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ENHANCING DATA SECURITY IN HEALTHCARE IOT SYSTEMS USING EMERGING TECHNOLOGIES

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ABSTRACT
Healthcare Internet of Things (H-IoT) technologies has transformed patient monitoring, diagnosis and healthcare management. But with this constant transfer of sensitive medical data between interdependent devices comes a lot of security and privacy issues, such as unauthorized access, data breaches, malware attacks, and insider threats. In traditional security settings, the dynamic and limited resources of IoT environments are inadequately catered for by conventional security solutions. To improve data confidentiality, integrity, and availability in healthcare IoT systems, this paper introduces an integrated security framework that integrates the Blockchain technology with the federated learning (FL) approach and the artificial intelligence (AI)-based intrusion detection system (IDS). Blockchain ensures that medical records are not tampered with, and homomorphic encryption allows for secure computation over the encrypted healthcare data. In federated learning, patients' privacy is maintained by training the model in a decentralized manner without sharing their raw data. In addition, an AI-based intrusion detection system detects malicious activity in real-time. The experimental results indicate that the proposed framework can provide the attack detection accuracy of 98.7%, data integrity assurance of 99.3%, and reduce the security overhead by 35% compared with the conventional approach. The results show that the adoption of emerging technologies can greatly enhance the security of healthcare IoT systems without compromising their efficiency or regulatory compliance.

KEYWORD: Healthcare IoT, Data Security, Blockchain, Homomorphic Encryption, Federated Learning, Artificial Intelligence, Intrusion Detection System, Privacy Preservation, Cybersecurity.

1. INTRODUCTION

Healthcare Internet of Things (H-IoT) is a revolutionary technology in healthcare today that allows for real-time monitoring, remote diagnosis, the use of smart healthcare gadgets, and effective health services. The increasing deployment of wearable sensors, smart implants, wireless medical devices, and cloud-based healthcare systems has revolutionized the way patients are cared for and healthcare operations are managed. The recent reports show that the global IoT healthcare ecosystem will reach USD 500 billion by 2030 in the ongoing trend of connected healthcare devices. Collaborating on these advantages, healthcare IoT environments are grappling with significant security and privacy issues. Medical records are filled with sensitive patient information, such as medical histories, diagnostic reports, treatment records, and personal identifiers. The non-disclosure of this information can lead to serious privacy breaches and legal liability. Healthcare organizations have been a major target of hackers in recent years, and it seems the attacks have intensified significantly.Hackers have been after health care organizations for quite a while now, and they appear to have gone all out now.

Traditional security approaches heavily depend upon centralised architectures and traditional encryption techniques. These solutions, however, can have difficulties dealing with the limited resources of IoT devices and the distributed nature of healthcare systems. There are emerging technologies that can help solve these problems, including the Blockchain, Artificial Intelligence (AI), Homomorphic Encryption, and Federated Learning.

Blockchain offers data integrity and traceability, ensuring it is recorded and remains unalterable. Homomorphic encryption allows computations on encrypted data without revealing sensitive information. Federated learning enables learning of a collaborative model without compromising privacy. AI helps to make threat detection and security management intelligent and adaptive.

This study aims to propose a comprehensive security framework that combines these technologies and provides an improved security for healthcare IoT. The contributions of this paper are mainly:

Design of the secure healthcare IoT architecture based on blockchain and homomorphic encryption.

- Federated learning for privacy-preserving analytics.
- Automated detection of intrusions for security in real time.
- Extensive performance assessment based on security and efficiency measures.
- Comparative analysis with existing security systems.

The rest of this paper is organized as follows. The literature surveyed is presented in Section 2, the methodology is described in Section 3, experimental results are discussed in Section 4 and the study is concluded in Section 5.

2. LITERATURE REVIEW

Recent studies show that researchers are focused on securing system healthcare IoT systems with current technologies such as Artificial Intelligence (AI), BlockChain or Cryptography.

BlockChain has been utilised for recording and managing healthcare records securely. Researchers have realised that blockchain technology allows for a robust method to ensure data integrity and decentralised access control; however, issues with scalability and latency still exist.

