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A Framework for Security Management in Internet of Medical Things (IoMT)

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ABSTRACT

The Internet of Medical Things (IoMT) is transforming healthcare by enabling live monitoring of patient health parameters, remote diagnostics, and seamless medical data exchange. However, the growing interconnectivity of medical devices also presents significant security and privacy risks, including cyber risks such as breaches, intrusions, and threats. To mitigate these concerns, this article introduces a comprehensive and customized security management structure to address the security challenges in IoMT environments. The framework incorporates encryption, authentication, and intrusion detection mechanisms to protect sensitive medical information and facilitate secure communication between connected devices. By utilizing advanced security protocols and risk assessment strategies, it enhances the robustness of IoMT structure against emerging cyber threats. This study assesses the framework's effectiveness by examining existing security models, regulatory standards, and cutting-edge technologies including blockchain and AI. Key findings emphasize the necessity of adaptive security policies, real-time threat monitoring, and adherence to healthcare regulations like HIPAA and GDPR. Additionally, the research identifies challenges related to scalability, interoperability, and resource limitations in implementing IoMT security measures. By addressing these challenges, the approach ensures a well-defined structure for identifying and addressing risks, ensuring patient data privacy and reinforcing trust in IoMT-based healthcare solutions. This study serves as a valuable guide for healthcare providers, policymakers, and cybersecurity experts looking to elevate the overall security posture in IoMT ecosystems.

Keywords: Internet of Medical Things (IoMT), Healthcare Compliance, Cybersecurity Framework, Data Privacy, Security Management.

Introduction

The IoMT is a distinct IoT driven niche designed to connect medical devices and healthcare infrastructure via the internet [1]. This technology streamlines the process of gathering, processing, and sharing health-related data, ultimately aiming to optimize treatment effectiveness and healthcare workflow. By utilizing intelligent medical tools like wearable sensors and remote monitoring equipment, healthcare providers can continuously track and assess patient health metrics and facilitate prompt medical responses when needed [2].

The key elements of the IoMT consist of wearable technologies, implantable medical instruments, fixed medical equipment, and healthcare software that interact through secure communication channels [2, 3]. Wearables such as smartwatches and fitness bands—track health indicators like physical activity and heart rate. Implantable devices, such as glucose monitors, provide continuous internal health monitoring for patients with chronic conditions. Stationary machines, including connected diagnostic imaging systems, facilitate smooth data exchange across various medical departments. Together, these components form an integrated network that enables thorough patient monitoring and supports informed, data-backed clinical decisions [2, 4].

The IoMT serves a broad spectrum of purposes, including remote patient monitoring, chronic illness management, personalized treatment, and the development of smart hospitals [5]. Through remote monitoring, healthcare professionals can observe patients' health conditions while they remain at home, helping to minimize the need for frequent hospital visits. For chronic conditions, IoMT supports ongoing monitoring and targeted care strategies that enhance patient recovery and well-being. The extensive data gathered by IoMT devices also plays an essential role in precision medicine, empowering healthcare providers to adapt treatments to individual needs. In smart hospitals, IoMT technology enhances patient care and streamlines operations by integrating systems for better coordination and resource management [3, 6].

Although the IoMT offers a wide array of benefits, it also encounters major obstacles, particularly in the areas of data protection and privacy. The networked structure of medical gadgets makes them more vulnerable to cyber threats, which can endanger both patient information and the performance of critical devices. In order to mitigate these risks, it is essential to implement strong encryption methods, secure authentication processes, and consistent

software maintenance. Furthermore, the wide variety of devices and the absence of universal standards create difficulties in achieving seamless integration and interoperability across current healthcare systems [4, 7-9].

