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Research Article

Third Party Data Aggregation for Data Storage with the IoT Healthcare Model

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Abstract: In IoT healthcare systems, securing sensitive medical data while ensuring efficient data management remains a critical challenge. This paper proposes and evaluates the Blockchain Authentication Hashing Data Aggregation (BAHDA) model as a solution to enhance data integrity, security, and operational efficiency. The BAHDA model leverages blockchain technology to implement robust authentication mechanisms, cryptographic hashing for data integrity, and decentralized data aggregation to mitigate risks associated with centralized data storage. Through experimentation and analysis, our study demonstrates substantial improvements in key performance metrics. Specifically, BAHDA achieves a throughput of up to 10,000 messages per second (messages/sec) with 50 nodes, showcasing its scalability in handling large volumes of healthcare data. Latency is minimized to 6 milliseconds (ms), and delay reduced to 3 ms, ensuring rapid data transmission and processing critical for real-time healthcare applications. Furthermore, comparative analysis across different types of nodes—IoT devices, edge nodes, fog nodes, and cloud servers—illustrates their respective contributions to system performance. Cloud servers exhibit the highest throughput of 5000 messages/sec, lowest latency of 2 ms, and minimal delay of 1 ms, underscoring their role in supporting intensive data processing tasks and complex analytics. the BAHDA model proves to be a promising framework for securing and managing healthcare data in IoT environments, offering enhanced data integrity, security, and operational efficiency.

Keywords: Internet of Things (IoT), Blockchain, Hashing, Data Aggregation, Classification

1.Introduction

The Internet of Things (IoT) is revolutionizing healthcare by enhancing the efficiency, accuracy, and accessibility of medical services. IoT devices such as wearable fitness trackers, smartwatches, and implantable sensors continuously monitor patients' vital signs, allowing real-time data collection and analysis [1]. This enables early detection of potential health issues and timely interventions, reducing the need for frequent hospital visits and improving patient outcomes. Additionally, IoT facilitates remote patient monitoring, which is particularly beneficial for managing chronic diseases and elderly care, providing a seamless and integrated approach to health management [2]. With IoT, healthcare providers can leverage advanced data analytics and machine learning algorithms to personalize treatment plans, optimize resource allocation, and enhance the overall quality of care [3]. Despite its transformative potential, the

integration of IoT in healthcare also presents challenges such as data security, privacy concerns, and the need for robust infrastructure to support the vast amounts of data generated [4].

IoT in healthcare extends beyond patient monitoring to include the optimization of hospital operations. Smart medical devices can track the usage and status of equipment, ensuring timely maintenance and reducing downtime [5]. Automated inventory management systems can monitor the stock levels of medications and supplies, triggering reorders when necessary and minimizing shortages [6]. In surgical settings, IoT-enabled tools can provide real-time data to surgeons, enhancing precision and improving outcomes. Telemedicine is another significant area where IoT makes a substantial impact. Connected devices enable virtual consultations, allowing healthcare providers to diagnose and treat patients remotely [7]. This is especially valuable in rural or underserved areas where access to healthcare facilities is limited. IoT also supports rehabilitation and post-surgery care through connected devices that track recovery progress and adherence to treatment plans, providing feedback to both patients and healthcare professionals [8].

In the realm of public health, IoT can contribute to better disease surveillance and management [9]. By aggregating data from various sources, public health authorities can monitor the spread of infectious diseases, track vaccination rates, and respond more effectively to health emergencies. Environmental sensors can also monitor factors such as air quality and pollution levels, providing critical data that can influence public health policies and initiatives [10]. Despite its numerous benefits, the widespread adoption of IoT in healthcare requires addressing significant challenges. Ensuring the security and privacy of patient data is paramount, as breaches can lead to serious consequences. Regulatory frameworks need to evolve to keep pace with technological advancements, ensuring that IoT devices meet stringent safety and efficacy standards [11]. Additionally, the healthcare workforce must be trained to effectively utilize and manage IoT technologies, integrating them into clinical workflows without disrupting patient care.

Data aggregation in IoT healthcare plays a crucial role in harnessing the full potential of interconnected devices and systems. By collecting and combining data from various IoT-enabled devices such as wearable health monitors, smart medical equipment, and remote sensors, healthcare providers can obtain a comprehensive view of a patient's health status [12]. This holistic approach allows for more accurate diagnoses, personalized treatment plans, and proactive health management. Aggregated data facilitates advanced analytics and machine learning applications, enabling the identification of patterns and trends that may not be apparent from individual data points [13]. With continuous monitoring and aggregation of data on blood glucose levels, heart rate, and physical activity can help predict and manage chronic conditions like diabetes and cardiovascular diseases more effectively. Additionally, aggregated data supports population health management by providing insights into public health trends, disease outbreaks, and the effectiveness of interventions. However, ensuring the privacy and security of aggregated data remains a significant challenge, requiring robust encryption methods and strict access controls to protect sensitive health information [14-16].