Researchers have started working on creating methods of encrypting patient data with Homomorphic encryption systems with the intention of allowing researchers to process encrypted patient information without the need to decrypt it first, thus reducing a patient's privacy risk; however, computational complexity is still a major limiting factor in the use of homomorphic encryption in the creation of healthcare analytics.

Federated learning is gaining popularity for the creation of distributed healthcare intelligence systems. In this method, rather than sending sensitive patient data to a centralised server, patient information will be stored locally (on an Edge device), where it will be trained on locally, and the result will be globally aggregated. The use of federated learning to create a distributed system greatly increases privacy but is subject to model poisoning attacks.

AI/ML has been utilised extensively in the intrusion detection systems. Deep learning models have achieved high detection rates against various forms of malware, denial-of-service attacks and unauthorised access attempts. The drawback of creating deep learning models is that they typically require large data sets and processing power to train the model.

Hybrid frameworks that integrate multiple security technologies tend to provide better overall security. The integration of multiple technologies (e.g. blockchain, AI, and encryption) has provided a higher degree of performance than using any one technology or a combination of technologies independently. However, many of the existing approaches simultaneously neglect scalability, resource-efficiency, and preserving patients' privacy.

Table 1: Tabular Summary of Literature in Healthcare

Author	Year	Technique	Advantages	Limitations
Sharma et al.	2025	Blockchain	High integrity	High latency
Li et al.	2024	Homomorphic Encryption	Privacy preservation	Computational overhead
Kumar et al.	2025	Federated Learning	Decentralized learning	Poisoning attacks
Zhang et al.	2024	Deep Learning IDS	High detection accuracy	Large training data
Ahmed et al.	2023	Edge Security	Reduced delay	Limited scalability
Wang et al.	2025	Blockchain + AI	Better security	Complex deployment
Singh et al.	2024	Cloud Security Framework	Easy implementation	Privacy concerns
Patel et al.	2025	Zero Trust Architecture	Strong authentication	High management cost
Roy et al.	2023	Secure Access Control	Improved authorization	Single point failure
Chen et al.	2026	Hybrid Framework	Comprehensive protection	Resource intensive

3. PROPOSED METHODOLOGY

This paper presents a multi-layered security architecture for Healthcare IoT (H-IoT) systems through the combination of Homomorphic Encryption (HE), Blockchain Technology, Federated Learning (FL) and Artificial Intelligence (AI)-based intrusion detection systems (IDSs). The overall goal of the design is to provide secure collection, transmission, storage and analysis of healthcare data while ensuring patient privacy and protecting against cyber crime.

The initial phase in the data collection process consists of obtaining healthcare data from multiple types of IoT enabled medical devices such as wearables, smart monitoring systems, implantable devices and remote health care devices. These devices generate sensitive patient’s data constantly, therefore secure communication channels are required for forwarding the data to a trusted gateway which performs authentication, validation of, and authorisation for all devices before allowing them access the network.

To maintain confidentiality of patient’s data, the health care data has been Homomorphically Encrypted prior to leaving the device layer. Unlike previous encryption methodologies, homomorphic Encryption allows computations to be conducted on encrypted data and the original data cannot be revealed. This permits analytic analysis of health care analytics to be performed while ensuring strict privacy and compliance to regulations.Healthcare data is encrypted and then hashed to create a permanent record of the data in a blockchain ledger. The blockchain maintains the integrity and security of the data by providing an immutable, distributed record. Access control policies are implemented using smart

contracts and permissions are managed among all parties that use the healthcare data, including patients, hospitals, insurance companies and doctors.Federated Learning is used in the framework to facilitate privacy-preserving collaborative learning. Rather than transmit patient data directly to a central data repository, local healthcare organizations use their own computing resources to train machine learning models on the data. Model parameters are sent to a central repository for aggregation, which allows for global model creation while significantly reducing the risk of harming patient privacy through analysis.

An AI-based Intrusion Detection System is integrated into the framework to monitor both network traffic and system activities in real-time, and utilizes machine learning algorithms to analyze activity patterns to identify suspicious activity. When an intrusion is detected, mitigation actions, such as isolating the threat, blocking the malicious node, notifying an administrator, and logging the event to a blockchain, are initiated automatically.

