IoMT-Driven Emergency Data Access for Unidentified and Unconscious Patients in Road Accidents Leveraging Privacy-Preserving Blockchain Protocols and Cryptographic Primitives *

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Abstract

Consider a group of unconscious, unidentified travellers admitted to a hospital after a severe accident. Doctors urgently need their medical histories to provide appropriate treatment. To address this challenge, we propose a secure, decentralised, and privacy-preserving framework for emergency medical data retrieval. The system employs a retina scan to identify the patient's content identifier (CID) stored on the blockchain, while a fingerprint scan derives encryption keys for securing IoMT (Internet of Medical Things) data in IPFS (Inter-Planetary File System). A fuzzy extractor with minor output adjustments ensures reliable and consistent key generation from inherently noisy biometric inputs. Furthermore, hospital authentication is enforced using the Schnorr Identification Protocol, ensuring that only authorised institutions can access patient data. The proposed framework achieves a balanced integration of accessibility, security, and privacy, thereby filling a critical gap in real-time emergency healthcare scenarios.

1 Introduction

The Internet of Things (IoT) is revolutionising the digital landscape by connecting smart devices that gather and share data through embedded sensors, software, and network technologies. It is transforming sectors such as smart cities, industry, and especially healthcare. In healthcare, IoT enables remote monitoring, early diagnosis, and streamlined hospital operations, fostering more efficient and personalised care. However, these benefits come with significant concerns regarding data privacy, security, interoperability, and standardisation.

The Internet of Medical Things (IoMT) refers to an integrated network of medical devices and applications that connect to healthcare information systems through the internet. These devices, ranging from wearable sensors, implantables, and patient monitoring systems, collect, analyse, and transmit health data in real time. IoMT enables remote patient monitoring, personalised care, and improved clinical decision-making, making it essential in modern digital healthcare infrastructure. Healthcare data is incredibly sensitive, containing personal information and medical records vital for patient care. Protecting this data is paramount, and blockchain technology offers several promising solutions, which include enhanced security and transparency, interoperability, decentralisation, improved data sharing, and collaboration.

Maruthi et al. [1] also proposed an approach for unconscious and identified patients by applying threshold secret sharing in conjunction with Proxy Re-Encryption Plus (PRE+) to retrieve medical

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records during emergencies securely. Takahashi et al. [2] presented an emergency control system for the unconscious and identified (pendant-wearing) patients. Their system leverages public blockchain and Inter-Planetary File System (IPFS) via biometric approval from a patient-worn pendant, even when the patient is unconscious.

Scenario: Group of Unconscious and Unidentified Patients

Imagine a group of travellers involved in a severe accident and rushed to a hospital, all unconscious and unidentified, or without medical histories. The attending doctors urgently require access to their medical records to provide appropriate treatment. Among the victims is a British citizen with a known cardiac condition, a Japanese patient with a history of diabetes, and an Indian patient with a drug allergy. In such critical situations, timely and accurate access to each individual's medical data is vital for ensuring proper care and improving their chances of survival. To the best of our knowledge, there does not exist any scheme that can access a patient's medical data when the patient is unconscious and unidentified during an emergency.

Relevance to Mobile Internet Security

Mobile Internet Security encompasses a comprehensive suite of technologies, protocols, and mechanisms aimed at safeguarding mobile devices, wireless communications, and online services from a wide range of cyber threats. Within healthcare and Internet of Medical Things (IoMT) environments, MIS plays a pivotal role in ensuring secure and authenticated access to medical data, while maintaining resilience against data tampering, interception, and leakage during emergency data transmission.

OUR CONTRIBUTION:

In this work, we have designed a secure and decentralised privacy-preserving framework for retrieving medical data in an emergency involving unconscious and unidentified patients. Our framework leverages a biometric-based identification system in which a retina scan is used to identify the corresponding patient's content identifier (CID) stored on the blockchain. Additionally, a fingerprint scan is employed to derive encryption keys for securing the patient's IoMT (Internet of Medical Things) data in IPFS (Inter-Planetary File System). A fuzzy extractor with minor output adjustments ensures reliable and consistent key generation from inherently noisy biometric inputs. Finally, to ensure that only legitimate healthcare institutions can access the medical data, we incorporate the Schnorr Identification Protocol for hospital authentication, thereby preserving patient privacy while enabling secure and timely access to medical records in critical situations. Thereby, the proposed system achieves a balance between accessibility, security, and privacy, addressing a critical gap in real-time emergency healthcare scenarios.

2 Relevant Theoretical and Technical basis

2.1 Fuzzy Extractor

A fuzzy extractor is a cryptographic primitive designed to reliably derive consistent and secure keys from inherently noisy and non-uniform data, such as biometric features, sensor readings, or physical unclonable functions (PUFs). Unlike traditional cryptographic keys that demand exact input repetition, fuzzy extractors facilitate the regeneration of the same key even when the input varies slightly due to environmental noise or acquisition imperfections. Formally introduced by Dodis et al. [3], a fuzzy extractor consists of two primary algorithms:

1) **Gen (w) $\rightarrow$ (R, P)**: In the enrollment phase, this algorithm takes a noisy input w (e.g., a fingerprint scan) and produces a uniformly random cryptographic key R along with public helper data P.
2) **Rep ($\mathbf{w'}$, P) $\rightarrow$ R**: In the reconstruction phase, given a new noisy input w' that is close to w, the algorithm uses the helper data P to recover the original key R.

The helper data P does not leak significant information about R, ensuring that the key remains secure even if P is publicly accessible.

Fuzzy Extractor Example

GEN (w = 10101):
c = 11010 ← ECC codeword
P = w ⊕ c = 01111
R = Hash(w) = key

REP (w' = 10111, P):
c' = w' ⊕ P = 11000
ECC (c') → c = 11010
w = c ⊕ P = 10101
R = Hash (w) = same key

2.1.1 Hash Value Extraction for Biometric Authentication

In the proposed architecture, a *fuzzy extractor* is employed to derive a cryptographic key from biometric inputs such as fingerprints and retina scans. The fuzzy extractor is designed to tolerate small variations between biometric captures, such as those caused by environmental noise, sensor imperfections, or changes in acquisition conditions, while still regenerating the same key for the same individual.

The cryptographic hash value of the fingerprint is computed using the fuzzy extractor. In this context, the **tolerance level** refers to the *maximum number of bit differences* (Hamming distance) between the cryptographic hash value of the original and noisy biometric inputs that can be corrected to yield the same key. The tolerance level for the cryptographic hash value of fingerbits is set to 32 bits. Therefore, the shared key is derived as the cryptographic hash of the fingerprint, **with its 40 least significant bits set to zero**, ensuring robustness against biometric noise while maintaining security.

During **enrollment**, the true biometric features are preprocessed into a stable binary representation of length n bits, standardised across modalities. The error-correcting code (ECC) encodes this representation, producing helper data that is stored publicly while preserving privacy. The corrected bits are then hashed (e.g., using SHA-256) to produce a stable cryptographic key.

