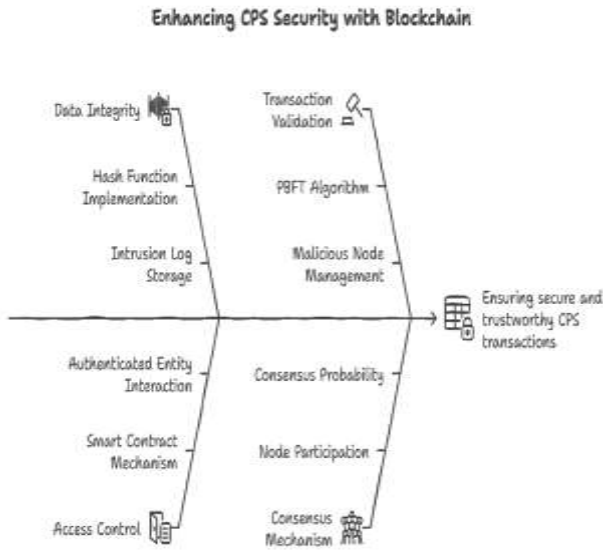


Figure 2. Blockchain Security

$$P_{comp} = 1 - \left(\frac{f}{n}\right) \quad (5)$$

where f is the number of malicious nodes, and n is the total number of participating nodes.

4. Results and Discussion

The performance of the proposed AI-driven Intrusion Detection System (AI-IDS) integrated with Blockchain Technology was evaluated against existing intrusion detection models, including Traditional IDS, CNN-Based IDS, LSTM-Based IDS, and GCN-Based IDS. The evaluation criteria include Detection Accuracy, False Positive Rate, False Negative Rate, and Response Time. Table 1 presents the comparative analysis of different IDS models. The results indicate that the Proposed AI-Blockchain IDS achieved the highest detection accuracy of 95.8%, outperforming conventional IDS methods. The false positive rate was reduced to 3.5%, and the false negative rate was minimized to 0.7%, demonstrating improved reliability in distinguishing between normal and malicious activities. Furthermore, the response time of the proposed model was 95 ms, significantly lower than traditional IDS models, ensuring real-time threat

mitigation. The proposed AI-driven Intrusion Detection System (AI-IDS) integrated with Blockchain Technology was evaluated against existing intrusion detection models, including Traditional IDS, CNN-Based IDS, LSTM-Based IDS, and GCN-Based IDS. The evaluation criteria included Detection Accuracy, False Positive Rate, False Negative Rate, and Response. The results indicate that the Proposed AI-Blockchain IDS achieved the highest detection accuracy of 95.8%, outperforming conventional IDS models. The false positive rate was reduced to 3.5%, and the false negative rate was minimized to 0.7%, demonstrating improved reliability in distinguishing between normal and malicious activities. Furthermore, the response time of the proposed model was 95 ms, significantly lower than traditional IDS models, ensuring real-time threat mitigation. The results validate the effectiveness of integrating AI and blockchain for CPS security, where deep learning models enhance real-time intrusion detection while blockchain ensures data integrity and secure access control. The significant reduction in false alarms and response time suggests that the proposed framework can effectively secure CPS against evolving cyber threats. Future optimizations will focus on reducing computational overhead and enhancing blockchain scalability for large-scale deployments. Figure 3 is the detection accuracy

