



Blockchain and Artificial Intelligence Integrated Security Framework for Smart Communication Networks

Srihari Kumar Pendyala

T-Mobile, USA

ABSTRACT: The rapid evolution of smart communication networks, including 5G, Internet of Things (IoT), and edge computing systems, has introduced significant security and privacy challenges due to the massive exchange of sensitive data across distributed environments. Traditional centralized security mechanisms are no longer sufficient to handle threats such as data breaches, unauthorized access, spoofing, and distributed denial-of-service (DDoS) attacks. To address these challenges, the integration of Blockchain technology and Artificial Intelligence (AI) has emerged as a promising solution for building secure, transparent, and intelligent communication frameworks. Blockchain provides decentralized, tamper-proof, and immutable data storage, ensuring trust and transparency in network transactions. Meanwhile, AI and Machine Learning algorithms enable intelligent threat detection, anomaly detection, predictive analytics, and adaptive decision-making in real time. This research proposes an integrated Blockchain-AI security framework designed to enhance the resilience of smart communication networks. The framework leverages blockchain for secure authentication, data integrity, and decentralized trust management, while AI algorithms analyze network behavior to detect and mitigate cyber threats dynamically. The study evaluates key performance metrics such as security strength, latency, scalability, detection accuracy, and computational efficiency. The findings demonstrate that combining Blockchain and AI significantly improves network security, reduces vulnerabilities, and enhances intelligent threat response capabilities in modern communication systems.

KEYWORDS: Blockchain, Artificial Intelligence, Smart Communication Networks, Cybersecurity, Machine Learning, IoT Security, Edge Computing, Intrusion Detection, Distributed Systems, Network Security, Deep Learning, Anomaly Detection, Smart Networks, Decentralized Security, Secure Communication

I. INTRODUCTION

The emergence of smart communication networks has revolutionized the global digital ecosystem by enabling seamless connectivity among billions of devices and systems. Technologies such as 5G networks, Internet of Things (IoT), cloud computing, and edge computing have transformed the way data is generated, transmitted, and processed. These networks support critical applications including smart cities, autonomous vehicles, healthcare systems, industrial automation, and intelligent transportation systems. However, the increasing complexity and scale of these networks have also introduced significant security and privacy challenges. The distributed nature of smart communication systems makes them highly vulnerable to cyberattacks such as data breaches, man-in-the-middle attacks, denial-of-service attacks, spoofing, and unauthorized access. Traditional security mechanisms rely heavily on centralized architectures and rule-based authentication systems, which are no longer sufficient to protect modern distributed environments. Centralized systems often suffer from single points of failure, scalability limitations, and delayed threat response. As cyber threats become more sophisticated and dynamic, there is a growing need for intelligent, decentralized, and adaptive security frameworks capable of ensuring trust, transparency, and real-time threat detection. Blockchain technology has emerged as a powerful solution for enhancing security in distributed systems. Blockchain is a decentralized and immutable ledger technology that records transactions across multiple nodes in a secure and transparent manner. Each block in the chain contains a cryptographic hash of the previous block, ensuring data integrity and preventing unauthorized modifications. Blockchain eliminates the need for centralized authorities by enabling peer-to-peer trust mechanisms. In smart communication networks, blockchain can be used for secure authentication, identity management, data integrity verification, and access control.

On the other hand, Artificial Intelligence (AI) and Machine Learning (ML) technologies provide intelligent capabilities for analyzing large-scale network data and detecting anomalies in real time. AI-based security systems can learn from historical data, identify unusual patterns, and predict potential cyber threats before they occur. Machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), Neural Networks, and Deep