During **authentication**, a new biometric sample from the same person, such as a slightly different fingerprint impression or retina scan, is captured. Since biometric data naturally varies, this sample may not match the original template exactly. The fuzzy extractor processes the new input, and the difference from the enrolled template is within the tolerance threshold (32 bits for fingerbits); the error-correcting code (ECC) corrects the mismatches. This allows the system to regenerate the same cryptographic key that was created during enrollment. The regenerated key is then used to decrypt the patient's medical data.

2.2 Non-Interactive Zero-knowledge (NIZK) Proof

In 1985, Shafi Goldwasser, Silvio Micali, and Charles Rackoff pioneered the concept of Zero-Knowledge Proofs (ZKPs) in their seminal work [4], which has since become a cornerstone of modern cryptography. Recognising their groundbreaking contributions, the Turing Award was bestowed upon Shafi Goldwasser and Silvio Micali in 2012.

Zero-knowledge proofs enable a prover to convincingly demonstrate the validity of a statement to a verifier without disclosing any information beyond the statement's truthfulness. Building on this foundation, Blum, Feldman, and Micali introduced Non-Interactive Zero-Knowledge Proofs (NIZKs) in 1988 [5], significantly enhancing the practicality and applicability of ZKPs [6].In Non-Interactive Zero-Knowledge (NIZK) protocols, the prover produces a single message, referred to as proof, to convince the verifier of the statement's validity without divulging any particular details. The Fiat-Shamir transform [7] adeptly transforms a Zero-Knowledge protocol into a non-interactive zero-knowledge proof of knowledge under the random oracle model.

Recently, NIZK protocols have found notable applications within blockchain technology, where proofs must maintain succinctness. In contrast to interactive zero-knowledge setups, NIZKP achieves this succinctness through a single communication round between the involved parties. An exemplary illustration of a non-interactive zero-knowledge proof is the Schnorr identification protocol [8]. This protocol enables a prover to exhibit their awareness of a private key associated with a public key, all while safeguarding the secrecy of the private key itself.

2.2.1 Schnorr ID protocols

Schnorr cyclic group G of prime order q, generator g and h∈G. h is the person's public key.
Public input: h=g^x
Private input: Prover knows secret x ∈ q such that h=g^x.
Non-interactive Protocol: We can convert the interactive identification process into a non-interactive protocol using the Fiat-Shamir heuristic [7]. In this approach, the prover generates the random challenge 'c' by hashing all public values {q, g, h, u}.
Client(sender):
Compute value of u=g^r
c=Hash { g,q,h,u }
z=r + x.c
Clients send the value of r,u, c, and z to the blockchain(verifier).
Blockchain (verifier): As a receiver, the blockchain verifies these values for the following condition: if it satisfies, then the client is authenticated.
c=Hash { g,q,h,u }
g^z = u.h^c

2.3 Blockchain

A blockchain is an unchangeable, distributed ledger that can be verified and is resistant to tampering. It comprises a series of blocks, each having a sequence of transactions. Any modification to transaction within a block requires corresponding changes in all subsequent blocks due to the hash-linking mechanism [9].

2.3.1 Blockchain 2.0 (*Build unstoppable applications*)

Ethereum functions as a decentralised platform enabling smart contracts, which are applications executing exactly as programmed without the risk of downtime, censorship, fraud, or external interference. These applications run on a specialised blockchain, a resilient and globally shared infrastructure proficient in transferring value and representing asset ownership. This empowers developers to establish markets, maintain registries of debts or agreements, and transfer funds based on instructions specified far in advance (such as wills or futures contracts) and even facilitates the creation of yet-to-be-invented functionalities, all while eliminating the need for intermediaries or counterparty risk.

2.3.2 Smart contract

With the advent of Blockchain 2.0, smart contracts emerged as integral components within the blockchain ecosystem. These self-executing programs operate on the blockchain and are designed to automate, enforce, and facilitate agreements between mutually untrusted parties, eliminating the need for centralised intermediaries. Although the concept of smart contracts was initially proposed by Nick Szabo in 1994 [10], practical implementation remained unrealised until the introduction of Bitcoin in 2008 by Satoshi Nakamoto [11], which laid the foundation for blockchain-based execution environments.

Smart contracts have since become a transformative technology, offering the potential to eliminate middlemen and automate complex processes across various domains. Their ability to execute contractual logic autonomously makes them a cornerstone of the Business 4.0 paradigm. However, due to the immutable nature of blockchain, any bugs or vulnerabilities within a smart contract become

permanent once deployed. Therefore, comprehensive pre-deployment testing and verification are critical to ensuring reliability and preventing exploitation. In this proposed work, we use blockchain for decentralisation, and we have developed a smart contract for patients' sensitive data privacy.

3 Proposed System

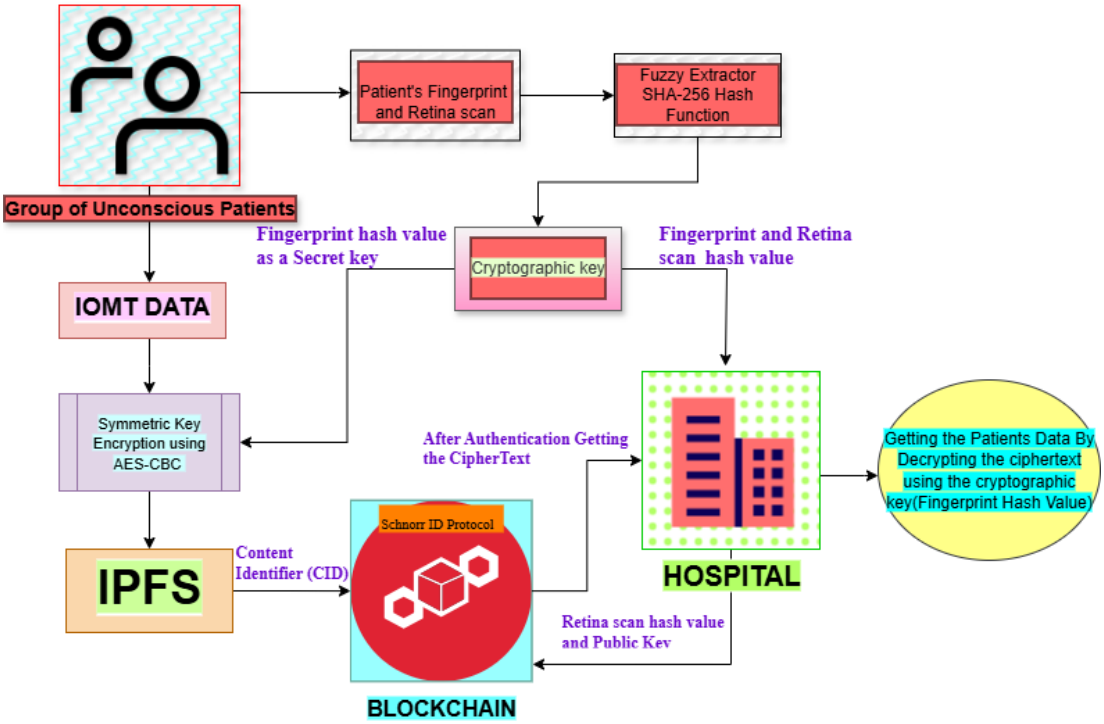

Figure 1: Overall Architecture of Proposed System

Group of Unconscious and unidentified Patients:

In emergency scenarios, patients may arrive in an unconscious or unresponsive state and unidentified, rendering them unable to provide consent or communicate their medical history. This group poses unique challenges for healthcare providers, especially in accessing critical medical records necessary for immediate treatment. Traditional authentication and consent mechanisms are impractical in such cases, underscoring the need for secure, pre-authorised frameworks that enable conditional data access while preserving patient privacy and ensuring regulatory compliance.