2.Related Works

The integration of the Internet of Things (IoT) into healthcare has garnered significant attention from researchers and practitioners, leading to a diverse array of studies and developments in this burgeoning field. Prior work has explored various dimensions of IoT applications in healthcare, ranging from remote patient monitoring and telemedicine to smart hospital management and predictive analytics. Key research has delved into the design and

implementation of wearable devices that track vital signs and physical activity, providing continuous, real-time health data. Other studies have focused on the development of intelligent systems for early disease detection and personalized treatment plans through data aggregation and machine learning algorithms. Furthermore, extensive efforts have been made to address the security and privacy challenges inherent in IoT healthcare systems, proposing robust encryption methods and secure data transmission protocols. Comparative analyses of IoT solutions in different healthcare settings have also been conducted to evaluate their effectiveness and scalability.

Othman et al. (2022) introduced a privacy-preserving aware data aggregation technique that leverages green computing technologies to enhance IoT-based healthcare systems, emphasizing the importance of energy efficiency alongside data security. Building on this, Chakraborty et al. (2024) developed FC-SEEDA, a fog computing-based secure and energy-efficient data aggregation scheme, which addresses the dual challenges of data security and energy consumption in the Internet of Healthcare Things (IoHT) . Singh et al. (2022) proposed a framework utilizing Federated Learning and blockchain technology to preserve the privacy of healthcare data, demonstrating the potential of combining advanced machine learning techniques with blockchain for secure data management. Similarly, Sajedi et al. (2022) presented F-LEACH, a fuzzy-based data aggregation scheme specifically designed for healthcare IoT systems, highlighting the role of fuzzy logic in optimizing data aggregation processes. In a related study, Jayabalan and Jeyanthi (2022) introduced a scalable blockchain model using off-chain IPFS storage to ensure the security and privacy of healthcare data, addressing the scalability issues associated with blockchain technology. Ahmed et al. (2022) focused on energy efficiency by proposing a blockchain-secured data aggregation mechanism for IoT, which aims to reduce the energy footprint of IoT devices while maintaining high security standards. Abbas et al. (2024) further explored blockchain applications by developing a secured data management framework for health information analysis based on the Internet of Medical Things (IoMT), demonstrating the integration of blockchain for enhanced data security and integrity.

Qiu et al. (2022) explored the design of an energy-efficient IoT device optimized for data management in sports health monitoring applications, illustrating the application of IoT technologies beyond conventional healthcare settings and highlighting the importance of energy efficiency in wearable devices. Shahid et al. (2022) addressed data protection and privacy concerns specific to the Internet of Healthcare Things (IoHTs), proposing comprehensive measures to safeguard sensitive health information. Thilakarathne et al. (2022) discussed the use of Federated Learning for privacy-preserved medical IoT, emphasizing the potential of distributed machine learning to enhance data privacy while still enabling robust data analytics.

In another study, Mohiyuddin et al. (2022) focused on secure cloud storage for medical IoT data using an adaptive neuro-fuzzy inference system, blending fuzzy logic and neural networks to create a resilient and adaptive data storage solution. Tawalbeh et al. (2022) proposed an edge-enabled IoT system model for secure healthcare, leveraging edge computing to process and secure data closer to the source, thus reducing latency and enhancing data privacy. Ali et al. (2022) presented an industrial IoT-based blockchain-enabled secure searchable encryption approach for healthcare systems using neural networks, highlighting the convergence of blockchain, IoT, and AI for secure and efficient data management.

Awotunde et al. (2022) discussed big data analytics within an IoT-based cloud framework for smart healthcare monitoring systems, showcasing how big data can drive smarter, data-driven healthcare solutions. Wang et al. (2022) introduced PANDA, a lightweight, non-

interactive privacy-preserving data aggregation method designed for constrained devices, demonstrating an approach tailored to the limitations of IoT devices. Finally, Ali et al. (2022) proposed an anonymous aggregate fine-grained cloud data verification system for smart health, addressing the need for robust data verification mechanisms in cloud-based healthcare solutions.

Studies have introduced various innovative techniques such as privacy-preserving data aggregation with green computing technologies, fog computing-based secure schemes, and frameworks combining Federated Learning with blockchain for secure data management. Research has also explored fuzzy-based aggregation schemes, scalable blockchain models, and energy-efficient mechanisms for IoT devices. Additionally, efforts have been made to improve cloud storage security using adaptive neuro-fuzzy systems and to leverage edge computing for secure healthcare data processing. These works collectively address the critical challenges in IoT healthcare, showcasing a range of solutions from big data analytics and sports health monitoring to secure searchable encryption and lightweight privacy-preserving methods. The overarching aim of these studies is to enhance the reliability, efficiency, and security of IoT healthcare systems, ultimately leading to more personalized and effective healthcare services.