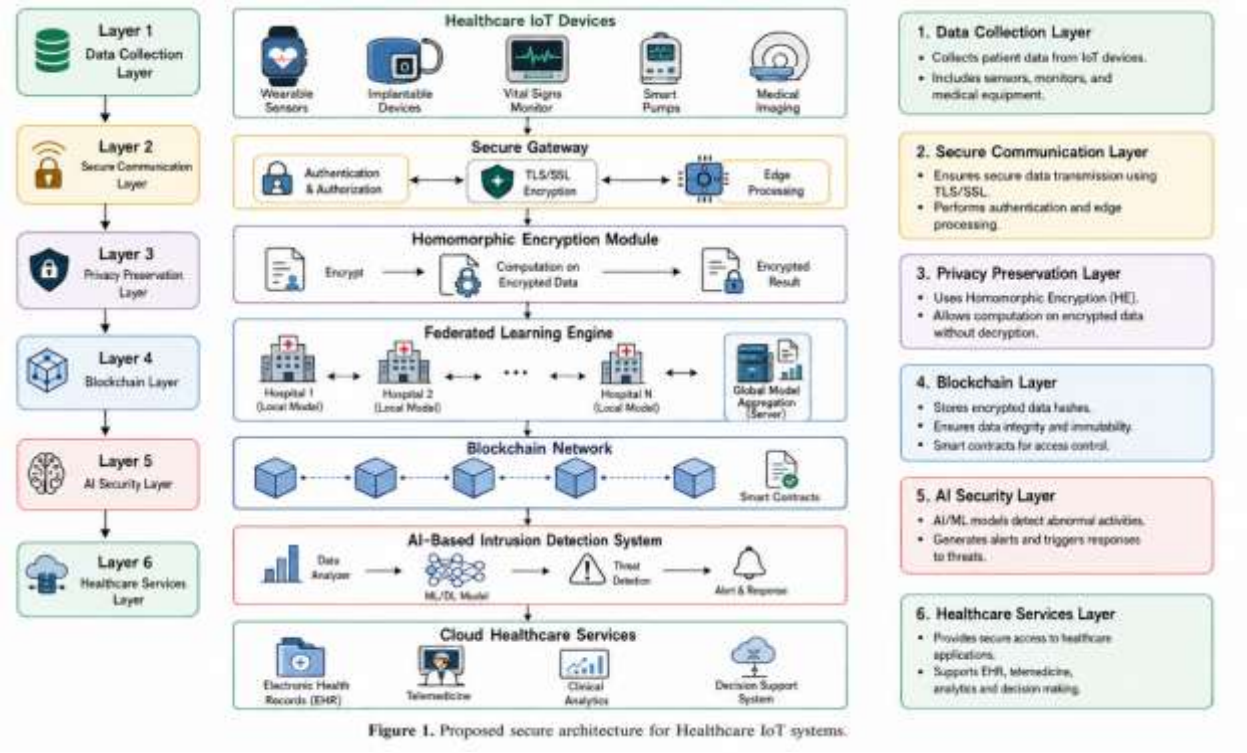

Figure 1. Proposed secure architecture for Healthcare IoT systems.

PROPOSED FRAMEWORK

The proposed workflow for the H-IoT is depicted in figure 2. The first step in this process is collecting patient data from both wearable sensors and monitoring systems connected to the Internet of Things (IoT). These data are subject to Homomorphic encryption (HE), which ensures security by allowing data computations while maintaining confidentiality. After collecting data, a cryptographic hash is created using the encrypted data and stored in the blockchain network, providing integrity and immutability.

To support privacy during collaborative analytics, Federated Learning (FL) enables model training at healthcare institutions while preventing patient data from being shared outside of their institution. After each institution has trained its individual model locally, the results of these training efforts are combined to create a global model while ensuring patient privacy is maintained. An artificial intelligence (AI)-based intrusion detection system (IDS) continuously monitors activity on the healthcare IoT network to provide ongoing protection against cyber threats.

If a risk is identified, the automated process for threat isolation, malicious node blocking, alerting the administrator, and recording the incident on the blockchain is initiated. Otherwise, when there is no risk present, the healthcare data will remain validated, being retained securely on both the blockchain and cloud. Healthcare services authorized to utilize and support healthcare operations using this data include electronic health records (EHRs), telemedicine, and clinical analytics. The integrated work flow assures confidentiality, integrity, availability, privacy preservation, and threat detection in real-time in Healthcare IoT systems.