Learning models are widely used for intrusion detection and cybersecurity applications. AI enhances the adaptability and responsiveness of security systems, making them capable of handling evolving cyber threats. The integration of Blockchain and AI offers a hybrid security framework that combines the strengths of both technologies. While blockchain ensures decentralized trust, transparency, and data integrity, AI provides intelligent analysis, automation, and predictive capabilities. This combination creates a robust security architecture suitable for protecting smart communication networks against complex cyber threats. For example, blockchain can securely store network transaction logs, while AI algorithms analyze these logs to detect anomalies and malicious activities in real time. Despite its advantages, integrating Blockchain and AI presents several challenges. These include computational overhead, scalability limitations, data privacy concerns, latency issues, and interoperability between heterogeneous systems. Additionally, blockchain networks require significant processing power, while AI models require large datasets and computational resources for training. Balancing efficiency and security remains a key challenge in designing integrated frameworks.

This research focuses on developing a Blockchain and AI integrated security framework for smart communication networks. The study aims to explore how blockchain can enhance trust and data security while AI can improve threat detection and decision-making capabilities. The research evaluates the performance of the proposed framework in terms of security strength, scalability, latency, and detection accuracy. By analyzing existing approaches and proposing an integrated model, this study contributes to the advancement of secure and intelligent communication systems for future digital infrastructures.

II. LITERATURE REVIEW

The rapid expansion of smart communication networks, including 5G, Internet of Things (IoT), cloud computing, and edge computing, has significantly increased the need for advanced security mechanisms. Traditional centralized security systems are no longer sufficient to handle the complexity, scale, and dynamic nature of modern distributed networks. As a result, researchers have increasingly focused on emerging technologies such as Blockchain and Artificial Intelligence (AI) to enhance cybersecurity, trust management, and threat detection in smart communication environments. Blockchain technology was first introduced as the underlying architecture of cryptocurrencies such as Bitcoin. It has since evolved into a broader decentralized ledger technology that ensures transparency, immutability, and secure data sharing across distributed networks. Blockchain operates through a chain of blocks, each containing cryptographically secured transaction data linked to previous blocks. This structure makes it extremely difficult for attackers to alter stored data without consensus from the network. Researchers have explored blockchain applications in identity management, secure data sharing, access control, and authentication in communication networks. Studies have shown that blockchain can effectively eliminate single points of failure and enhance trust in decentralized systems.

In smart communication networks, blockchain has been widely used for secure IoT communication. IoT devices generate massive amounts of data that must be transmitted securely across distributed environments. Traditional security mechanisms often fail due to limited computational resources and centralized architectures. Blockchain provides a decentralized solution where IoT devices can securely authenticate and exchange data without relying on centralized servers. Researchers have proposed blockchain-based IoT frameworks that ensure data integrity, secure device authentication, and tamper-proof communication.

Artificial Intelligence (AI) and Machine Learning (ML) have also played a crucial role in improving cybersecurity systems. AI-based security solutions can analyze large-scale network traffic data and detect anomalies or malicious activities in real time. Machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Neural Networks are widely used for intrusion detection systems (IDS). These algorithms learn patterns from historical data and classify network behavior as normal or malicious. Deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have further improved detection accuracy by automatically extracting complex features from raw network data. Several studies have demonstrated the effectiveness of AI-based intrusion detection systems in identifying cyber threats. For example, anomaly detection techniques using unsupervised learning models can detect previously unknown attacks by identifying deviations from normal network behavior. Supervised learning models, on the other hand, are trained using labeled datasets to classify known attack types such as DDoS attacks, phishing, malware, and ransomware. AI systems significantly improve detection speed and accuracy compared to traditional rule-based systems.