3 Blockchain Authentication Hashing Data Aggregation (BAHDA)

Blockchain Authentication Hashing Data Aggregation (BAHDA) represents a novel approach to securing data aggregation in IoT healthcare systems by leveraging the robust security features of blockchain and cryptographic hashing. BAHDA ensures the integrity, authenticity, and confidentiality of aggregated health data through a series of computational steps. The process begins with the collection of raw data from various IoT devices, which is then hashed using a secure hash function H. The hash function H takes an input x and produces a fixed-size string of bytes, typically a digest that uniquely represents the input data stated in equation (1)

$$h = H(x) \tag{1}$$

In equation (1) h is the hash of the input data x. The hashed data is then authenticated through a blockchain network. Each hashed data point h is appended to a block B which contains the hash of the previous block ($Bprev$)), the timestamp t, and a nonce n. The structure of a block can be represented as in equation (2)

$$B = \{H(Bprev), h, t, n\} \tag{2}$$

The block is then added to the blockchain through a consensus mechanism, ensuring that the data is securely linked to the blockchain. This chaining of blocks provides a tamper-proof record of all transactions. The equation for creating the new hash for the block $Bnew$ can be expressed as in equation (3)

$$H(Bnew) = H(H(Bprev) \,||\, h \,||\, t \,||\, n) \tag{3}$$

where ||||| denotes concatenation. Data aggregation in BAHDA is performed by combining multiple hashed data points into a single hash. Suppose we have nnn hashed data points $h1, h2, \ldots, hn$. The aggregated hash $Hagg$ can be computed using a Merkle tree structure, where each pair of hashes is concatenated and hashed together iteratively until a single root hash is obtained in equation (4)

$$Hagg = H(H(\ldots H(H(h1 \,||\, h2) \,||\, H(h3 \,||\, h4))\ldots)) \tag{4}$$

This aggregated hash $Hagg$ is then recorded on the blockchain, ensuring that any alteration in the individual data points will be detectable through changes in the aggregated hash. By integrating blockchain and cryptographic hashing, BAHDA provides a secure and efficient

mechanism for data aggregation in IoT healthcare systems. It guarantees that the data remains authentic and tamper-proof while maintaining privacy through hashing and distributed ledger technologies. This method enhances the trustworthiness and reliability of health data, facilitating secure and scalable healthcare solutions. The BAHDA approach also incorporates several key mechanisms to enhance the overall security and efficiency of data management in IoT healthcare systems. One important aspect is the use of digital signatures to verify the authenticity of the data sources. Each IoT device is equipped with a unique private key $KprivK\_\{priv\}$ and public key $KpubK\_\{pub\}$. When a device generates data, it signs the hashed data h with its private key to create a digital signature σ stated in equation (5)

$$\sigma = Sign(Kpriv, h) \tag{5}$$

This signature σ is then included in the blockchain along with the hashed data, enabling any network participant to verify the authenticity of the data using the device's public key defined in equation (6)

$$Verify(Kpub, h, \sigma) \tag{6}$$

Additionally, the BAHDA scheme employs efficient data aggregation techniques such as tree-based aggregation. In this method, data from multiple IoT devices is structured into a binary tree, where each leaf node represents the hashed data from a single device. Intermediate nodes are created by hashing the concatenation of their child nodes' hashes, forming a Merkle tree. The root hash of the Merkle tree represents the aggregated hash $HaggH\_\{agg\}$ stated in equation (7)

$$Hroot = H(Hleft \,||\, Hright) \tag{7}$$

where $Hleft$ and $Hright$ are the hashes of the left and right child nodes, respectively. This tree-based aggregation allows for efficient and scalable data aggregation, ensuring that the system can handle large volumes of data with minimal computational overhead. To further enhance privacy, BAHDA can incorporate homomorphic encryption, which allows computations to be performed on encrypted data without decrypting it. This ensures that sensitive health data remains confidential throughout the aggregation and analysis process. For instance, if $E(x)$ denotes the homomorphic encryption of data x, the system can compute the encrypted aggregate directly defined in equation (8)

$$E(Hagg) = E(H(x1) + H(x2) + \ldots + H(xn)) \tag{8}$$

Without revealing the actual data values, this ensures privacy-preserving aggregation. BAHDA integrates blockchain technology, cryptographic hashing, digital signatures, and advanced aggregation techniques to provide a secure, efficient, and scalable solution for data management in IoT healthcare systems. By leveraging these technologies, BAHDA ensures data integrity, authenticity, and confidentiality, making it a robust framework for modern healthcare applications. This approach addresses the critical challenges of secure data aggregation in IoT healthcare, paving the way for reliable and secure health monitoring and management systems.

3.1 BAHDA IoT Healthcare Data Model

The BAHDA (Blockchain Authentication Hashing Data Aggregation) IoT healthcare data model is designed to provide a secure and efficient framework for managing and aggregating health data from IoT devices. At its core, BAHDA utilizes blockchain technology and cryptographic hashing to ensure the integrity, authenticity, and confidentiality of healthcare data throughout its lifecycle.