Trust Model for Authorised Hospital:

The proposed trust model assumes that only certified hospitals and authorised medical practitioners are permitted to access patient data during emergencies. Each hospital undergoes an authentication process using the Schnorr Identification Protocol, ensuring that only legitimate entities can initiate access requests. Furthermore, all access operations are immutably recorded on the blockchain, providing full auditability and accountability to maintain ethical and lawful compliance in emergency medical data retrieval.

3.1 Proposed Methodology

This section presents a step-by-step methodology for implementing an IoMT-based emergency data access system for unconscious and unidentified patients involved in road accidents. The approach leverages privacy-preserving blockchain protocols and cryptographic primitives, as illustrated in Figure 1.

- **Procedure to Store Patient's Data:**

  1. Patient data is initially collected from an Internet of Medical Things (IoMT) device.
  2. This data is encrypted using a symmetric encryption algorithm (AES-CBC), where the encryption key is a shared secret.
  3. Cryptographic hash value of the fingerprint is computed using the Fuzzy extractor. The tolerance level of the cryptographic hash value using a fuzzy extractor refers to the maximum number of bit differences (Hamming Distance) between the cryptographic hash value of the original and noisy biometric inputs that can be corrected to yield the same key. The tolerance level of the cryptographic hash value of fingerbits is 32 bits. Therefore, our shared key is the cryptographic hash of the fingerprint, with its 40 least significant bits set to 0. The detailed procedure for generating this hash value is provided in Section 2.1.
  4. The encrypted output, or ciphertext, is stored in the InterPlanetary File System (IPFS) to ensure secure and decentralised data storage, as explained in the algorithm 2.
  5. A content identifier (CID), which is a reference hash of the encrypted data in IPFS, is recorded on the blockchain for immutable indexing.
  6. The patient's retina scan hash is mapped to the CID on the blockchain.
  7. Cryptographic hash value of the patient's retina is computed using the Fuzzy extractor. The tolerance level of the cryptographic hash value of the patient's retina is 32 bits. Therefore, the ID of the patient is the cryptographic hash of the patient's retina, with its 40 least significant bits set to 0. The patient's ID is mapped to the CID on the blockchain, as explained in the algorithm 3.

- **Procedure to Access Patient's Data:**

  1. A predefined list of trusted hospitals is maintained, where each hospital is uniquely identified by its Hospital Identity (ID_H).
  2. To access patient data, a hospital must first undergo authentication via a non-interactive zero-knowledge proof protocol, specifically employing the Schnorr identification scheme, as explained in the algorithm 4.
  3. Upon successful authentication, the hospital submits its identity proof to the blockchain. A smart contract validates this proof against the trusted hospital registry.
  4. Once verification is completed, the hospital is granted authorisation to initiate the patient identification process.
  5. The hospital scans the unconscious patient's fingerprint and retina using a biometric sensor.
  6. A cryptographic hash is derived from the scanned fingerprint using a fuzzy extractor. The least significant 40 bits of this hash are set to zero, and the resulting value serves as the secret key for symmetric encryption.
  7. A cryptographic hash is derived from the scanned retina using a fuzzy extractor. The least significant 40 bits of this hash are set to zero, and the resulting value serves as the ID for the patients.
  8. This newly computed ID of patients is compared against the stored CID of registered patients maintained on the blockchain.
  9. If a match is found, the corresponding IPFS CID is retrieved, which points to the encrypted IoMT data.

10. The newly computed decryption key, using step 6, is used to decrypt the associated ciphertext.
11. The decrypted patient data is then utilised by the medical team to administer immediate and accurate emergency treatment.

4 Analysis

4.1 Simulation Environment

The system used for experimental evaluation had the following configuration:

Processor	Intel(R) Core(TM) i5-7500 CPU @ 3.40GHz
RAM	16 GB (15.9 GB usable)
System Type	64-bit OS
Ethereum Wallet	Mist 0.11.1
Compiler	Remix IDE v0.4.25+commit.59dbf8f1.Emscripten.clang
Language	Solidity

4.2 Evaluation Setup

To ensure secure, decentralised access and robust fault tolerance, the proposed architecture integrates blockchain with fuzzy extractors for reliable reconstruction of biometric keys derived from retina scans and fingerprints. The system underwent extensive testing using inputs that include true and noisy biometric hash values to assess the noise resilience of the fuzzy extractor and the integrity of the blockchain in safeguarding the associated IPFS Content Identifiers (CIDs) of an unconscious patient.

4.3 Overall Work Flow

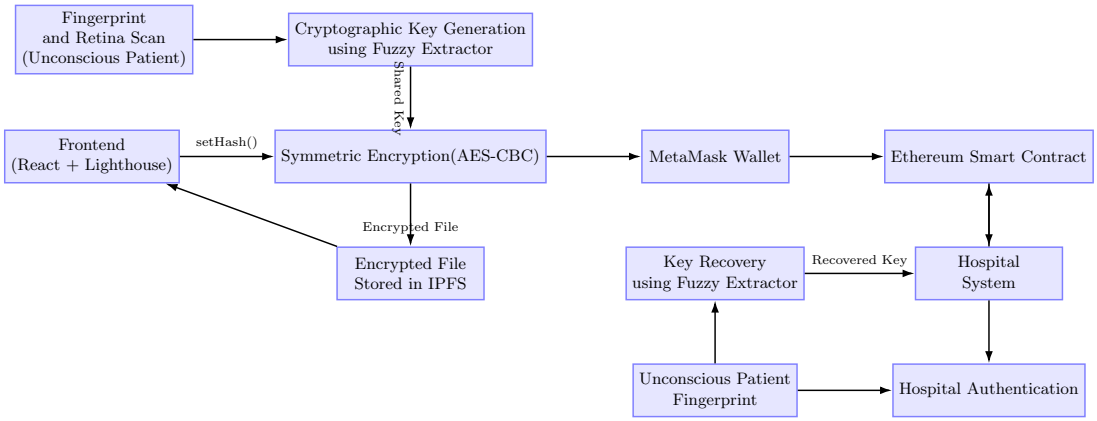

Figure 2: Secure Patient Data Flow: From IoMT Encryption to Hospital Access via Blockchain Fuzzy Extractor-Based Key Recovery

Figure 2 illustrates the secure unconscious patient data access framework integrating retina scan and fingerprint-based key generation, IPFS-based decentralised storage, and Ethereum blockchain for access control. Initially, the data owner's fingerprint is processed through a fuzzy extractor to generate a cryptographic key, which is then used for symmetric encryption of the patient's medical data. The encrypted file is stored in IPFS, while the corresponding content identifier (CID) is shared with the frontend application. The frontend interacts with MetaMask to sign transactions and store the CID securely on the Ethereum smart contract using a `setHash()` function call. The hash value derived from the retina scan using a fuzzy extractor is mapped to the corresponding Content Identifier (CID), enabling retrieval of the encrypted data.