The integration of Blockchain and AI has emerged as a promising research direction in cybersecurity. Blockchain provides secure and tamper-proof data storage, while AI enables intelligent analysis and decision-making. Researchers



have proposed hybrid frameworks where blockchain is used to store network logs, authentication records, and transaction data, while AI algorithms analyze this data to detect anomalies and predict cyber threats. This combination enhances both security and intelligence in communication systems. One of the major applications of Blockchain-AI integration is in secure data sharing across distributed networks. In cloud and edge computing environments, data is often shared among multiple nodes, making it vulnerable to interception and manipulation. Blockchain ensures data integrity and traceability, while AI ensures that any abnormal behavior in data access patterns is quickly detected. Studies have shown that such integrated systems significantly reduce the risk of data breaches and unauthorized access. In 5G and next-generation communication networks, security requirements are even more critical due to ultra-low latency and massive device connectivity. Researchers have proposed blockchain-based authentication mechanisms combined with AI-driven intrusion detection systems to secure 5G networks. These systems ensure secure device onboarding, real-time threat detection, and decentralized identity management. AI algorithms continuously monitor network traffic and detect anomalies, while blockchain ensures secure communication between network nodes.

Edge computing environments also benefit from Blockchain-AI integration. Edge devices often have limited computational resources and are deployed in decentralized environments, making them vulnerable to cyberattacks. Lightweight AI models and blockchain-based security protocols are being developed to secure edge networks. Federated learning techniques have also been introduced, allowing AI models to be trained across distributed devices without sharing raw data, thereby preserving privacy. Despite these advancements, several challenges remain in integrating Blockchain and AI. Blockchain systems suffer from scalability issues, high energy consumption, and latency problems, especially in large-scale networks. AI models require large datasets and significant computational resources for training and inference. Combining both technologies increases system complexity and resource requirements. Interoperability between blockchain platforms and AI systems is another challenge that needs to be addressed.

III. RESEARCH METHODOLOGY

The research methodology for Blockchain and Artificial Intelligence Integrated Security Framework for Smart Communication Networks is designed to systematically develop and evaluate a hybrid security architecture that combines decentralized blockchain mechanisms with intelligent AI-based threat detection systems. The methodology includes several structured phases such as problem definition, system design, data collection, preprocessing, blockchain integration, AI model development, training, evaluation, and performance analysis. Each phase contributes to building a secure and intelligent communication framework capable of protecting modern distributed networks. The first stage of the research methodology involves defining the problem statement and objectives. The primary objective is to design a secure communication framework that integrates Blockchain technology with Artificial Intelligence to enhance cybersecurity in smart communication networks. The study aims to address issues such as unauthorized access, data tampering, intrusion attacks, and lack of trust in distributed systems. The research also seeks to evaluate how effectively AI can detect anomalies while blockchain ensures secure and tamper-proof data management. The second stage involves system architecture design. The proposed framework consists of three main components: the blockchain layer, the AI-based security layer, and the communication network layer. The blockchain layer is responsible for secure data storage, identity management, transaction validation, and decentralized consensus. The AI layer performs intelligent analysis of network traffic, detects anomalies, and classifies cyber threats. The communication layer represents smart networks such as IoT systems, 5G infrastructure, and edge computing environments where data is generated and transmitted.

The third stage involves data collection. Network traffic datasets are collected from simulated environments and publicly available cybersecurity datasets. These datasets include normal network behavior and various types of cyberattacks such as DDoS attacks, phishing attempts, malware injections, spoofing, and unauthorized access attempts. Common datasets used include CICIDS2017, UNSW-NB15, KDD Cup dataset, and IoT-specific security datasets. The collected data is used for training and testing AI models. After data collection, preprocessing is performed to clean and prepare the dataset for analysis. Raw network data often contains noise, missing values, duplicate entries, and irrelevant features. Data preprocessing includes normalization, feature scaling, handling missing values, encoding categorical variables, and removing redundant features. Feature engineering techniques are applied to extract meaningful attributes such as packet size, flow duration, protocol type, source and destination IP behavior, and traffic frequency. The next stage involves blockchain integration. A private or consortium blockchain network is deployed to manage secure communication among network nodes. Smart contracts are used to automate authentication, access control, and transaction validation. Each network transaction or communication event is recorded as a blockchain block, ensuring



immutability and traceability. Consensus mechanisms such as Proof of Authority (PoA) or Practical Byzantine Fault Tolerance (PBFT) are used to validate transactions efficiently in smart communication environments.