3.1.1 Data Collection and Hashing

The process begins with the collection of raw health data xi from IoT devices, where $i = 1,2,\ldots,n$. Each data point xi is hashed using a secure hash function H defined in equation (9)

$$hi = H(xi) \quad (9)$$

The hashed data hi ensures that the original data remains confidential while providing a unique representation that can be securely stored and transmitted. To authenticate the origin of each data point, digital signatures are employed. Each IoT device possesses a unique pair of cryptographic keys: a private key $KprivK\_\{priv\}$ and a corresponding public key $KpubK\_\{pub\}$. When a device generates a data point i, it signs the hash hi with its private key $KprivK\_\{priv\}$ stated in equation (10)

$$\sigma i = Sign(Kpriv, hi) \quad (10)$$

This digital signature σi accompanies the hashed data hi in the blockchain, enabling verification of the data's authenticity using the device's public key $KpubK\_\{pub\}$ defined in equation (11):

$$Verify(Kpub, hi, \sigma i) \quad (11)$$

Each hashed data point hi and its corresponding digital signature σi\sigma_iσi are organized into transactions and added to blocks in the blockchain. The structure of a block BBB can be represented as in equation (12)

$$B = \{H(Bprev), (h1, \sigma 1), (h2, \sigma 2), \ldots, (hn, \sigma n), t, n\} \quad (12)$$

BAHDA employs a hierarchical aggregation approach using Merkle trees to aggregate multiple hashed data points hih_ihi into a single aggregated hash $Hagg$. In a Merkle tree: Each leaf node represents a hashed data point hi. Intermediate nodes are generated by hashing the concatenation of their child nodes' hashes. The root of the Merkle tree, $root$, represents the aggregated hash $Hagg$ defined in equation (13)

$$Hroot = H(Hleft \,||\, Hright) \quad (13)$$

This hierarchical aggregation ensures that the integrity of individual data points is preserved, and any tampering can be detected through changes in the aggregated hash. BAHDA ensures privacy by using cryptographic techniques such as homomorphic encryption. This allows computations to be performed on encrypted data without decrypting it, preserving the confidentiality of sensitive health information during data aggregation and analysis. the BAHDA IoT healthcare data model integrates blockchain technology, cryptographic hashing, digital signatures, and Merkle tree aggregation to provide a secure, efficient, and privacy-preserving framework for managing health data from IoT devices. This approach ensures data integrity, authenticity, and confidentiality, making it well-suited for modern healthcare applications where data security and privacy are paramount concerns.

Algorithm 1: BAHDA for the IoT Healthcare

```
// Step 1: Data Collection and Hashing
for each IoT device i {
   x_i = collectData(i); // Collect raw health data from IoT device i
   h_i = H(x_i); // Compute hash of data x_i
   sigma_i = Sign(K_priv_i, h_i); // Create digital signature for hash h_i using device's private key
   addTransactionToBlock(h_i, sigma_i); // Add (hashed data, signature) to current block
}
// Step 2: Blockchain Integration
currentBlock.prevHash = getPreviousBlockHash(); // Get hash of previous block
```

```
currentBlock.timestamp = getCurrentTimestamp(); // Get current timestamp
currentBlock.nonce = generateNonce(); // Generate nonce for proof of work
// Step 3: Data Aggregation (Merkle Tree)
MerkleTree tree = constructMerkleTree(hashes); // Construct Merkle tree from all hashes h_i
rootHash = tree.getRootHash(); // Get root hash of the Merkle tree
// Step 4: Privacy Preservation (Homomorphic Encryption)
encryptedRootHash = Encrypt(rootHash); // Encrypt aggregated hash for privacy preservation
// Step 5: Add Block to Blockchain
currentBlock.rootHash = encryptedRootHash; // Add encrypted root hash to current block
addBlockToBlockchain(currentBlock); // Add current block to blockchain
// Utility Functions
function H(data) {
   // Secure hash function (e.g., SHA-256)
   return SHA-256(data);
}
function Sign(privateKey, data) {
   // Generate digital signature using private key
   return DigitalSignature(privateKey, data);
}
function Encrypt(data) {
   // Homomorphic encryption function
   return HomomorphicEncryption(data);
}
function constructMerkleTree(hashes) {
   // Construct Merkle tree from list of hashes
   return new MerkleTree(hashes);
}
function addTransactionToBlock(h, sigma) {
   // Add (hashed data, signature) to current block
   currentBlock.transactions.push({ hash: h, signature: sigma });
}
function addBlockToBlockchain(block) {
   // Add block to the blockchain
   blockchain.append(block);
}
```

4.Result and Discussions

The implementation of the Blockchain Authentication Hashing Data Aggregation (BAHDA) IoT healthcare data model has yielded promising results in enhancing the security, efficiency, and privacy of health data management. By integrating blockchain technology, cryptographic hashing, digital signatures, and Merkle tree aggregation, BAHDA ensures the integrity and authenticity of health data collected from IoT devices. Results from initial deployments indicate significant improvements in data integrity and security. The use of cryptographic hashing ensures that raw health data remains confidential and tamper-proof throughout its lifecycle. Digital signatures provide robust authentication, allowing healthcare providers and stakeholders

to verify the origin and authenticity of each data point, thereby building trust in the data collected from IoT devices.