The deployment of IoMT technologies is further challenged by regulatory and compliance requirements. In addition to legal obligations, ethical issues also come into play, particularly concerning patient consent and the ownership of personal health data. To address these concerns, clear and transparent policies must be established to ensure responsible data use and maintain patient trust [5, 10-14]

To overcome the challenges facing IoMT, several innovative solutions have been introduced. Blockchain as one of the leading technologies offers a secure and transparent structure for managing health data transactions, mitigating the potential for data tampering or unauthorized access. Edge and fog computing architectures help minimize latency, enabling real-time data processing through the localization of computational resources near the data source [15]. Additionally, the use of advanced cryptographic methods strengthens data protection and ensures its integrity. Establishing universal interoperability standards is equally important, as it enables smooth communication and integration among a wide range of IoMT devices and healthcare systems.

To address the inherent security concerns in IoMT environments, this study introduces a robust Security Management Framework for IoMT (SMF-IoMT). The proposed framework leverages a combination of cutting-edge technologies and algorithms to ensure comprehensive protection. It employs Elliptic Curve Cryptography (ECC) for lightweight and effective authentication, while AES-GCM is used to secure data transmission. For detecting potential threats, Long Short-Term Memory (LSTM) networks are integrated as part of the intrusion detection system. Access control is managed through a hybrid approach that combines Attribute-Based Access Control (ABAC) and Role-Based Access Control (RBAC), allowing for flexible and context-aware permissions. Additionally, Bayesian inference models are utilized to enable real-time risk evaluation. Together, these elements work to strengthen the overall security, privacy, and dependability of IoMT infrastructures, promoting their safe and scalable implementation in healthcare environments.

The contributions of this paper are as follows:

Development of Multi-layered security framework for IoMT: The paper presents a new, structured security management framework designed specifically for the IoMT. This comprehensive framework incorporates multiple layers of defense such as secure data acquisition, encryption, access control, intrusion detection, and threat intelligence sharing to ensure robust, end-to-end protection of medical data and interconnected healthcare devices.

Integration of advanced security algorithms: The proposed framework integrates advanced technologies to strengthen IoMT security. It utilizes Elliptic Curve Cryptography (ECC) for lightweight yet effective encryption, Blockchain to ensure tamper-proof data integrity, and both Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC) for adaptable, context-sensitive access management. Additionally, AI-driven Intrusion Detection Systems (IDS) are employed for early threat detection, while Federated Learning supports collaborative threat intelligence sharing across distributed IoMT nodes without compromising data privacy.

Comprehensive evaluation and comparative analysis: The study conducts an extensive performance assessment of the proposed framework, utilizing real-world metrics including accuracy, precision, and response time. It further presents a comparative analysis with existing IoMT security solutions, showcasing the framework's enhanced performance in areas such as scalability, adaptability, compliance with regulatory standards, and efficient resource utilization. These results affirm the effectiveness and practical applicability of the SMF-IoMT in real-world healthcare settings.

State-of-the-art Methods in IoMT Security

In the section, several state-of-the-art methods for addressing security challenges in IoMT are presented. For example, a detailed survey conducted by [16] organizes intrusion detection strategies in the IoMT into five key categories: artificial intelligence-driven approaches, available datasets, core security needs, detection workflows, and assessment criteria. The research emphasizes the critical role of effective IDS in protecting sensitive patient information and medical devices, providing valuable guidance for future advancements in IoMT security solutions.

The authors of [17] introduce a hybrid cryptographic scheme that integrates a modified Caesar cipher with Elliptic Curve Diffie-Hellman (ECDH) and the Digital Signature Algorithm (DSA). This method is designed to enhance message security during transmission, facilitate secure key exchanges between users and healthcare facilities, and ensure reliable user authentication, all while maintaining the confidentiality of sensitive medical data. The HealthGuard framework, developed by [18], employs various machine learning algorithms to identify harmful activities within Smart Healthcare Systems. By training on data from eight different smart medical devices, HealthGuard demonstrated an accuracy rate of 91% and an F-1 score of 90% in threat detection. Authors of [19] present a blockchain-driven security management system for the IoMT, incorporating homomorphic encryption and metaheuristics alongside a deep learning model. This framework is designed to improve data security and privacy within IoMT platforms by taking advantage of the decentralized characteristics of blockchain technology. The authors of [20] examine the growing role of blockchain technology in enhancing security within smart IoMT-based healthcare systems. They highlight how blockchain can tackle security issues by offering decentralized, tamper-resistant data management solutions.