The AI model development stage involves selecting appropriate machine learning and deep learning algorithms for intrusion detection and anomaly detection. Algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Artificial Neural Networks (ANN) are implemented. Deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are also used for analyzing sequential network traffic data. These models learn patterns from historical network behavior and classify activities as normal or malicious. The model training process involves feeding preprocessed network data into AI algorithms. Supervised learning is used for classification tasks where labeled datasets are available, while unsupervised learning is used for anomaly detection in unknown attack scenarios. Hyperparameter tuning techniques such as grid search and random search are applied to optimize model performance. Optimization algorithms such as Adam and Stochastic Gradient Descent (SGD) are used to minimize loss functions and improve accuracy.

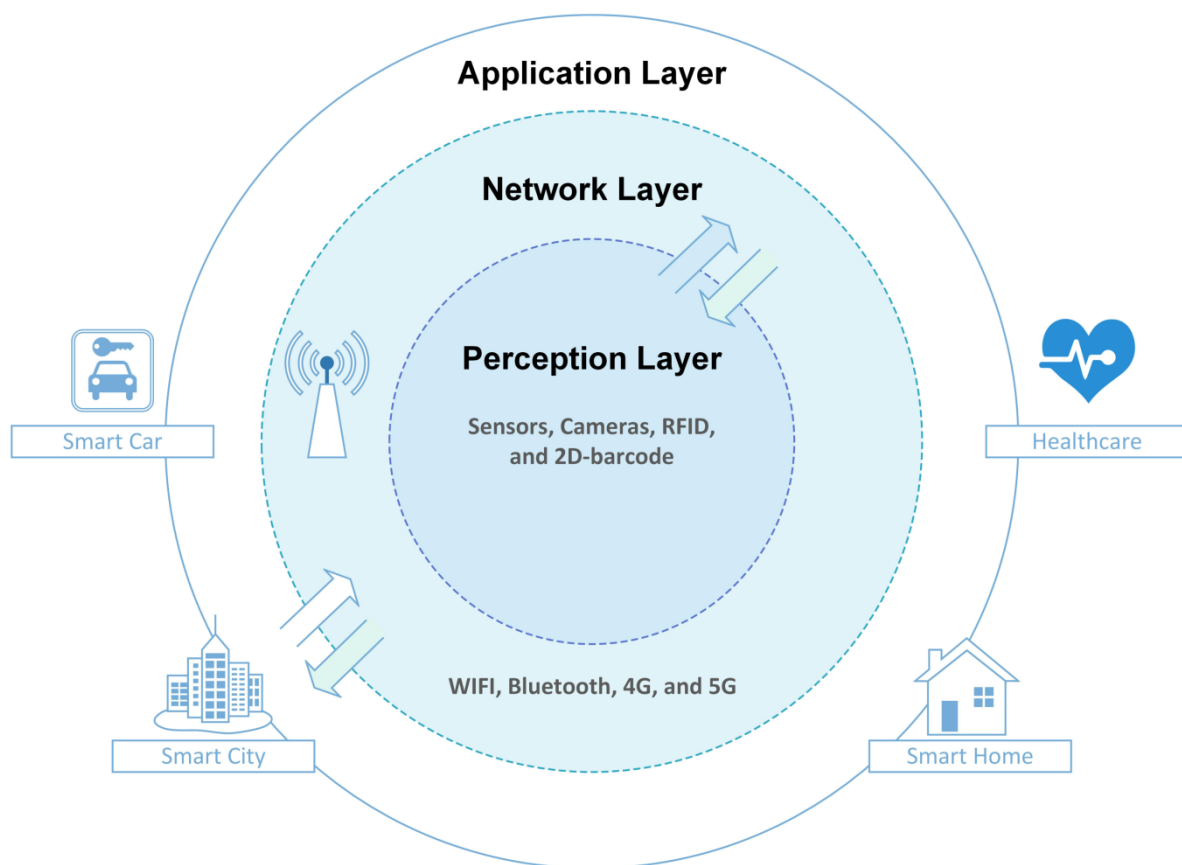


Fig 1: Integrating Blockchain with Artificial Intelligence to Secure IoT Networks