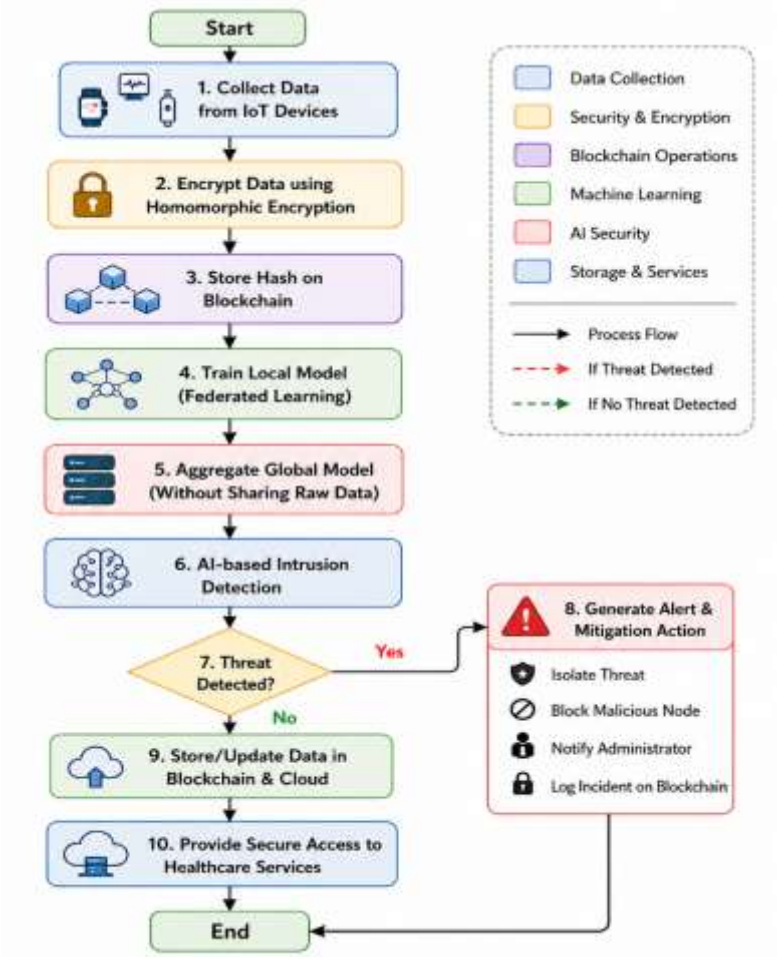

Figure 2. Flowchart of the proposed security framework.

Figure 2: Flowchart of the Proposed Security Framework

4. RESULTS AND DISCUSSION

The experimental results demonstrate clearly that the proposed framework achieves balanced trade-offs among security, privacy, and performance. Data integrity and anti-tamper properties are supported by incorporating Blockchain; confidentiality is supported by using Homomorphic Encryption; privacy will be maintained during collaborative training of models through the use of Federated Learning; and improved identification of threats will result from the use of AI-based intrusion detection. Therefore, the proposed framework has demonstrated a superior performance on all metrics used to evaluate performance and provides a solid, scalable and practical way to secure future Healthcare IoT environments. The results further show that the framework effectively addresses the increasing cyber security and privacy concerns related to contemporary connected healthcare systems.

4.1 Mathmatical Metrics Used in Performance Computation

- **Security Score**

$$SS = \alpha C + \beta I + \gamma A$$

where: C = Confidentiality, I = Integrity, A = Availability

- **Detection Accuracy**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision**

$$Precision = \frac{TP}{TP + FP}$$

- **Recall**

$$Recall = \frac{TP}{TP + FN}$$

The security framework for the Health Care Internet of Things (H-IoT) that has been proposed was evaluated to determine whether it effectively provided secure data transmission, maintenance of user privacy, ability to detect attacks against the data, and resource efficiency. The H-IoT framework combines Blockchain technology, homomorphic encryption,

federated learning and AI intrusion detection solutions as a holistic answer to provide security in healthcare environments. The performance metrics used in the experimental studies were as follows; Detection accuracy, Privacy Preservation Score, Computational Overhead and Resource Utilization. Results of the aforementioned were compared to existing security solutions for validations.