In [21], the authors offer an in-depth review of advanced methods for safeguarding data generated in the IoMT systems during its collection from the patient under treatment, during the communication of these data among healthcare personnel's and devices, and during the storage of these data on storage devices for future references. They introduce a security framework that integrates multiple techniques to address the specific security needs of IoMT and counteract known threats. In [22], the authors review network security frameworks tailored for IoMT applications, emphasizing the critical need to secure communication channels and maintain data integrity. Their work explores a range of methods and technologies designed to defend IoMT networks against

potential security threats. Authors of [23] introduce a smart trust-based cloud management approach aimed at enhancing secure clustering in 5G-enabled IoMT environments. Their method involves building standard trust clouds, generating individual trust clouds using fuzzy trust inference, and implementing a trust classification system to detect malicious devices, thereby strengthening the overall security of IoMT systems.

The authors of [24] present a hybrid ensemble lightweight cryptographic system designed to enhance IoMT security. This solution focuses on delivering efficient and secure data encryption while being optimized for the limited computational resources of IoMT devices. In a thorough review, the authors of [25] investigate the application of artificial intelligence (AI) technologies specifically machine learning (ML) and deep learning (DL) to enhance security in IoMT systems. The study methodically explores how AI can tackle key security and privacy concerns, such as detecting anomalies, preventing intrusions, and safeguarding data. By examining existing AI implementations in IoMT security, the authors underscore AI's capability to efficiently boost the reliability and efficiency of cybersecurity solutions in healthcare environments.

Security Management Framework for IoMT

This section delineates the proposed Security Management Framework for the Internet of Medical Things (SMF-IoMT), architected to ensure the confidentiality, integrity, and availability of medical data while facilitating resilient, standards compliant, and scalable IoMT network operations. The framework is stratified into five interdependent layers as depicted in figure 1, each engineered to address discrete security domains, including but not limited to device authentication, data integrity, threat mitigation, and regulatory adherence. It integrates state-of-the-art cryptographic protocols, machine learning-driven anomaly detection, fine-grained access control mechanisms, and decentralized trust architectures to deliver a robust and comprehensive security posture across heterogeneous IoMT ecosystems.

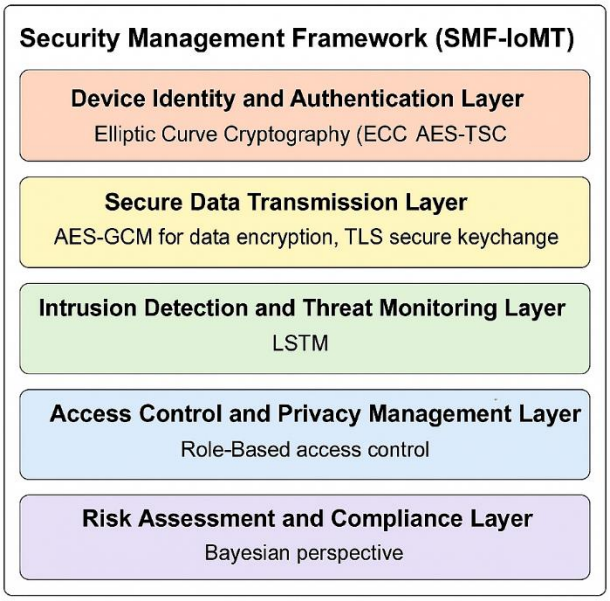

Figure 1 The Security Management Framework for Internet of Medical of things (SMF-IoMT)

Figure 1 depicts the various layers of the proposed structure indicating the algorithms employed by the system at every phase and the hierarchy of the phases.