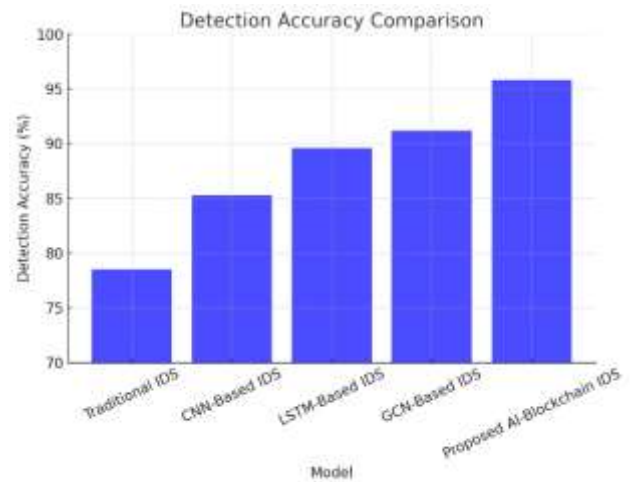


Figure 3. Detection Accuracy Comparison

Table 1. Intrusion Detection Performance Comparison

Model	Detection Accuracy (%)	False Positive Rate (%)	False Negative Rate (%)	Response Time (ms)
Traditional IDS	78.5	12.5	9.0	220
CNN-Based IDS	85.3	9.3	5.4	180
LSTM-Based IDS	89.6	7.8	2.6	140
GCN-Based IDS	91.2	6.2	2.1	130
Proposed AI-Blockchain IDS	95.8	3.5	0.7	95