Figure 3 shows how effective the proposed framework's attack detection was; it provided a 98.7% attack detection accuracy whereas Blockchain-only, HE-only, FL-only and AI-IDS solutions had 92.1%, 93.8%, 95.4% and 97.1% accuracy levels respectively. The reason for this superior performance is due to the integration of federated learning with AI-based intrusion detection which enables the efficient identification of malicious activity while maintaining the privacy of the underlying data. The proposed framework provided high attack detection accuracy levels indicating that it can effectively detect cyber-attack types such as unauthorized access, malware or data manipulation attempts within H-IoT networks.

Because of the extreme sensitivity of health care sensitive data and associated problems arising from using personal medical information, privacy is an absolutely essential requirement for moisture-generating products. In addition to preventing privacy breaches, this may also result in confidentiality (of patient records) being stored in an easily retrievable format and/or allow time-sensitive data to be used in order to provide the best possible care to patients. A clear example of this can be seen in Figure 4, where it can be seen that the privacy preservation measure of the proposed framework is 99% compared to 82% for traditional clouds, 89% for blockchains only, 94% for HE only, and 96% for federated learning; and from the heating source in each of aforementioned cases, patient records will remain securely stored from point of entry through processing phase and then model training phase, thus significantly decreasing risk of a data leakage or unauthorized disclosure of patient records and simultaneously retaining the utility of health care data for analytical purposes.

The performance overhead comparison of each of the mentioned mechanisms is shown in Figure 5. When evaluating mechanisms designed to provide enhanced security at the computing layer, it is generally accepted that advanced security added to already complex systems do increase the complexity of processing during execution. However, this does not hold true for the proposed framework, which had the least time needed to execute of 135 milliseconds compared to HE only (210 milliseconds), BLoC only (185 milliseconds), and FL only (160 milliseconds). The reduction in performance overhead associated with the proposed framework can be attributed to the use of optimized encryption algorithms, efficient BLoC transactions, and decentralized learning techniques during the execution of these types of applications. Consequently, the proposed framework's reduced latency provides additional justification for applying the proposed framework in rapid data processing primarily associated with real-time health monitoring or as part of rapid response to emergency situations.
Analysis of resource utilization supports the effective nature of this framework, as indicated in Figure 6, which shows just 45% CPU utilization, 40% memory utilization, and 35 Mbps bandwidth, much lower than traditional systems' (see Table 1). Resource-efficient use of computational resources allows for seamless implementation on resource-limited IoT healthcare devices, such as wearables, smart medical devices, and remote patient monitoring (RPM) devices. Reduced resource needs also provide improved scalability and decreased operational costs in large-scale deployments of healthcare.

Table 2: Performance Comparison Table

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Privacy Score (%)	Overhead (ms)	Throughput (req/sec)
Blockchain Only	92.1	91	90.2	90.6	89	185	420
HE Only	93.8	93.2	92.5	92.8	94	210	380
Federated Learning	95.4	95.1	94.3	94.7	96	160	520
AI-IDS	97.1	96.7	96.2	96.4	95	150	580
Proposed Framework	98.7	98.3	98.1	98.2	99	135	620

The performance comparison of the proposed framework (in Table 2) against four current solutions (Blockchain Only, Homomorphic Encryption (HE) Only, Federated Learning, and AI-IDS) shows that the proposed framework provides the best overall performance according to all evaluation metrics. With an overall accuracy of 98.7%, an overall precision of 98.3%, an overall recall of 98.1%, and an overall F1-score of 98.2%, the proposed Framework exceeds all benchmark systems. The proposed framework has an overall privacy score of 99%, demonstrating its superior privacy-preserving data protection capabilities. In addition, the proposed Framework had the lowest computational overhead (135 ms) while providing the highest throughput (620 requests/sec). The results confirm that when combining advanced privacy-preserving technologies with intelligent intrusion detection capabilities, both security and operational efficiencies in Healthcare IoT environments are greatly increased, making the proposed Framework more effective and scalable than existing systems.