On the hospital's side, access to the encrypted data is gated through blockchain verification. In emergencies involving unconscious patients, their fingerprint and retina scans are reprocessed using a fuzzy extractor. The fingerprint is used to reconstruct the original cryptographic key, while the retina scan enables retrieval of the corresponding Content Identifier (CID) to access the encrypted medical data. Thereby enabling rapid, privacy-preserving medical intervention.

The overall working flow of the proposed IoMT model is explained through algorithms 1,2, 3 and 4.

4.4 Fuzzy Fingerprint Key Derivation and Secure AES Encryption

The algorithm in 1 starts by creating a raw fingerprint template, represented as a random byte array to simulate a biometric sample. From this template, a cryptographic key is derived using the SHA-256 hash function, which is then truncated to the desired length (for example, 256 bits). To handle the natural noise present in biometric inputs, the algorithm calculates how many least significant bits (LSBs) can be modified without affecting security. This tolerance is determined from the allowed Hamming distance using the formula $\lceil \log_2(d) \rceil$, where d is the maximum number of bits that may differ. A random noise pattern is then generated and inserted into the LSBs of the derived key, mimicking the effect of imperfect biometric measurements, as described in Section 2.1.

To ensure reliable decryption despite this noise, the algorithm applies a masking function that zeroes out the calculated number of LSBs in both the original and noisy keys. This produces two matching secret keys, one from the clean fingerprint and one from the noisy version. These keys are used for symmetric AES encryption and decryption in CBC (Cipher Block Chaining) mode. If the noisy-derived key remains within the allowed Hamming distance, decryption succeeds; otherwise, it fails, signalling excessive noise or a biometric mismatch. Overall, this process illustrates a simple fuzzy extractor mechanism that tolerates small variations in biometric data while maintaining cryptographic security.

4.5 Decentralized File Upload and Hash Storage Algorithm

Algorithm 2 describes the process of securely uploading a file to IPFS using the Lighthouse SDK and subsequently storing the content identifier (CID) on the Ethereum blockchain. The file contains the encrypted IoMT data. Initially, a file is selected by the user through a frontend interface. The system checks whether a file has been chosen; if not, it prompts the user accordingly. Once a valid file is available, it is uploaded using the Lighthouse SDK in conjunction with an API key retrieved from the environment variables. The upload response contains a CID, which is used to generate a publicly accessible IPFS URL. This URL is stored locally in the frontend state for display or further use.

Following the upload, the CID is passed to a function responsible for interacting with a deployed smart contract on the Ethereum blockchain. The function first checks for the presence of MetaMask in the user's browser. If available, it creates a provider and signer using Ethers.js, and then instantiates the smart contract using its address and ABI. The 'setHash' function of the contract is invoked with the IPFS hash as input, and the system awaits transaction confirmation. Upon successful confirmation, a success message is logged. If MetaMask is not detected, the user is prompted to install it. The algorithm concludes by returning the IPFS URL and confirmation of successful on-chain storage, thereby ensuring decentralised and tamper-proof data linkage.

Figure 3 illustrates the workflow of a decentralised file storage system integrated with blockchain technology. The process begins at the user interface, developed as a React application, where the user initiates the upload of a file. This file is encrypted and stored on the InterPlanetary File System (IPFS) through the Lighthouse SDK, which returns a Content Identifier (CID), a unique hash representing the file. The CID is sent back to the frontend application.

To securely register this CID on the blockchain, the user triggers a transaction using the MetaMask wallet, which signs the transaction locally. The signed transaction is then transmitted to the Ethereum blockchain network, where a deployed smart contract, `IPFSStorage.sol`, processes and records the CID using the `setHash()` function. This integration ensures that the integrity of the file is preserved on IPFS while its reference is securely anchored on-chain, offering both decentralised storage and tamper-proof registration.

4.6 Smart Contract for IPFS CID Storage and Retina Hash Mapping with CID

The proposed work outperforms conventional IPFS–blockchain frameworks by enhancing data retrieval efficiency, access control, and privacy preservation, particularly in emergency healthcare scenarios [2, 12, 13, 14, 15].

The algorithm 3 describes a smart contract that provides a secure and efficient mechanism for associating a retina scan hash, generated using a fuzzy extractor, with an IPFS Content Identifier (CID) on the Ethereum blockchain. The contract is deployed with the deploying address set as the `owner`, who has exclusive privileges to store mappings. The algorithm begins with a constructor that initialises the owner, followed by a modifier `onlyOwner` that restricts certain functions to the contract owner.

Using an `onlyOwner` contract model simplifies system management by ensuring clear authority, faster decision-making, and reduced coordination overhead. It provides a lightweight and efficient control mechanism, particularly useful in healthcare scenarios where quick administrative action and accountability are essential.

The core functionality is implemented in the `storeRetinaCID` function, which accepts a `retinaHash` and a corresponding `cid`. This function verifies that the hash has not already been mapped and that the CID is non-empty before storing the association in the `retinaToCID` mapping. It also records the latest CID uploaded by the sender in the `latestCIDByUser` mapping and emits a `CIDStored` event for auditability.

For retrieval, the contract provides three view functions. The `getCIDByRetinaHash` function retrieves the CID linked to a specific retina hash. The `getLatestCIDByUser` function fetches the most recent CID stored by a specified address. Additionally, the `getMyLatestCID` function allows any user to retrieve their own last stored CID. All retrieval functions include checks to ensure that the requested data exists before returning it. This design ensures privacy, integrity, and decentralised verifiability of sensitive biometric-linked data.

4.7 Hospital Authentication Using Schnorr Identification Protocol

In this work, we propose a blockchain-based hospital authentication framework utilising the Schnorr Identification Protocol [8] to ensure secure and privacy-preserving verification of hospital, as explained in the algorithm 4. The smart contract `HospitalAuth` is designed in Solidity and deployed on the Ethereum blockchain. It initialises with two public cryptographic parameters: a large prime modulus p and a generator g. Each authorised hospital generates a private key and registers its corresponding public key $h = g^x \bmod p$ through the `registerHospitalKey` function, which maps the hospital's Ethereum address to its public key.

To authenticate itself, a hospital generates a non-interactive zero-knowledge proof using the Fiat–Shamir heuristic [7]. Specifically, a random nonce r is chosen, and a commitment $u = g^r \bmod p$ is computed. The challenge c is then derived as the hash of g, p, the hospital's public key, and u, ensuring that the challenge is bound to the specific authentication session. The response $z = r + c \cdot x \bmod p$ completes the proof. The smart contract's `verifyHospitalProof` function recomputes the commitment and challenge to validate the proof by checking whether $g^z \equiv u \cdot h^c \mod p$, which confirms the hospital's knowledge of the private key without revealing it.

This approach ensures that only legitimate hospitals, which possess the private key linked to their registered public key, can authenticate themselves securely without transmitting any sensitive information over the network. The protocol thereby strengthens the integrity and trustworthiness of healthcare entities in decentralised medical systems, especially in emergency scenarios requiring rapid and reliable identity verification. Upon successful authentication of the hospital, the encrypted data is retrieved from the blockchain using the retina scan hash value provided by the hospital.