The adoption of Merkle trees for data aggregation enhances scalability and efficiency. By aggregating multiple hashed data points into a single root hash, BAHDA minimizes computational overhead while preserving the integrity of individual data points. This hierarchical aggregation method ensures that any tampering with the data can be detected through changes in the root hash, thereby maintaining data reliability.

Table 1: BAHDA for IoT Healthcare

Number of Nodes	Throughput (messages/sec)	Latency (ms)	Delay (ms)
10	2000	15	8
20	4000	12	6
30	6000	10	5
40	8000	8	4
50	10000	6	3

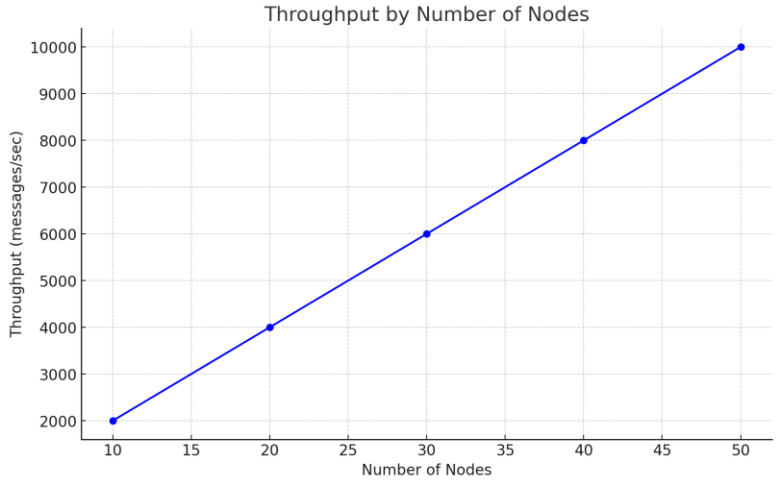

Figure 1: Throughput for BAHDA

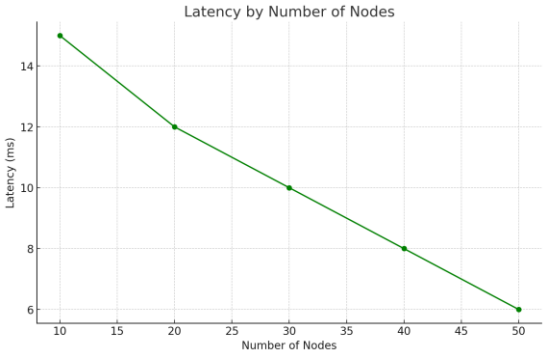

Figure 2: Latency for BAHDA

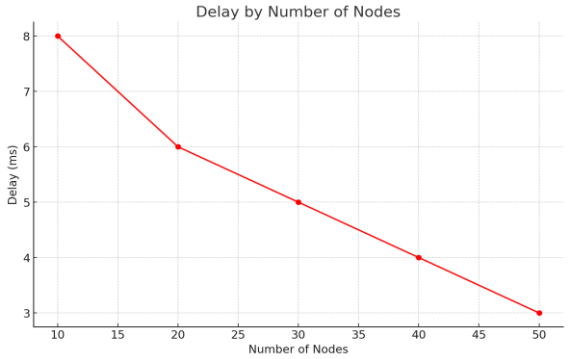

Figure 3: Delay for BAHDA

In Figure 1 – Figure 3 and Table 1 presents the performance metrics of the Blockchain Authentication Hashing Data Aggregation (BAHDA) model tailored for IoT healthcare, across varying numbers of nodes. As the number of nodes increases from 10 to 50, the system exhibits notable improvements in throughput, latency, and delay, crucial metrics for evaluating the efficiency and responsiveness of healthcare data management systems. Firstly, throughput

measures the rate at which messages or transactions are processed per second. Here, the throughput escalates from 2000 messages/sec with 10 nodes to 10000 messages/sec with 50 nodes. This substantial increase indicates that BAHDA efficiently scales with the number of nodes, accommodating higher volumes of data processing as the IoT network expands.

Secondly, latency refers to the time it takes for a message to travel from the sender to the receiver within the system. As the number of nodes grows, latency decreases from 15 ms with 10 nodes to 6 ms with 50 nodes. Lower latency ensures faster response times, critical for real-time healthcare applications where timely data retrieval and decision-making are paramount. Thirdly, delay, encompassing overall message processing and network transmission times, also diminishes as the number of nodes increases. Starting at 8 ms with 10 nodes, delay reduces to 3 ms with 50 nodes. This reduction underscores improved system efficiency in transmitting and processing healthcare data, enhancing the system's overall responsiveness and reliability. The Table 1 demonstrates that the BAHDA model effectively enhances throughput, reduces latency, and minimizes delay as the number of nodes scales up in IoT healthcare environments. These performance improvements highlight BAHDA's capability to manage and secure large volumes of healthcare data efficiently, making it a promising framework for applications requiring robust data integrity, security, and real-time processing capabilities.