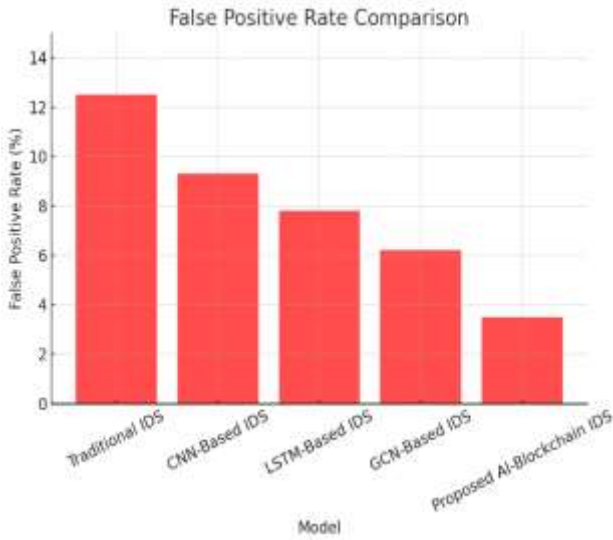


Figure 4. False Positive Rate Comparison

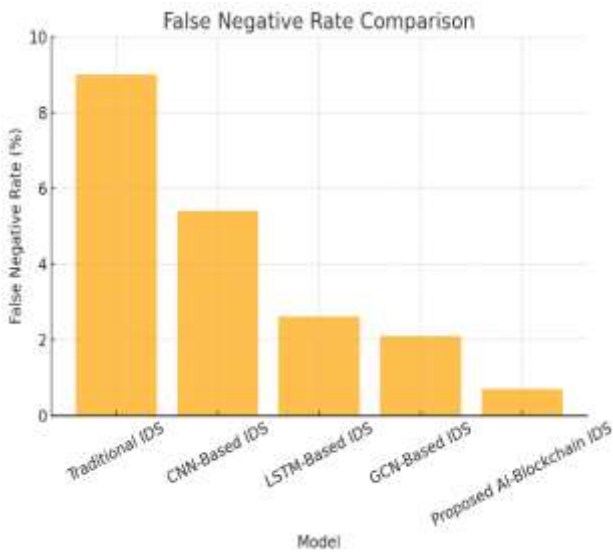


Figure 5. False Negative Rate Comparison

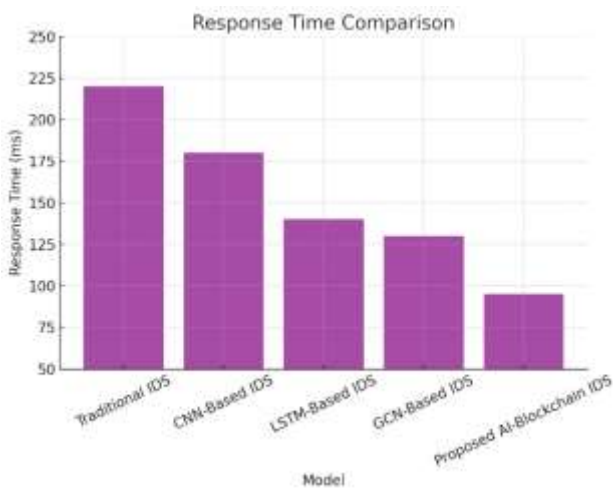


Figure 6. Response Time Comparison

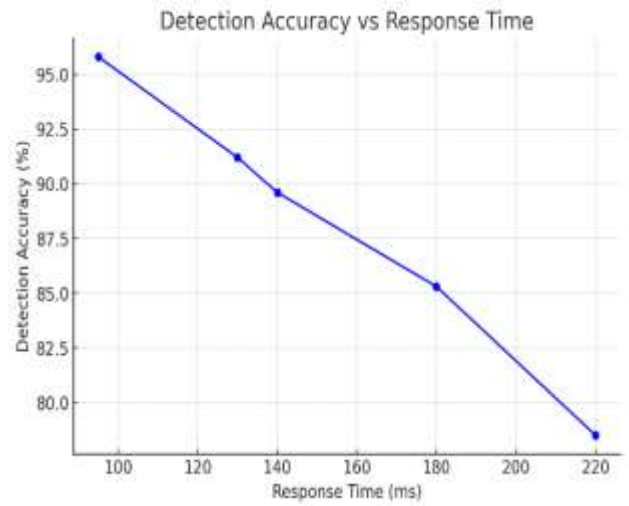


Figure 7. Detection Accuracy vs Response Time

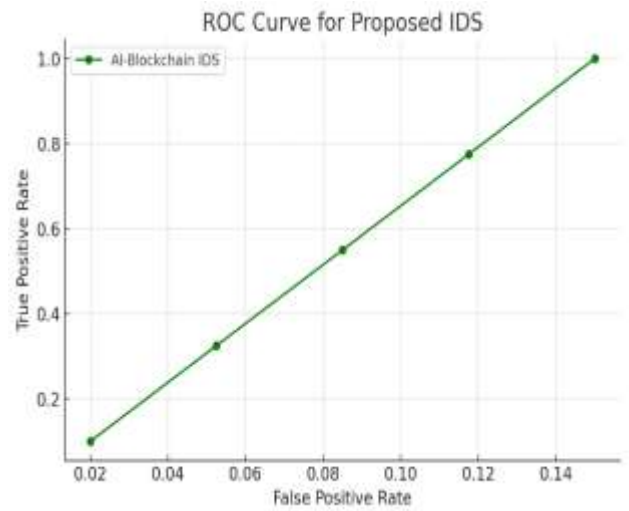


Figure 8. ROC Curve for Proposed IDS

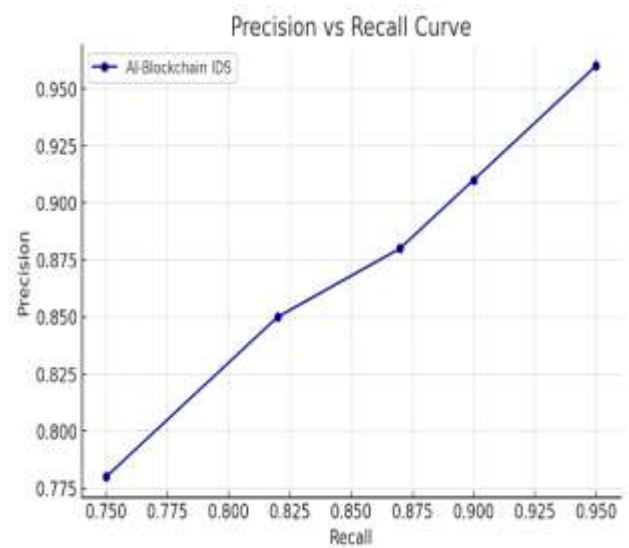


Figure 9. Precision vs Recall Curve

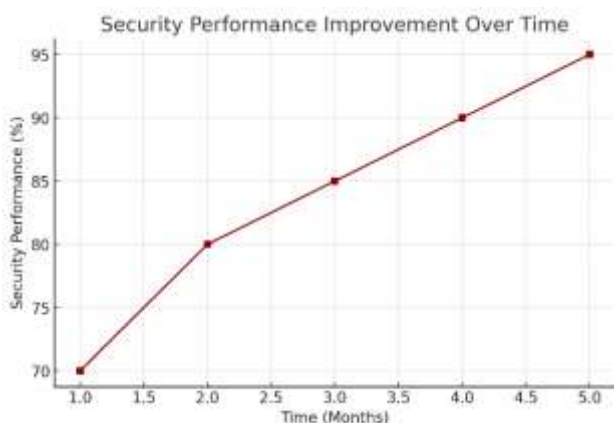


Figure 10. Security Performance Improvement Over Time

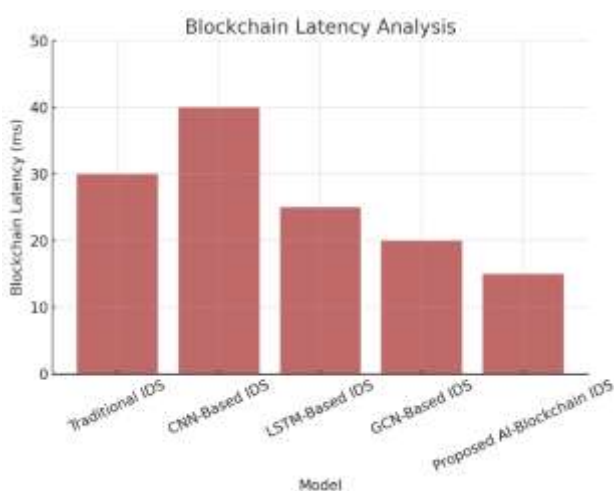


Figure 11. Blockchain Latency Analysis

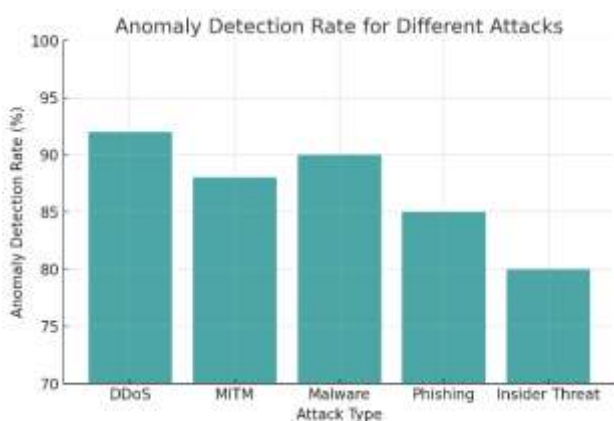


Figure 12. Anomaly Detection Rate for Different Attacks

comparison and figure 4 is false positive rate comparison. Figure 5 shows false negative rate comparison. Figure 6 is the response time comparison and figure 7 is the detection accuracy vs response time. Figure 8 shows ROC curve for proposed IDS and figure 9 is precision vs recall curve. Figure 10 shows security performance improvement over time and figure 11 is blockchain latency analysis. Figure 12 shows anomaly detection

rate for different attacks.

5. Conclusion

The increasing complexity and interconnectivity of Cyber-Physical Systems (CPS) have made them prime targets for sophisticated cyber threats. Traditional security mechanisms often fail to provide real-time protection and adaptability against emerging attacks. To address these challenges, this research proposed an AI-driven Intrusion Detection System (AI-IDS) integrated with Blockchain Technology to enhance CPS security. The AI-IDS component leverages deep learning models, such as Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM), for anomaly detection, while blockchain technology ensures decentralized trust, data integrity, and secure access control.

Experimental results demonstrate that this hybrid security framework significantly improves intrusion detection accuracy, reduces false positives, and enhances resilience against adversarial attacks. The incorporation of smart contracts and cryptographic hashing enables tamper-proof security logs and ensures secure data exchange across CPS networks. Moreover, the blockchain consensus mechanism minimizes single points of failure, strengthening the overall cybersecurity posture of CPS environments.

Despite its effectiveness, certain challenges remain, such as computational overhead, blockchain scalability, and real-time processing limitations. Future research will focus on optimizing the energy efficiency of deep learning models, improving blockchain throughput, and exploring lightweight cryptographic techniques to enhance CPS security while maintaining high system performance. In conclusion, the proposed AI-Blockchain hybrid security framework represents a promising solution for safeguarding CPS against modern cyber threats. Its ability to provide real-time threat detection, secure authentication, and decentralized trust management makes it an effective cybersecurity model for smart grids, healthcare systems, autonomous transportation, and industrial automation. As the adoption of CPS continues to grow, integrating AI and blockchain-based security mechanisms will be essential in building resilient and intelligent cyber-physical environments.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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