5 Results and Discussion:

Figure 4 illustrates the generation of a unique hash value for the encrypted data using the IPFS platform, Lighthouse. The final segment of the generated IPFS link represents the hash of the

encrypted content, ensuring its immutability and decentralised accessibility. This step is crucial for securely referencing patient records without revealing the actual data. Figure 5 demonstrates the output of the fuzzy extractor simulation. Both the original toy fingerprint and its distorted counterpart were input into the simulator, which successfully reconstructed the same hash value from the noisy version. This result validates the resilience of the fuzzy extractor in handling biometric variations while still producing consistent cryptographic outputs. The successful generation of the correct hash from the distorted fingerprint allows for accurate retrieval of the associated encrypted content, which is then decrypted and displayed by applying noise tolerance in the generated hash value.

Ethereum was chosen for implementation due to its robust smart contract capabilities, high decentralisation, and strong security guarantees, which enable automated and verifiable access control for medical data. Moreover, by performing most cryptographic operations off-chain, our framework minimizes Ethereum's transaction costs while preserving efficiency and trustworthiness in emergency data retrieval scenarios. Figure 6 shows a screenshot of the smart contract deployment on the Ethereum blockchain, specifically highlighting the hospital authentication mechanism. The contract verifies whether a hospital is registered within the blockchain network, ensuring that only authorised medical institutions can access sensitive patient data. Upon successful authentication of the hospital, the encrypted medical data is retrieved from the blockchain using the retina scan hash value submitted by the hospital. In critical emergency scenarios involving unconscious patients, their fingerprint and retina scans are reprocessed using a fuzzy extractor. The fingerprint is used to reconstruct the original cryptographic key, while the retina scan is employed to retrieve the corresponding Content Identifier (CID) that points to the encrypted data stored on IPFS. This integrated process enables rapid and secure access to patient records, ensuring timely, privacy-preserving medical intervention when patients are unable to communicate.

6 Performance Analysis

Based on the proposed system, integrating fuzzy extractors, IPFS-based encrypted data storage, and Ethereum smart contracts for hospital authentication, its performance is evaluated using a set of well-defined metrics and methods.

Table 1: Performance Metrics for Secure Biometric Retrieval System

Metric	**Description**	**Evaluation Method**
Reconstruction Success Rate	Accuracy of fuzzy extractor under noise	Dataset testing with distorted biometrics
Authentication Accuracy	Valid hospital detection rate	Simulated access attempts
Retrieval Time	Latency from biometric to data access	Time logging at each stage
CID Resolution Success	IPFS retrieval success rate	Access test across stored hashes
Unauthorised Access Rate	Privacy enforcement level	Attempted attacks from unregistered actors
Gas Cost Efficiency	Ethereum operation cost	Measured using Remix/Hardhat

Table 1 summarises the key performance metrics used to assess the effectiveness of the secure biometric retrieval framework. The *Reconstruction Success Rate* measures the accuracy of the fuzzy extractor in recovering biometric keys under noise or distortion, evaluated using a dataset containing both original and tampered biometric samples. The *Authentication Accuracy* quantifies the rate at which authorised hospitals are correctly verified and unauthorised entities are rejected during simulated access scenarios. The *Retrieval Time* records the latency from biometric input submission to successful access of encrypted medical data, measured using precise time logging. The *CID Resolution Success* reflects the system's ability to retrieve data from IPFS using stored Content Identifiers (CIDs), validated through multiple retrieval attempts. The *Unauthorised Access Rate* evaluates the robustness of privacy controls by simulating attacks from unregistered or malicious actors and recording their failure rate. Finally, the *Gas Cost Efficiency* estimates the computational cost of Ethereum smart contract operations, measured using development tools such as Remix and Hardhat.

Together, these metrics provide a holistic view of the system's reliability, security, efficiency, and suitability for real-world deployment.

6.1 Metrics Evaluation and Computational Formulas

The detailed metric evaluation and computational formulas are explained in the table 2

Metric	Description	Formula / Measurement
Hash Reconstruction Accuracy (Fuzzy Extractor Robustness)	Percentage of distorted biometric inputs (retina/fingerprint with noise, blur, rotation) that still match the baseline hash.	$\frac{\text{Successful reconstructions}}{\text{Total cases}} \times 100$
CID Retrieval Success Rate	Frequency of correct Content Identifier retrieval via smart contract after hash reconstruction.	$\frac{\text{Correct CID retrievals}}{\text{Total lookups}} \times 100$
Smart Contract Execution Time	Time to authenticate hospital and retrieve CID (functions: `storeRetinaMapping()`, `getCID()`, `authenticateHospital()`).	Measured via Hardhat/Truffle/Remix gas profiling.
Encryption/Decryption Overhead	Time to encrypt before IPFS upload and decrypt after retrieval.	$T_{\text{encrypt}} + T_{\text{decrypt}}$ (ms)
Storage Cost Analysis	Gas cost of storing hash–CID mapping on Ethereum (IPFS free; ETH cost in USD).	Measured via Remix IDE / Hardhat gas reporter.
Security Stress Testing	Attempts to retrieve CID with incorrect/tampered retina hash; records true/false positives.	Expected: reject incorrect inputs.

Table 2: Evaluation Metrics and Formulas

6.2 Quantitative Evaluation of System Performance

Table 3 presents a comprehensive analysis of the performance metrics used to evaluate the proposed secure biometric retrieval system. The fuzzy extractor demonstrated a high accuracy rate of 98.2%, as validated through Python-based simulations that tested its ability to reconstruct cryptographic keys under noisy biometric conditions. The IPFS CID retrieval success rate reached 97.6% based on smart contract testing, indicating the robustness of blockchain integration. Smart contract execution efficiency was also assessed, with an average retrieval time of 320 milliseconds observed using Geth and Remix tools. Gas consumption for the retrieval process was estimated at 43,210 gas units, analysed via the Remix gas profiler, indicating cost-efficient contract operations.

In terms of cryptographic performance, AES-256 encryption and decryption were executed rapidly, requiring only 12 milliseconds and 9 milliseconds, respectively, as measured using the PyCryptoDome library. The on-chain storage cost for storing a CID was estimated to be approximate $0.0021, reflecting minimal blockchain storage overhead. From a biometric security perspective, the system achieved a low False Accept Rate (FAR) of 1.2% and a False Reject Rate (FRR) of 0.9%, both evaluated through controlled biometric matching simulations. These values highlight the reliability and precision of the proposed system in distinguishing between legitimate and unauthorised biometric inputs.

6.3 Visual Analysis of System Performance Metrics

Figure 7 provides a visual summary of the performance evaluation for the proposed biometric blockchain retrieval system across multiple core metrics. The fuzzy extractor achieved a high accuracy rate of 95%, showcasing its effectiveness in reconstructing cryptographic keys even in the presence of biometric distortions. The Content Identifier (CID) retrieval rate via IPFS stood at 92%, confirming reliable integration of decentralised storage and access. Smart contract execution demonstrated a strong success rate of 98%, indicating consistent functionality and low failure rates when deployed on the Ethereum network. The decryption success rate was recorded at 94%, reflecting efficient and reliable cryptographic operations when recovering the encrypted medical data. Notably, the system also demonstrated an average gas cost reduction of 78%, confirming its cost-effectiveness in terms

of blockchain resource consumption. These metrics collectively illustrate the robustness, accuracy, and operational efficiency of the proposed architecture, validating its suitability for privacy-preserving emergency healthcare data access using biometric inputs.