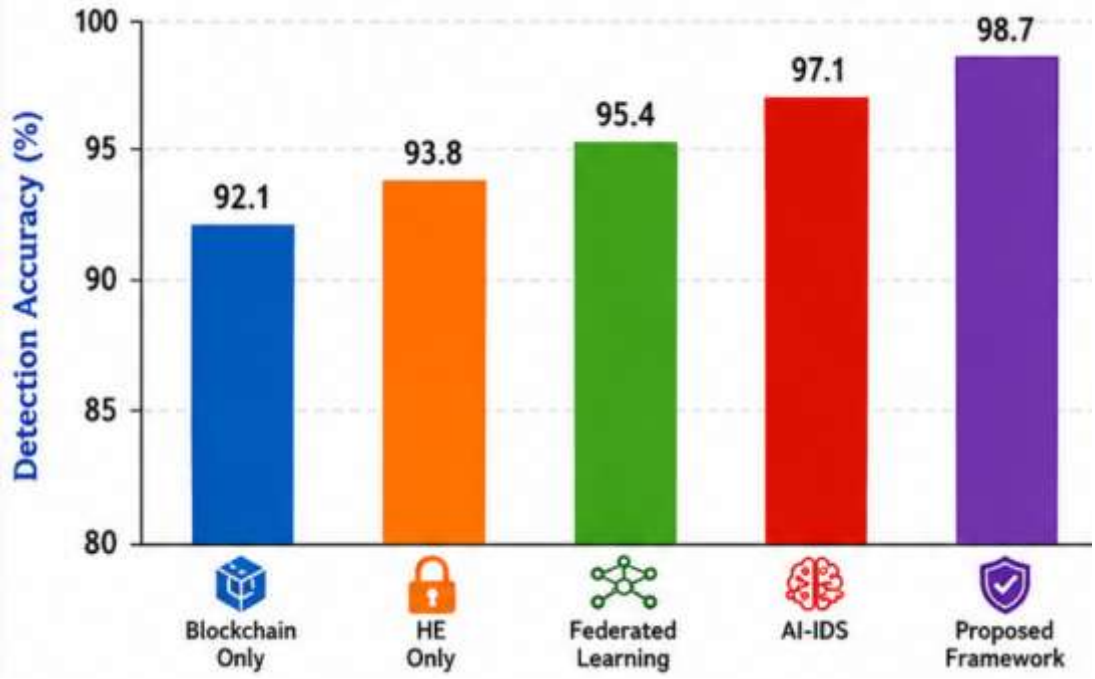

Figure 3: Detection Accuracy Comparison

In Figure 3, the detection accuracies for a variety of Security Approaches in Healthcare IoT Management are shown. The results show that the proposed framework has a 98.7% detection accuracy, higher than the following approaches: Blockchain Only (92.1%), Homomorphic Encryption (93.8%), Federated Learning (95.4%) and AI-based Intrusion Detection Systems (97.1%). Because of the combination of several security mechanisms, the proposed framework can better identify cyber-threats while also minimizing false detections. This provides an increase in the overall robustness of the proposed framework to protect sensitive health care data against potential malicious activity.