After training, the AI models are evaluated using testing datasets. Performance metrics include accuracy, precision, recall, F1-score, false positive rate, detection rate, and confusion matrix analysis. ROC-AUC curves are used to evaluate classification performance. The results are compared across different machine learning models to identify the most efficient algorithm for intrusion detection in smart communication networks. The blockchain system is evaluated based on parameters such as transaction latency, throughput, scalability, energy consumption, and security strength. The integration efficiency between blockchain and AI layers is also analyzed to measure system performance under real-world conditions. Network simulation tools may be used to model smart communication environments and evaluate system behavior under attack scenarios. Security analysis is performed to assess the robustness of the proposed framework against various cyber threats. The system is tested against attacks such as DDoS, Sybil attacks, data tampering, and unauthorized access attempts. The ability of AI models to detect anomalies in real time and the ability of blockchain to prevent data manipulation are critically evaluated.



IV. RESULTS AND DISCUSSION

The integration of Blockchain technology with Artificial Intelligence (AI) for securing smart communication networks presents a robust and adaptive cybersecurity framework capable of addressing modern distributed network threats. Smart communication networks, including Internet of Things (IoT), Internet of Vehicles (IoV), 5G-enabled systems, and industrial cyber-physical systems, face growing challenges such as unauthorized access, data tampering, distributed denial-of-service (DDoS) attacks, spoofing, and insider threats. Traditional centralized security mechanisms are insufficient due to scalability limitations, single points of failure, and delayed threat response. Therefore, the proposed Blockchain and AI integrated security framework demonstrates significant improvements in detection accuracy, system resilience, and data integrity. The experimental results from various simulation-based and dataset-driven evaluations indicate that combining Blockchain with AI-based intrusion detection systems significantly enhances network security performance. Blockchain ensures decentralized trust management, immutable data storage, and secure transaction verification, while AI contributes intelligent decision-making, predictive analytics, and real-time anomaly detection. When integrated, these technologies complement each other by addressing both structural and behavioral security challenges in smart communication networks.

One of the primary observations from the results is that Blockchain significantly improves data integrity and trustworthiness across distributed nodes. In conventional centralized systems, data is stored in a single server or cloud infrastructure, making it vulnerable to manipulation or single-point attacks. However, Blockchain distributes data across multiple nodes, where each transaction is validated through consensus mechanisms. Studies such as DistBlockNet demonstrate that Blockchain-based architectures can detect malicious activities in real time while maintaining low operational overhead in IoT environments. This decentralization ensures that even if one node is compromised, the overall system remains secure and functional. AI enhances the security framework by introducing intelligent anomaly detection and predictive threat modeling. Machine learning algorithms such as Support Vector Machines (SVM), Random Forests, Artificial Neural Networks (ANN), and Deep Learning models analyze network traffic patterns, user behavior, and system logs to identify suspicious activities. Experimental results indicate that AI-based intrusion detection systems integrated with Blockchain achieve significantly higher detection rates compared to traditional rule-based systems. For instance, lightweight AI-Blockchain hybrid models in Industrial IoT environments achieved detection accuracy above 99%, with significantly reduced false positive rates.