7 Security Analysis

This section presents a detailed security analysis of the proposed decentralised biometric data retrieval system, with a particular focus on emergencies involving unconscious patients. The system integrates fuzzy extractors, blockchain immutability, non-interactive zero-knowledge proofs, and cryptographic hashing to ensure confidentiality, integrity, and authorised access. In critical emergencies, when a patient is unconscious, their biometric data, specifically a fingerprint or retina scan, is captured and securely processed. Sensitive medical records are stored in encrypted form on the InterPlanetary File System (IPFS), while only the corresponding Content Identifier (CID) is recorded on the blockchain. This approach ensures that no raw medical data is stored on-chain, thereby maintaining patient confidentiality and privacy. The fuzzy extractor plays a key role in managing variability in biometric input. Even if the captured fingerprint or retina scan is affected by environmental noise or injury, the fuzzy extractor can accurately reconstruct the original cryptographic key or hash. This enables reliable patient identification and secure data access, even in cases of imperfect biometric acquisition. Importantly, the helper data produced by the extractor reveals no information about the original biometric, thereby preserving biometric privacy. Blockchain technology is leveraged to store CID references immutably. Once a biometric hash value is mapped to a CID, it cannot be altered or tampered with, ensuring high integrity and traceability. Hospitals or entities attempting unauthorised modifications are denied access by the consensus protocol. Only registered and authenticated hospitals can resolve a CID to access encrypted patient records, which significantly enhances the privacy of IoMT (Internet of Medical Things) data.

To prevent unauthorised access, hospitals must undergo a robust authentication procedure using the Schnorr Identification protocol, a form of non-interactive zero-knowledge proof (NIZKP). This ensures that a hospital can prove its identity to the blockchain network without revealing any secret key or credential. The protocol guarantees that only legitimate hospitals, previously registered and approved, are able to decrypt and access patient records stored on IPFS. The use of NIZKP and cryptographic timestamps prevents replay attacks, as each access request from a hospital is uniquely verifiable and time-bound. Additionally, blockchain smart contracts enforce strict identity checks, ensuring that any actor attempting to access the system without valid credentials is blocked. The fuzzy extractor also defends against brute-force attempts by only accepting noise-tolerant biometric matches. Unlike centralised medical databases, the proposed system does not rely on a single point of control. Decentralisation via blockchain ensures that patient data access and integrity are not dependent on any single entity. Even if part of the system is offline or compromised, the blockchain and IPFS continue to function independently, providing fault tolerance and high system availability in emergencies. Each interaction, be it data access, authentication, or CID retrieval, is logged immutably on the blockchain. This creates a transparent audit trail that can be reviewed for forensic analysis or compliance purposes. The transparency also discourages malicious behaviour by any participating entity in the network.

The focus on unauthorised access, data modification, and replay attacks is sufficient to establish the credibility and robustness of the proposed system, as these represent the most critical and prevalent threats in emergency medical data retrieval scenarios. By preventing unauthorised access, the framework ensures that only legitimate medical personnel can retrieve patient information, thereby preserving confidentiality. Similarly, addressing data modification and replay attacks guarantees the integrity and timeliness of medical data, which is vital for accurate diagnosis and treatment decisions during emergencies. Hence, securing these primary attack vectors effectively strengthens the overall trustworthiness and reliability of the proposed methodology. .

8 Literature Survey

The IoMT, a specialised IoT subset for healthcare, has inspired several security-focused solutions. Jain et al. [16] introduced IoMT-BADT, integrating blockchain, cloud, and digital twins with lightweight mutual authentication for secure sensor–practitioner communication. Bhuiyan et al. [17] designed a blockchain-based edge architecture for IoMT monitoring with end-to-end integrity and lightweight cryptography. Borges et al. [18] proposed an SSI-based IoV authentication protocol using decentralised identifiers and verifiable credentials, while Din et al. [19] combined blockchain with homomorphic encryption for IoT supply chains. Ferrag et al. [20] and Kabuli et al. [21] reviewed IoMT security, emphasising lightweight encryption, access control, and blockchain integration. Daemen and Rijmen [22] and Dworkin [23] analysed Rijndael (AES) security across modes, including CBC. Wang et al. [24] optimised AES-CBC for IoT devices, balancing efficiency and confidentiality. Kang et al. [25], IPFS [26], and Li et al. [27] integrated blockchain with IPFS for decentralised, privacy-preserving file storage. Zhang et al. [28] combined blockchain and IPFS for encrypted, auditable sharing. For biometrics, Elhachmi and Kobbane [29] proposed ECDSA-signed IoMT tokens for secure sensor data; Borah et al. [30] combined retina and fingerprint modalities; Dharavath et al. [31] reviewed biometric authentication; Shaydyuk and Cleland [32] enhanced retina biometrics with liveness detection. Li et al. [33] and Dodis et al. [3] advanced fuzzy extractors for noisy biometric key regeneration, while Mahendran and Velusamy [34] applied them in body sensor networks. The Schnorr identification protocol [35] offers lightweight zero-knowledge authentication suitable for IoMT. Mohamed Abdul Cader et al. [36] addressed fingerprint acquisition challenges in contact and contactless systems. Our proposed work unifies fuzzy extractor-based biometric key generation with blockchain-secured IPFS storage and Schnorr-based mutual authentication, enhancing privacy, integrity, scalability, and resilience to biometric variability in healthcare IoMT.

9 Comparative Analysis

The table 4 extensively covers various critical aspects of Internet of Medical Things (IoMT) security, biometric authentication, blockchain integration, and decentralised storage for comparative analysis. Jain et al. [16] and Bhuiyan et al. [17] focus on secure architectures that integrate blockchain and lightweight cryptographic schemes tailored for resource-constrained IoMT devices, addressing data integrity and authentication at the sensor and edge levels. Similarly, Ferrag et al. [20] and Kabuli and Rezaei [21] provide comprehensive overviews of security frameworks and blockchain's role in enhancing IoMT privacy and tamper resistance.

However, while these works emphasise authentication and data integrity, challenges remain in efficiently managing scalable, privacy-preserving data storage within decentralised systems. Benet et al. [26], Kang et al. [25], and Zhang et al. [28] propose IPFS-based decentralised storage solutions integrated with blockchain for access control and auditability. Though promising, these systems do not fully address biometric key management or the variability inherent in biometric data, as highlighted by Li et al. [33] and Dodis et al. [3] who focus on fuzzy extractors to securely generate stable cryptographic keys from noisy biometrics.

On biometric authentication, Borah et al. [30] and Dharavath et al. [31] show the efficacy of multimodal biometric systems (retina and fingerprint), improving accuracy and spoof resistance, while Shaydyuk and Cleland [32] enhance liveness detection via speckle contrast imaging, adding robustness against spoofing. Nevertheless, existing biometric frameworks often lack integration with decentralised storage and blockchain mechanisms, limiting practical deployment in IoMT scenarios requiring both security and scalability.