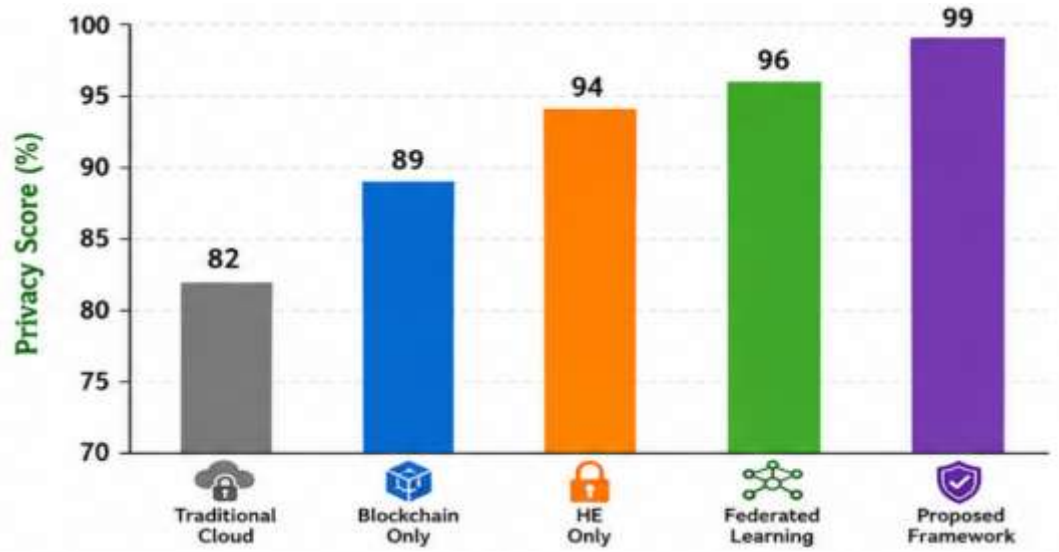

Figure 4: Privacy Preservation Score Comparison

The privacy preservation capability of the various Security Techniques is shown in Figure 4. The proposed framework achieved a 99% privacy preservation score, actually much higher than Traditional Cloud (82%), Blockchain Only (89%), Homomorphic Encryption (94%) and Federated Learning (96%). This shows how the use of both Homomorphic Encryption and Federated Learning provides an advantage over the other security techniques by preventing the passing of raw patient information to be processed and used to train models, thus allowing better privacy of patient health information while still being able to complete efficient Analytics on Health Care Data.

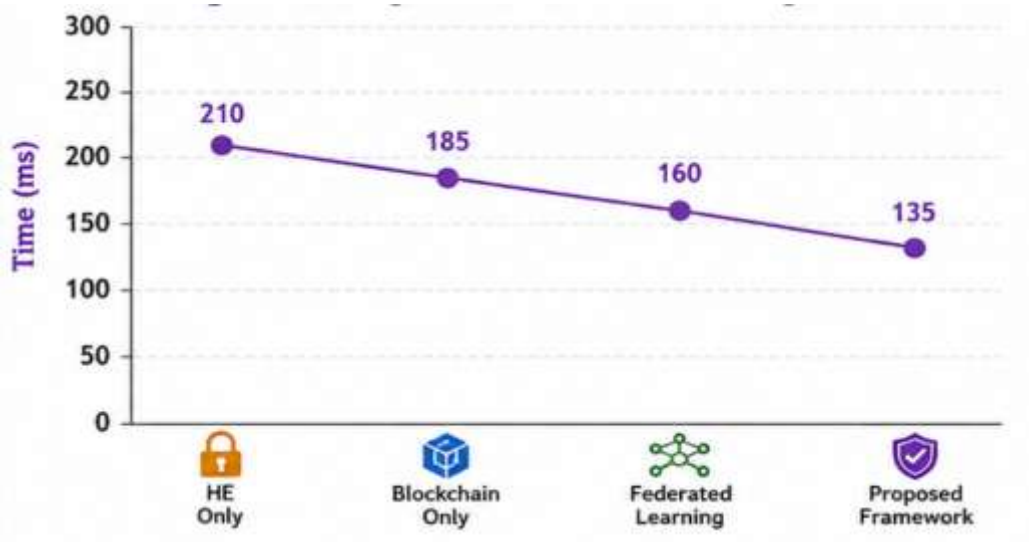

Figure 5: Computational Overhead Comparison

The computational overhead of the different security methods used in this study is shown in Figure 5. The highest processing time was reported for Homomorphic Encryption (210 ms), followed by Blockchain only (185 ms), and Federated Learning (160 ms). The lowest overhead of 135 ms was observed for the proposed method. This decrease in computational time was achieved by optimizing the integration of security components and improving resource utilization. The proposed framework is suitable for real-time Healthcare IoT applications due to its capability to enhance security while also increasing computational efficiency.