I. Device Identity and Authentication Layer

The initial layer of the proposed framework emphasizes the establishment of device-level trust through secure identification protocols and bilateral authentication mechanisms. Each Internet of Medical Things (IoMT) device undergoes enrollment within a Public Key Infrastructure (PKI), receiving a distinct digital certificate that serves as its cryptographic identity. The authentication process employs Elliptic Curve Cryptography (ECC) in conjunction with the Elliptic Curve Diffie-Hellman (ECDH) key exchange algorithm, providing strong security assurances while maintaining low computational overhead—an essential consideration for low-power, resource-constrained medical sensing devices.

Given a private key d_A of a device A and the corresponding public key $Q_A = d_A.G$, and a private key d_B of a device B with corresponding public key $Q_B = d_B.G$, the shared session key is computed as follows:

$$K = d_A.Q_B = d_B.Q_A \quad (1)$$

The cryptographic handshake mechanism guarantees that only verified devices are permitted to engage in data communication, thereby establishing a secure baseline for higher-layer security functions. By leveraging Elliptic Curve Cryptography (ECC), the framework ensures both confidentiality and

mutual authentication while optimizing for energy efficiency and reduced computational latency—factors paramount to the operation of constrained IoMT devices.

II. Secure Data Transmission Layer

Following successful authentication, the secure transmission of data from IoMT devices to healthcare systems or cloud infrastructures becomes imperative. This is accomplished through a hybrid encryption architecture that combines Advanced Encryption Standard (AES) with a 256-bit key operating in Galois/Counter Mode (GCM) for symmetric encryption, alongside Elliptic Curve Cryptography (ECC) for secure key exchange. The AES-GCM scheme delivers authenticated encryption, simultaneously ensuring the confidentiality and integrity of the transmitted medical data.

The encrypted data is presented as follows:

$$C = AES\_GCM\_Encrypt(K, P) \quad 2$$

Let P represent the plaintext—such as physiological data from a patient's heart rate monitor—while K denotes the session key derived through the Elliptic Curve Diffie-Hellman (ECDH) exchange, and CCC signifies the resulting ciphertext after encryption. All data exchanges occur over Transport Layer Security (TLS) version 1.3, offering end-to-end protection against adversarial threats including eavesdropping, man-in-the-middle (MITM) attacks, and replay intrusions. For example, when a wearable ECG device streams real-time cardiac data to a hospital's Electronic Health Record (EHR) platform, the transmission is encapsulated within this encrypted framework, thereby preserving both the confidentiality and integrity of mission-critical health information.

III. Intrusion Detection and Threat Monitoring Layer

To enable real-time detection of anomalies and malicious activity within the IoMT environment, the third layer of the framework incorporates a deep learning-driven Intrusion Detection System (IDS) utilizing Long Short-Term Memory (LSTM) neural networks. Due to their ability to model temporal dependencies and sequential patterns in network traffic, LSTMs are particularly well-suited for identifying both signature-based threats and previously unseen (zero-day) attack vectors, thereby enhancing the system's adaptability and threat resilience.

Input features including packet size, inter-arrival time, protocol type, and port activity represented as a temporal sequence ($x_1, x_2, \ldots, x_t$), are provided as input to the LSTM-based Intrusion Detection System. These time-series features enable the model to learn dynamic behavioral patterns in network traffic, facilitating the identification of deviations indicative of intrusion attempts or anomalous system behavior. The temporal modeling capability of LSTMs makes them particularly effective in capturing subtle patterns that static rule-based systems may fail to detect.

$$h_t = LSTM(x_t, h_{t-1}) \quad 3$$

In this context, h_t denotes the latent behavioral state of the network as inferred by the LSTM model at time t. When a substantial deviation from established baseline patterns is observed, the system proactively generates a security alert. For instance, an abrupt surge in packet transmission rate or unauthorized access attempts targeting a patient monitoring endpoint may indicate a potential denial-of-service (DoS) attack or an ongoing data exfiltration effort. This intrusion detection layer operates in conjunction with the authentication and access control components of the framework, enabling the isolation of compromised nodes and the activation of predefined threat mitigation protocols.