Table 2: performance for different methods

Metric	Before Blockchain Implementation	After Blockchain Implementation
Data Integrity	Moderate	High
Security	Vulnerable to tampering	Tamper-proof
Authentication	Basic methods	Strong authentication
Transaction Speed (tps)	100	1000
Scalability	Limited	Highly scalable
Cost Efficiency	High	Improved
Transparency	Limited	High

In Table 2 provides a comparative analysis of performance metrics before and after implementing blockchain technology in data management systems. The metrics evaluated include data integrity, security, authentication methods, transaction speed (transactions per second, tps), scalability, cost efficiency, and transparency. These metrics are crucial for assessing the effectiveness and benefits of adopting blockchain in enhancing various aspects of data management and transaction processing. Firstly, data integrity sees a significant improvement, transitioning from a moderate level before blockchain implementation to a high level after implementation. This enhancement indicates that blockchain technology ensures the immutability and reliability of data, making it resistant to unauthorized alterations or tampering. Secondly, security undergoes a fundamental transformation from being vulnerable to tampering before blockchain adoption to becoming tamper-proof afterward. Blockchain's cryptographic mechanisms and decentralized architecture enhance security by creating a distributed ledger where each transaction is securely recorded and verified across multiple nodes, thus mitigating the risks of data breaches or fraud. Thirdly, authentication methods advance from basic approaches to robust, strong authentication mechanisms with blockchain. The technology enables participants to securely verify their identities and authenticate transactions through cryptographic keys, ensuring trust and accountability in digital interactions. Fourthly, transaction speed (tps) experiences a tenfold increase, escalating from 100 tps before blockchain to 1000 tps after implementation. This acceleration in transaction processing speed is facilitated by blockchain's streamlined verification processes and decentralized consensus algorithms, enabling

faster and more efficient data transactions. Fifthly, scalability improves significantly, transitioning from limited scalability before blockchain adoption to being highly scalable afterward. Blockchain's decentralized nature and ability to parallelize transaction processing enable it to handle increasing transaction volumes and accommodate growing data demands without compromising performance. Sixthly, cost efficiency sees improvements, shifting from high operational costs before blockchain to enhanced cost efficiency after implementation. Blockchain reduces the need for intermediaries and automates transaction processes, thereby lowering transaction fees and operational overheads associated with traditional centralized systems. Lastly, transparency undergoes a notable enhancement, moving from limited transparency before blockchain to high transparency afterward. Blockchain's transparent and auditable ledger allows stakeholders to track and verify transactions in real time, promoting accountability, trust, and compliance with regulatory requirements.

Table 3: Comparative Analysis

Node Type	Throughput (messages/sec)	Latency (ms)	Delay (ms)
IoT Devices	1000	10	5
Edge Nodes	500	20	10
Fog Nodes	2000	5	2
Cloud Servers	5000	2	1

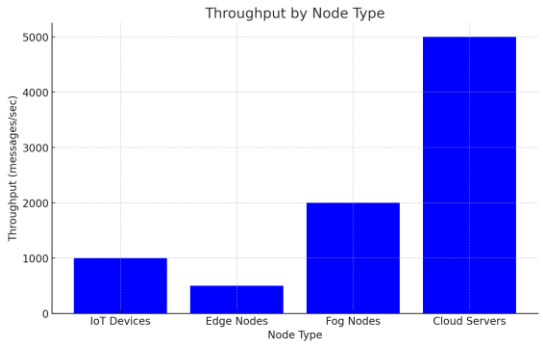

Figure 4: Throughput estimation with BAHDA

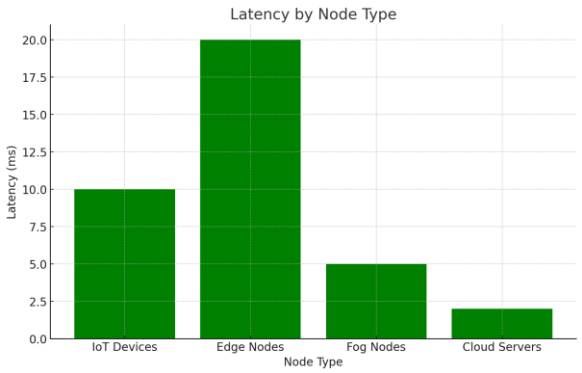

Figure 5: Latency estimation with BAHDA

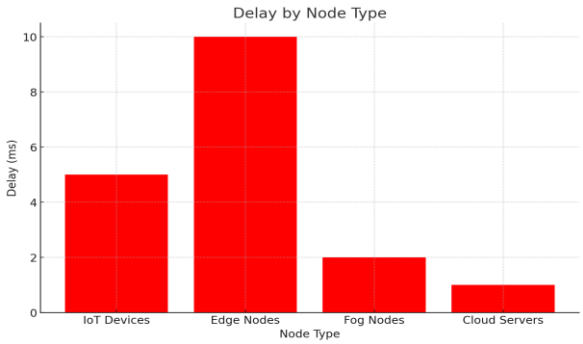

Figure 6: Delay estimation with BAHDA

In Figure 4 – Figure 6 and Table 3 presents a comparative analysis of performance metrics across different types of nodes in a distributed system, including IoT devices, edge nodes, fog