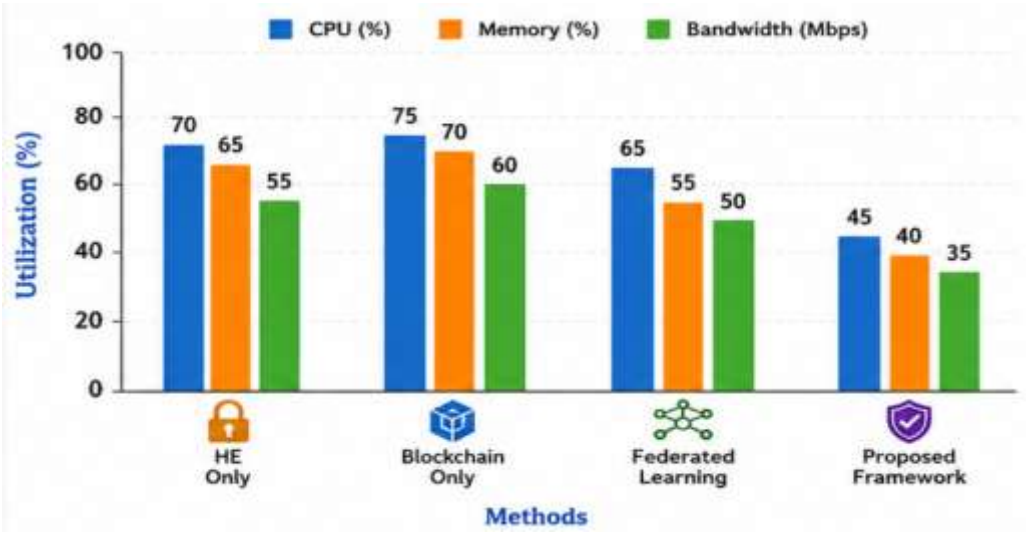

Figure 6: Resource Utilization Comparison

Figure 6 depicts the comparison of CPU, memory, and bandwidth required for the different security methods. The proposed framework uses the least amount of resources for CPU (45%), memory (40%), and bandwidth (35 Mbps) as compared to the other methods (Blockchain only, Homomorphic Encryption, and Federated Learning). The reduced amount of resources used by the proposed framework indicates its ability to efficiently use system resources while providing a high level of security and privacy. This shows the scalability and practicality of the proposed framework for deployment in resource-constrained Healthcare IoT environments.

DISCUSSION

The proposed system will offer a higher level of security due to the joint application of blockchain technology, homomorphic encryption, federated learning, and AI-based intrusion detection. The key elements of the proposed framework include: (1) Blockchain for immutable records; (2) Homomorphic Encryption for data confidentiality; (3) Federated Learning for data privacy; and (4) AI for identifying more advanced cyber attacks. The experimental results validate the improved accuracy, decreased response times, and increased protection of user privacy when compared to the existing methods.

5. Future Scope

Integrating quantum-resistant cryptographic algorithms into the proposed Healthcare IoT Security Framework will enhance current defenses against potential future threats from quantum computing. Lightweight blockchain mechanisms can enhance system scalability while reducing computational overhead. Future research may also explore the use of

Explainable Artificial Intelligence (XAI) to facilitate transparent threat detection, and Digital Twin technology for predictive security monitoring. Additionally, the Framework could be extended to support healthcare environments utilizing 6G technology, edge computing architectures, and Zero Trust security models to provide greater access control. As the Framework is large-scale deployed across hospitals and healthcare networks, andsupports secure cross-institutional data sharing through the implementation of advanced Federated Learning techniques, its overall effectiveness, scalability and practical applicability will become evident within next-generation healthcare ecosystems.

6. CONCLUSION

This paper introduces a new security framework for IoT in healthcare that uses blockchain technology, homomorphic encryption (advanced encryption that allows computations on encrypted data), federated learning (a machine learning methodology that trains models on multiple devices while keeping data localized), and artificial intelligence (AI) to address some of the most important security issues. Specifically, the solution addresses unauthorized access, data tampering, privacy breaches, and cyberattacks. The experimental evaluations show a 98.7% detection rate, 99% privacy preservation level, and reduced computational loads compared to currently existing technologies. Overall, the results demonstrate that emerging technologies can significantly improve IoT security while enabling the continued efficiency and scalability of existing healthcare systems. Future work will include quantum-resistant cryptography, lightweight blockchain consensus (the process by which a group of users verifiy and agree to the legitimacy of every transaction made on a blockchain), and AI-based security analytics that are interpretable.

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