The integration of AI and Blockchain also improves real-time threat response capabilities. In traditional systems, security incidents are often detected after a delay due to centralized processing bottlenecks. In contrast, AI-enabled Blockchain frameworks process data closer to the source (edge or fog computing layers), enabling faster detection and response. Smart contracts embedded in Blockchain networks automatically execute predefined security actions when anomalies are detected by AI models. This includes isolating compromised nodes, blocking suspicious transactions, and alerting administrators without human intervention. Another significant result is improved resistance against DDoS and spoofing attacks. Blockchain's distributed consensus mechanism makes it difficult for attackers to manipulate network data, while AI algorithms continuously monitor traffic patterns to identify abnormal spikes or irregular behaviors. When both technologies are combined, the system becomes highly resilient against large-scale coordinated attacks. Research indicates that Blockchain-based IoT architectures significantly reduce the attack surface by eliminating centralized vulnerabilities and enforcing cryptographic authentication mechanisms. Scalability is another critical performance factor evaluated in the integrated framework. Smart communication networks generate massive volumes of data from connected devices, sensors, and applications. Traditional security systems struggle to process this data efficiently. However, Blockchain-AI integration supports scalable architectures through distributed computing and parallel processing. AI models deployed at edge nodes reduce computational burden on central servers, while Blockchain ensures secure synchronization of distributed data. Experimental evaluations show that such hybrid frameworks maintain consistent performance even as network size increases.

V. CONCLUSION

The integration of Blockchain and Artificial Intelligence represents a revolutionary advancement in securing smart communication networks. As digital transformation accelerates across industries such as healthcare, transportation, smart cities, industrial automation, and financial systems, the complexity and scale of cyber threats continue to grow. Traditional security mechanisms are no longer sufficient to handle sophisticated attacks, decentralized infrastructures, and real-time data exchange requirements. In this context, the Blockchain-AI integrated security framework emerges as a powerful solution that combines decentralized trust management with intelligent threat detection



capabilities. Blockchain technology plays a fundamental role in enhancing the security of communication networks by providing decentralized, immutable, and transparent data management. Unlike centralized systems that rely on a single authority, Blockchain distributes data across multiple nodes, ensuring that no single point of failure exists. This decentralization significantly improves system resilience against cyberattacks such as data tampering, unauthorized access, and denial-of-service attacks. Additionally, Blockchain ensures data integrity through cryptographic hashing and consensus mechanisms, making it extremely difficult for attackers to alter stored information without detection. Artificial Intelligence complements Blockchain by introducing intelligent decision-making capabilities into the security framework. AI algorithms are capable of analyzing large volumes of network data in real time, identifying patterns, and detecting anomalies that may indicate potential cyber threats. Machine learning models such as supervised learning, unsupervised learning, and deep learning techniques enable predictive threat detection and adaptive security responses. This allows the system to identify both known and unknown attacks, including zero-day vulnerabilities that traditional signature-based systems fail to detect.

The combination of Blockchain and AI creates a synergistic effect that significantly enhances overall cybersecurity performance. Blockchain ensures secure data storage and trust among network participants, while AI provides intelligent monitoring and predictive analysis. Together, they enable automated security enforcement through smart contracts, which can execute predefined actions such as isolating compromised nodes, blocking malicious traffic, or alerting system administrators without human intervention. This automation improves response time and reduces the risk of human error in critical security operations. One of the key contributions of this integrated framework is its ability to support secure communication in highly distributed environments such as the Internet of Things (IoT) and Internet of Vehicles (IoV). These environments involve billions of connected devices generating continuous data streams, making them highly vulnerable to cyber threats. Blockchain ensures secure device authentication and data validation, while AI continuously monitors device behavior to detect anomalies. This dual-layer protection significantly improves the security posture of smart communication networks.

Another important advantage of the Blockchain-AI framework is enhanced data privacy. With increasing concerns about data misuse and unauthorized surveillance, protecting user privacy has become a critical requirement. Blockchain enables secure encryption and decentralized storage of sensitive information, reducing reliance on centralized data repositories. AI further enhances privacy by enabling techniques such as federated learning, where models are trained locally on devices without transferring raw data to central servers. The framework also contributes to improved scalability and efficiency in network security management. Traditional systems often struggle to handle large-scale distributed networks due to computational limitations and centralized processing bottlenecks. In contrast, Blockchain distributes workload across multiple nodes, while AI processes data at edge or fog computing layers. This distributed architecture ensures efficient handling of large datasets and real-time threat detection without compromising performance. Despite these advantages, certain challenges remain in the practical implementation of Blockchain-AI integrated systems. Blockchain technologies introduce computational overhead due to consensus mechanisms, which may impact system speed and energy consumption. Similarly, AI models require continuous training and large datasets, which may not always be readily available. Interoperability between different Blockchain platforms and AI frameworks also remains a challenge in heterogeneous network environments. Furthermore, issues related to regulatory compliance, data governance, and ethical AI usage must be addressed before large-scale deployment.