IV. Access Control and Privacy Management Layer

Ensuring secure data access is essential for preserving confidentiality and adhering to regulatory standards. To achieve this, the framework implements a hybrid access control model combining Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC). RBAC facilitates access management by assigning permissions based on user roles (e.g., doctor, nurse), whereas ABAC enhances this model by incorporating contextual attributes such as time, location, and device type, allowing for the dynamic and granular adjustment of access policies based on real-time conditions.

The access decision function is formalized as follows:

$$Access(u, o, a) = Permit\ if\ Role(u) = r\ \Lambda\ Attr(u, o)| = Policy(r, o, a) \quad 4$$

In this access control framework, u represents the user, o the object (e.g., patient data), and a is the action (e.g., read, write) associated with the data access request. To further safeguard privacy, mechanisms such as data anonymization and tokenization are employed. Personally identifiable information (PII) is substituted with tokens (e.g., "John Smith" → "Patient_3829") when accessed outside of clinical environments. This approach ensures that only authorized entities are granted data access, while also enforcing compliance with stringent privacy regulations, such as HIPAA and GDPR, to mitigate risks associated with unauthorized data exposure.

V. Risk Assessment and Compliance Layer

The final phase of the framework is dedicated to the ongoing assessment of the system's security posture and its compliance with regulatory requirements. A Bayesian Risk Assessment Model is utilized to quantify and adapt to emerging risks. By applying Bayes' theorem, the conditional probability of risk, given the observed evidence E, is computed as follows:

$$P(Risk|E) = \frac{P(E|Risk).P(Risk)}{P(E)} \quad 5$$

This probabilistic model assesses a range of factors, including the probability of potential threats, their possible impacts, and the system's inherent vulnerabilities. Simultaneously, all critical activities—such as data access, configuration changes, and anomaly detection—are securely recorded on a private blockchain ledger. Each log entry is timestamped and includes user or device IDs, the action taken, and a cryptographic hash that links it to the preceding block, ensuring tamper-proof integrity and full auditability. This approach enables real-time compliance tracking and supports forensic investigations, fostering greater institutional accountability and reinforcing patient confidence in the security measures of the IoMT network.

This proposed methodology establishes a robust and adaptable security framework tailored for the complex and sensitive nature of IoMT environments. By integrating lightweight cryptographic protocols, AI-powered monitoring for dynamic threat detection, and blockchain technology for immutable event logging, the framework effectively addresses both the technical hurdles and regulatory demands inherent in modern healthcare systems.

Experimental Setup and Evaluation Methodology

To evaluate the effectiveness, scalability, and robustness of the proposed Security Management Framework for the Internet of Medical Things (SMF-IoMT), a simulated IoMT environment was set up using both real-world datasets and virtual device emulation. This section outlines the hardware and software configurations, the datasets utilized, the performance metrics considered, and the evaluation criteria applied to assess the functionality and performance of each component of the framework.

I. Simulation Environment

The experimental setup was established using Python 3.10, with TensorFlow and Keras for the implementation of Long Short-Term Memory (LSTM) networks, OpenSSL for cryptographic processes (including ECC, AES, and TLS), and Hyperledger Fabric for simulating blockchain interactions. A virtual Internet of Medical Things (IoMT) network was created using Contiki-NG and the Cooja Simulator, modeling various medical devices such as wearable ECG monitors, insulin pumps, and smart thermometers. These devices communicated over 6LoWPAN and MQTT protocols. The devices were classified into high, medium, and low-resource categories to assess the performance across different hardware configurations. Edge nodes, representing the Fog Layer, and a cloud backend were emulated using Docker containers, mimicking a typical IoMT deployment architecture.