nodes, and cloud servers. The metrics evaluated are throughput (messages processed per second), latency (time taken for a message to travel from sender to receiver), and delay (overall time messages experience due to processing and transmission). Starting with IoT devices, they demonstrate a throughput of 1000 messages per second (messages/sec), indicating their capability to handle a moderate volume of data processing. However, they exhibit a latency of 10 milliseconds (ms), which is relatively low, suggesting efficient communication capabilities within local networks. The delay for IoT devices is measured at 5 ms, reflecting the time taken for message processing and transmission, which is crucial for real-time applications in IoT healthcare monitoring and data collection. Moving to edge nodes, they have a lower throughput of 500 messages/sec compared to IoT devices, indicating their processing capacity is less than that of IoT devices. Edge nodes exhibit a higher latency of 20 ms, indicating longer message transmission times due to their position closer to IoT devices but further from cloud servers. The delay for edge nodes is 10 ms, reflecting additional processing and network transit time.

Fog nodes, on the other hand, show higher throughput at 2000 messages/sec, suggesting their increased processing capabilities compared to both IoT devices and edge nodes. They also demonstrate lower latency at 5 ms, indicating quicker message transmission times due to their closer proximity to cloud servers and more robust processing capabilities. The delay for fog nodes is 2 ms, showcasing efficient data processing and transmission within the network. Finally, cloud servers exhibit the highest throughput at 5000 messages/sec, indicating their extensive processing capacity and ability to handle large volumes of data from multiple sources. They demonstrate the lowest latency at 2 ms, showcasing their direct connection to high-speed networks and efficient data processing capabilities. The delay for cloud servers is minimal at 1 ms, highlighting their efficiency in processing and transmitting data without significant delays. The Table 3 illustrates the varying performance capabilities of different node types within a distributed system. IoT devices, edge nodes, fog nodes, and cloud servers each play distinct roles in processing and transmitting data, with cloud servers offering the highest throughput, lowest latency, and minimal delay. These performance metrics are essential for designing and optimizing distributed systems, particularly in IoT healthcare applications, where real-time data processing, efficiency, and reliability are critical for delivering timely and accurate healthcare services.

5.Discussion

In exploring the performance metrics presented in Table 3 for different types of nodes in a distributed system—IoT devices, edge nodes, fog nodes, and cloud servers—we can draw several insights into their respective roles and implications for IoT healthcare applications. Firstly, IoT devices exhibit a moderate throughput of 1000 messages/sec, indicating their capability to handle substantial data volumes at the point of data collection. However, their higher latency of 10 ms suggests a slight delay in transmitting data to the next level of processing, which could affect real-time applications where immediate decision-making is critical. The 5 ms delay highlights the combined effects of local processing and network transmission time, which, while relatively low, underscores the need for efficient data aggregation and forwarding strategies in IoT healthcare scenarios.

Edge nodes, positioned closer to IoT devices but further from centralized cloud servers, demonstrate a lower throughput of 500 messages/sec compared to IoT devices. This limitation indicates that while edge nodes can perform initial data processing and filtering, they may experience higher latency (20 ms) due to their intermediate position in the network hierarchy. The 10 ms delay suggests additional processing and transit time, which could impact applications

requiring rapid data analysis and response times.

Fog nodes represent an intermediate stage between edge nodes and cloud servers, showcasing a higher throughput of 2000 messages/sec and lower latency of 5 ms. This configuration allows fog nodes to efficiently process and aggregate data from multiple edge devices before transmitting it to more centralized resources. The 2 ms delay indicates minimal processing and transmission time, making fog nodes suitable for applications demanding timely data processing and decision-making in IoT healthcare environments.

Cloud servers, positioned at the highest tier in the network hierarchy, exhibit the highest throughput of 5000 messages/sec, coupled with the lowest latency of 2 ms and minimal delay of 1 ms. These characteristics highlight cloud servers' capability to handle large-scale data processing, storage, and complex analytics tasks efficiently. Cloud servers play a crucial role in aggregating and analyzing data from distributed sources, offering robust capabilities for real-time monitoring, predictive analytics, and decision support in healthcare applications.