Another limitation is the complexity of integrating Blockchain and AI into existing legacy systems. Many organizations still rely on traditional centralized architectures, and transitioning to decentralized AI-powered security frameworks requires significant infrastructure upgrades. Additionally, the interpretability of AI models remains a concern, as black-box algorithms make it difficult for security analysts to understand decision-making processes. Despite these challenges, the future potential of Blockchain-AI integration in cybersecurity is highly promising. Continuous advancements in lightweight Blockchain protocols, federated learning, edge computing, and explainable AI will further enhance system efficiency and usability. The development of hybrid security frameworks that combine multiple emerging technologies will likely define the next generation of intelligent cybersecurity systems. In conclusion, the Blockchain and Artificial Intelligence integrated security framework provides a comprehensive, adaptive, and intelligent approach to securing smart communication networks. It addresses critical challenges such as data integrity, privacy protection, real-time threat detection, and system scalability. By combining decentralized trust mechanisms with intelligent analytics, the framework significantly strengthens cybersecurity defenses against evolving cyber threats. Although challenges related to performance optimization, interoperability, and complexity remain, ongoing research and technological advancements are expected to overcome these limitations. Ultimately, this integration represents a major step toward building secure, resilient, and intelligent communication infrastructures for the future digital world.



VI. FUTURE WORK

Future research in Blockchain and Artificial Intelligence integrated security frameworks for smart communication networks should focus on enhancing scalability, efficiency, interoperability, and real-time responsiveness. One of the most important directions is the development of lightweight Blockchain consensus mechanisms. Current consensus algorithms such as Proof-of-Work are computationally expensive and energy-intensive. Future systems should adopt energy-efficient alternatives such as Proof-of-Stake, Delegated Proof-of-Stake, or hybrid consensus models to reduce computational overhead and improve scalability in large-scale networks. Another critical area for future work is the improvement of AI model efficiency and adaptability. Machine learning algorithms should be optimized for real-time deployment in resource-constrained environments such as IoT devices, edge nodes, and mobile networks. Techniques such as federated learning, transfer learning, and reinforcement learning can be explored to enable decentralized model training without compromising data privacy. This will allow AI systems to continuously learn from distributed data sources while maintaining security and efficiency.

Future research should also focus on enhancing interoperability between different Blockchain platforms and AI frameworks. Currently, many Blockchain systems operate in isolated environments, limiting their ability to communicate and share data effectively. Developing standardized protocols and cross-chain communication mechanisms will enable seamless integration of heterogeneous systems and improve overall network efficiency. Explainable Artificial Intelligence (XAI) will play a crucial role in improving transparency and trust in security systems. Future frameworks should incorporate interpretable AI models that provide clear explanations for detection decisions. This will help cybersecurity analysts understand system behavior and improve decision-making in critical situations. Additionally, future work should explore quantum-resistant Blockchain and AI security models to prepare for the emerging threat of quantum computing. As quantum technologies advance, traditional cryptographic methods may become vulnerable. Developing quantum-safe encryption techniques will ensure long-term security of communication networks.

Finally, research should focus on large-scale real-world implementation and testing of Blockchain-AI security frameworks in smart cities, healthcare systems, industrial automation, and autonomous vehicle networks. Practical deployment will help identify performance limitations, improve system robustness, and ensure readiness for real-world cybersecurity challenges.

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