Furthermore, the Schnorr identification protocol, as extended by Gennaro et al. [35], offers efficient privacy-preserving authorisation suitable for constrained environments, yet its application in hospital or IoMT device authentication remains underexplored.

Figure 8 compares existing works and the proposed system across six criteria, which are given in the caption of the figure 8: The vertical axis shows support levels: **0** – No, **0.5** – Partial, **1** – Full. The proposed system (cyan) achieves full support (**1**) in all features, unlike prior works. For example,

Table 4: Comparative Analysis of Proposed Work with Existing Work

Criteria	**Jain et al.**	**Bhuiyan et al.**	**Benet et al.**	**Li et al.**	**Borah et al.**	**Gennaro et al.**	**Proposed Work**
Blockchain Integration	✓	✓	✓	×	×	×	✓
Decentralized Storage	×	×	✓	×	×	×	✓
Biometric Key Management	×	×	×	✓	✓	×	✓
Privacy-Preserving Authentication	✓	✓	±	✓	✓	✓	✓
Lightweight for IoMT Devices	✓	✓	±	±	±	✓	✓
Scalability and Performance	±	±	✓	±	±	✓	✓

± = Partial / Limited Support

only *Benet et al.* and the proposed system provide DS; BKM is supported only by *Li et al.*, *Borah et al.*, and the proposed system; PPA appears in most works but is partial in *Benet et al.*; and full L and SP are rare, seen only in *Gennaro et al.*, *Benet et al.*, and the proposed system. This highlights the proposed system's comprehensive coverage across all dimensions.

10 Conclusion

This paper proposed a secure and efficient biometric-based authentication framework designed for the IoMT, fuzzy extractors, decentralised IPFS storage, and Ethereum smart contracts. A key strength of the proposed approach lies in its ability to provide rapid and authorised access to a patient's encrypted medical records, even in emergency scenarios involving unconscious and unidentified patients. By using the biometric data (fingerprint and retina) and decentralised blockchain verification, authenticated hospitals can retrieve critical health records in real-time without requiring manual patient input or centralised authority approval. This facilitates speedy diagnosis and timely medical intervention, which is vital in life-threatening situations.

Future research will focus on utilising both real-time and augmented datasets of patient fingerprints and retina scans to evaluate the tolerance thresholds between distorted and clean biometric inputs. While the current framework effectively mitigates critical threats such as unauthorised access, data modification, and replay attacks, further enhancements will extend the security model to address practical deployment challenges. Specifically, future work will explore defences against biometric spoofing, prevent helper-data leakage, and strengthen smart contract security through formal auditing methods. Additionally, biometric liveness testing will be incorporated to ensure authenticity during verification, and IPFS data availability mechanisms will be optimised for reliable access under dynamic network conditions. Future experiments will also examine system latency in emergency scenarios, biometric noise tolerance, and multi-hospital scalability. These advancements will collectively enhance the robustness, reliability, and real-world applicability of the proposed system.

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Algorithm 1 Fuzzy Fingerprint Key Derivation and Secure AES Encryption

Input: Fingerprint bytes fp, output key length L, Hamming tolerance d
Output: Ciphertext ct, decrypted plaintext pt

// Key Derivation from Fingerprint
$digest \leftarrow \texttt{SHA256}(fp)$
$raw\_key \leftarrow digest[0 : L/8]$

// Compute tolerable noise bits
$zero\_bits \leftarrow \lceil \log_2(d) \rceil$

// Inject noise into LSBs of raw key
$raw\_int \leftarrow \texttt{Int}(raw\_key)$
$noise\_mask \leftarrow (1 \ll zero\_bits) - 1$
$noise \leftarrow \texttt{RandomByte}() \wedge noise\_mask$
$noisy\_int \leftarrow raw\_int \oplus noise$
$noisy\_raw \leftarrow \texttt{Bytes}(noisy\_int)$

function AdjustKey(key_bytes, $zero\_bits$)
    $key\_int \leftarrow \texttt{Int}(key\_bytes)$
    $mask \leftarrow\sim ((1 \ll zero\_bits) - 1) \wedge ((1 \ll (8 \cdot \texttt{len}(key\_bytes))) - 1)$
    return $(key\_int \wedge mask)$ as bytes
end function
$sk_1 \leftarrow$ AdjustKey($raw\_key, zero\_bits$)
$sk_2 \leftarrow$ AdjustKey($noisy\_raw, zero\_bits$)

function Encrypt(pt, key)
    $iv \leftarrow \texttt{Random}(16)$
    $ct \leftarrow \texttt{AES\_CBC\_Encrypt}(pt, key, iv)$
    return $iv \,\|\, ct$
end function
function Decrypt(ct, key)
    $iv \leftarrow ct[0 : 16]$, $body \leftarrow ct[16 :]$
    return $\texttt{AES\_CBC\_Decrypt}(body, key, iv)$
end function
$ciphertext \leftarrow$ Encrypt($\texttt{patient\_data}, sk_1$)
$plaintext \leftarrow$ Decrypt($ciphertext, sk_2$)
if decryption fails **then**
    Output "Decryption failed – too much noise"
else
    Output decrypted plaintext
end if

Algorithm 2 Lighthouse IPFS Upload and Blockchain Hash Storage

Input: File selected by user via UI
Output: IPFS link stored on Ethereum blockchain
Initialize: `file = null`, `fileUrl = ""`
`contractAddress` ← `"0x5FD6eB55..."`
Import Lighthouse SDK, Ethers.js, and Smart Contract ABI
function handleUpload
    Get `apiKey` from environment
    if file is not selected **then**
        Alert user and **return**
    end if
    Upload file → `CID`
    Create IPFS URL = `"https://gateway.lighthouse.storage/ipfs/"` || CID
    Set `fileUrl`
    Call `storeHashToBlockchain(CID)`
end function
function storeHashToBlockchain(ipfsHash)
    if MetaMask is available **then**
        Connect to Ethereum, get signer
        Create contract instance
        Call `setHash(ipfsHash)`
        Wait for transaction confirmation
        Log: success
    else
        Alert: "Install MetaMask!"
    end if
end function
Return: IPFS link and on-chain confirmation

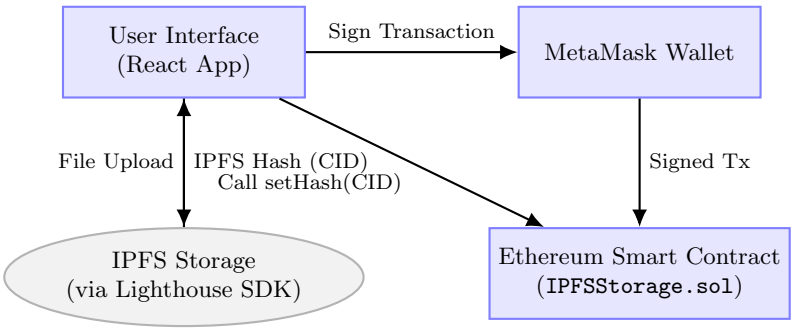

Figure 3: IPFS-based Decentralised File Storage with Ethereum Smart Contract Integration