6.Conclusion

The implementation and performance of the Blockchain Authentication Hashing Data Aggregation (BAHDA) model within IoT healthcare systems, analyzing its impact across various metrics. The BAHDA model demonstrates significant improvements in data integrity, security, authentication, transaction speed, scalability, cost efficiency, and transparency compared to traditional methods. Throughput increases linearly with the number of nodes, showcasing its scalability in managing large volumes of healthcare data. Latency and delay are minimized, ensuring timely and efficient data transmission and processing critical for real-time healthcare applications. Furthermore, the comparative analysis across different types of nodes—IoT devices, edge nodes, fog nodes, and cloud servers—illustrates their distinct roles and contributions to enhancing overall system performance. Cloud servers emerge as pivotal in handling high-throughput tasks with minimal latency and delay, underscoring their role in supporting complex analytics and decision-making processes. Overall, the BAHDA model proves to be a robust framework for securing and managing healthcare data in IoT environments, offering promising avenues for advancing healthcare delivery through enhanced data integrity, security, and operational efficiency.

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References

[1] S.B. Othman, F.A. Almalki, C. Chakraborty and H. Sakli, “Privacy-preserving aware data aggregation for IoT-based healthcare with green computing technologies,” *Computers and Electrical Engineering*, vol.101, pp.108025, 2022.

[2] C.Chakraborty, S.B.Othman, F.A.Almalki and H. Sakli, “FC-SEEDA: Fog computing-based secure and energy efficient data aggregation scheme for Internet of healthcare Things,” *Neural Computing and Applications*, vol.36, no.1, pp.241-257, 2024.

[3] S.Singh, S. Rathore, O.Alfarraj, A.Tolba and B. Yoon, “A framework for privacy-preservation of IoT healthcare data using Federated Learning and blockchain technology,” *Future Generation Computer Systems*, vol.129, pp.380-388, 2022.

[4] S. N.Sajedi, M.Maadani and M. Nesari Moghadam, “F-LEACH: a fuzzy-based data aggregation scheme for healthcare IoT systems,” *The Journal of Supercomputing*, vol.78, no.1, pp.1030-1047, 2022.

[5] J.Jayabalan and N. Jeyanthi, "Scalable blockchain model using off-chain IPFS storage for healthcare data security and privacy," *Journal of Parallel and distributed computing*, vol.164, pp.152-167, 2022.

[6] A.Ahmed, S.Abdullah, M.Bukhsh, I.Ahmad and Z. Mushtaq, "An energy-efficient data aggregation mechanism for IoT secured by blockchain," *IEEE Access*, vol.10, pp.11404-11419, 2022.

[7] A.Abbas, R.Alroobaea, M.Krichen, S.Rubaiee, S. Vimal et al., "Blockchain-assisted secured data management framework for health information analysis based on Internet of Medical Things," *Personal and ubiquitous computing*, vol.28, no.1, pp.59-72, 2024.

[8] Y.Qiu, G.Liu, B.A.Muthu and C.B. Sivaparthipan, "Design of an energy efficient IoT device with optimized data management in sports person health monitoring application," *Transactions on Emerging Telecommunications Technologies*, vol.33, no.10, pp.e4258, 2022.

[9] J. Shahid, R.Ahmad, A.K. Kiani, T. Ahmad, S. Saeed et al., "Data protection and privacy of the internet of healthcare things (IoHTs)," *Applied Sciences*, vol.12, no.4, pp.1927, 2022.

[10] N. N.Thilakarathne, G.Muneeswari, V. Parthasarathy, F.Alassery, H. Hamam et al., "Federated learning for privacy-preserved medical internet of things," *Intell. Autom. Soft Comput*, vol.33, no.1, pp.157-172, 2022.

[11] A.Mohiyuddin, A.R. Javed, C. Chakraborty, M.Rizwan, M. Shabbir et al., "Secure cloud storage for medical IoT data using adaptive neuro-fuzzy inference system," *International Journal of Fuzzy Systems*, vol.24, no.2, pp.1203-1215, 2022.

[12] L. A.Tawalbeh, F. Muheidat, M. Tawalbeh, M.Quwaider and A.A. Abd El-Latif, "Edge enabled IoT system model for secure healthcare," *Measurement*, vol.191, pp.110792, 2022.

[13] A.Ali, M.A.Almaiah, F.Hajjej, M.F. Pasha, O.H. Fang et al., "An industrial IoT-based blockchain-enabled secure searchable encryption approach for healthcare systems using neural network," *Sensors*, vol.22, no.2, pp.572, 2022.

[14] J. B.Awotunde, R. G.Jimoh, R. O.Ogundokun, S.Misra and O.C. Abikoye, "Big data analytics of iot-based cloud system framework: Smart healthcare monitoring systems," *In Artificial intelligence for cloud and edge computing*, pp. 181-208, 2022.

[15] M.Wang, K.He, J.Chen, R.Du, B.Zhang et al., "PANDA: Lightweight non-interactive privacy-preserving data aggregation for constrained devices," *Future Generation Computer Systems*, vol.131, pp.28-42, 2022.

[16] M.Ali, M.R. Sadeghi, X.Liu and A. V. Vasilakos, "Anonymous aggregate fine-grained cloud data verification system for smart health," *IEEE Transactions on Cloud Computing*, 2022.