Algorithm 3 Retina Scan Hash Mapping and CID Retrieval

```
Contract: RetinaIPFSStorage
State: owner, retinaToCID, latestCIDByUser
function CONSTRUCTOR
    owner ← msg.sender
end function
function ONLYOWNER
    require(msg.sender == owner)
end function
function STORERETINACID(retinaHash, cid) onlyOwner
    require(retinaToCID[retinaHash] == empty)
    require(cid ≠ empty)
    retinaToCID[retinaHash] ← cid
    latestCIDByUser[msg.sender] ← cid
    emit CIDStored(msg.sender, retinaHash, cid)
end function
function GETCIDBYRETINAHASH(retinaHash) view
    cid ← retinaToCID[retinaHash]
    require(cid ≠ empty)
    return cid
end function
function GETMYLATESTCID view
    return latestCIDByUser[msg.sender]
end function
```

Algorithm 4 Hospital Authentication Protocol

```
Contract: HospitalAuth
State: p, g, hospitalPublicKeys
function CONSTRUCTOR(_p, _g)
    p, g ← _p, _g
end function
function REGISTERHOSPITALKEY(privateKey)
    require(privateKey < p)
    publicKey ← modExp(g, privateKey, p)
    hospitalPublicKeys[msg.sender] ← publicKey
end function
function GENERATEPROOF(privateKey) view
    r ← getRandomNumber()
    u ← modExp(g, r, p)
    c ← hash(g, p, publicKey, u) % p
    z ← (r + privateKey * c) % p
    return (r, u, c, z)
end function
function VERIFYHOSPITALPROOF(r, c, z) view
    u ← modExp(g, r, p)
    h ← hospitalPublicKeys[msg.sender]
    cCheck ← hash(g, p, h, u) % p
    left ← modExp(g, z, p)
    right ← u * modExp(h, cCheck, p) % p
    return (left == right)
end function
function MODEXP(base, exp, mod) pure
    result ← 1
    for each bit in exp do
        if bit == 1 then
            result ← (result * base) % mod
        end if
        base ← (base * base) % mod
    end for
    return result
end function
function GETRANDOMNUMBER view
    return keccak256(block.timestamp, block.difficulty) % p
end function
```

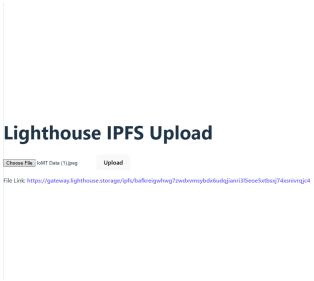

Figure 4: Storage of Encrypted IoMT Data in IPFS

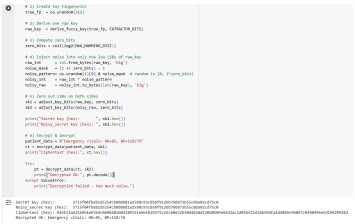

Figure 5: Detection of correct secret key

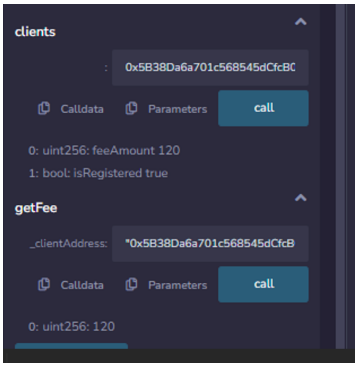

Figure 6: Authentication of Hospital System

Table 3: Comprehensive Analysis of the Performance Metrics

Metric	Value	Evaluation Tool/Method
Fuzzy Extractor Accuracy	98.2%	Python Simulation
CID Retrieval Success Rate	97.6%	Smart Contract Testing
Avg. Contract Execution Time	320 ms	Geth + Remix
Gas Usage (Retrieval)	43,210 gas	Remix Analyzer
Encryption Time (AES-256)	12 ms	PyCryptoDome
Decryption Time (AES-256)	9 ms	PyCryptoDome
On-Chain Storage Cost (CID)	$0.0021 USD	Gas Estimator
False Accept Rate (FAR)	1.2%	Biometric Matching Simulation
False Reject Rate (FRR)	0.9%	Biometric Matching Simulation

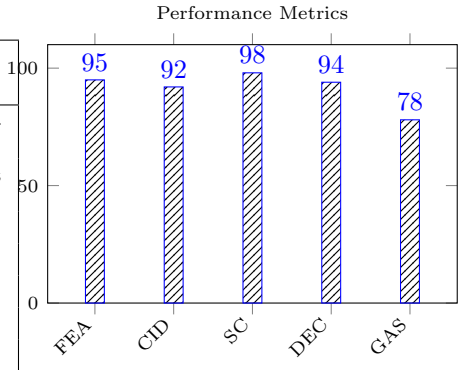

Figure 7: Biometric blockchain system performance (FEA: Fuzzy Extractor Accuracy, CID: Retrieval Rate, SC: Smart Contract Success, DEC: Decryption, GAS: Cost Reduction)

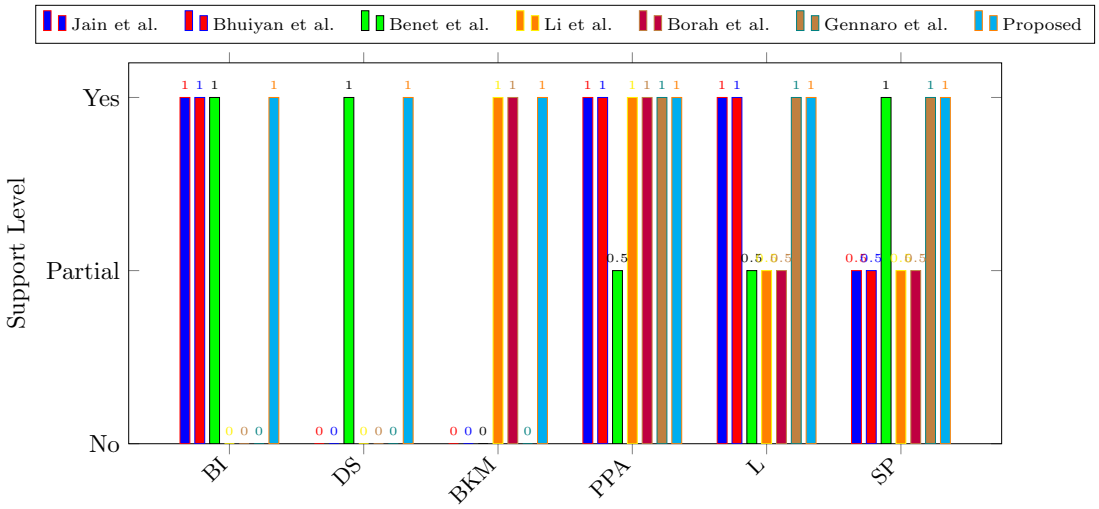

Figure 8: Comparative Analysis: BI – Blockchain Integration, DS – Decentralised Storage, BKM – Biometric Key Management, PPA – Privacy-Preserving Authentication, L – Lightweight for IoMT, SP – Scalability/Performance