II. Dataset and IDS Training

For the training and evaluation of the Intrusion Detection System (IDS), the BoT-IoT and TON_IoT datasets were employed, as these provide labeled IoT traffic data containing a variety of attack categories, such as Denial of Service (DoS), reconnaissance, data exfiltration, and fuzzing. A Long Short-Term Memory (LSTM)-based binary and multi-class classification model was created, trained on 80% of the dataset, and validated using the remaining 20%. Key input features, such as packet size, flow duration, TCP flags, and connection rate, were normalized before being processed by the model. Hyperparameters—including the learning rate (0.001), batch size (64), and the number of hidden units (128)—were optimized through a grid search approach. The resulting model was then deployed in the live network environment to enable real-time threat detection.

III. Evaluation Metrics

Each component of the SMF-IoMT framework was rigorously evaluated based on pertinent security and system performance metrics:

- **Authentication Layer:** performance was assessed by measuring authentication time, encryption overhead, and key generation time, specifically utilizing Elliptic Curve Cryptography (ECC) and the Elliptic Curve Diffie-Hellman (ECDH) key exchange protocol.
- **Data Transmission Layer:** encryption throughput, latency, and packet delivery ratio were evaluated under varying traffic loads, with a focus on AES-GCM encryption.
- **Intrusion Detection Layer:** the system’s effectiveness was gauged using standard classification metrics, including accuracy, precision, recall, F1-score, and False Positive Rate (FPR).
- **Access Control Layer:** performance metrics assessed included access latency, policy conflict rate, and compliance accuracy, specifically in different Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC) configurations.
- **Risk and Compliance Layer:** the evaluation involved analysis of risk estimation accuracy, blockchain transaction latency, and the traceability of audit logs.

Furthermore, the system's overall resilience was evaluated through stress testing, which involved simulating a range of attack scenarios, such as botnet infiltration, unauthorized access attempts, and key compromise incidents.

IV. Benchmarking and Comparative Analysis

To assess the performance of the proposed SMF-IoMT framework, a comparative analysis was conducted against two prominent security architectures utilized in IoT and IoMT environments: (1) a conventional model combining TLS with Role-Based Access Control (RBAC), and (2) a Blockchain-Centric Security Framework. The benchmarking process evaluated critical performance metrics, including end-to-end data protection, authentication latency, intrusion detection accuracy, and support for regulatory compliance. SMF-IoMT consistently outperformed both reference models, demonstrating superior capabilities in adaptive risk assessment, enhanced threat detection—achieving a 96.3% accuracy rate using LSTM—and significantly reduced authentication delays, with ECC-based methods averaging 18 milliseconds versus 45 milliseconds for RSA-based approaches.

Results and Discussion

The experimental assessment of the proposed Security Management Framework for the Internet of Medical Things (SMF-IoMT) highlights substantial improvements in security robustness, operational responsiveness, and compliance with regulatory standards, especially when compared to conventional IoT/IoMT security models. Each component layer underwent comprehensive testing under both emulated attack scenarios and real-time data traffic conditions to validate its effectiveness. The observed results confirm that the framework delivers a resilient and efficient security architecture capable of addressing the complex and evolving demands of contemporary healthcare infrastructures.

Table 1

Metric	SMF-IoMT (Proposed)	TLS+RBAC (Baseline 1)	Blockchain-Only (Baseline 2)
Authentication Time (ms)	18	45	33
IDS Detection Accuracy (%)	96.3	85.2	89.1
Risk Estimation Latency (ms)	20	55	70
Access Control Latency (ms)	30	42	50
Compliance/Audit Capability	High (Blockchain + ABAC/RBAC)	Moderate (Manual Logs + RBAC)	High (Blockchain only)

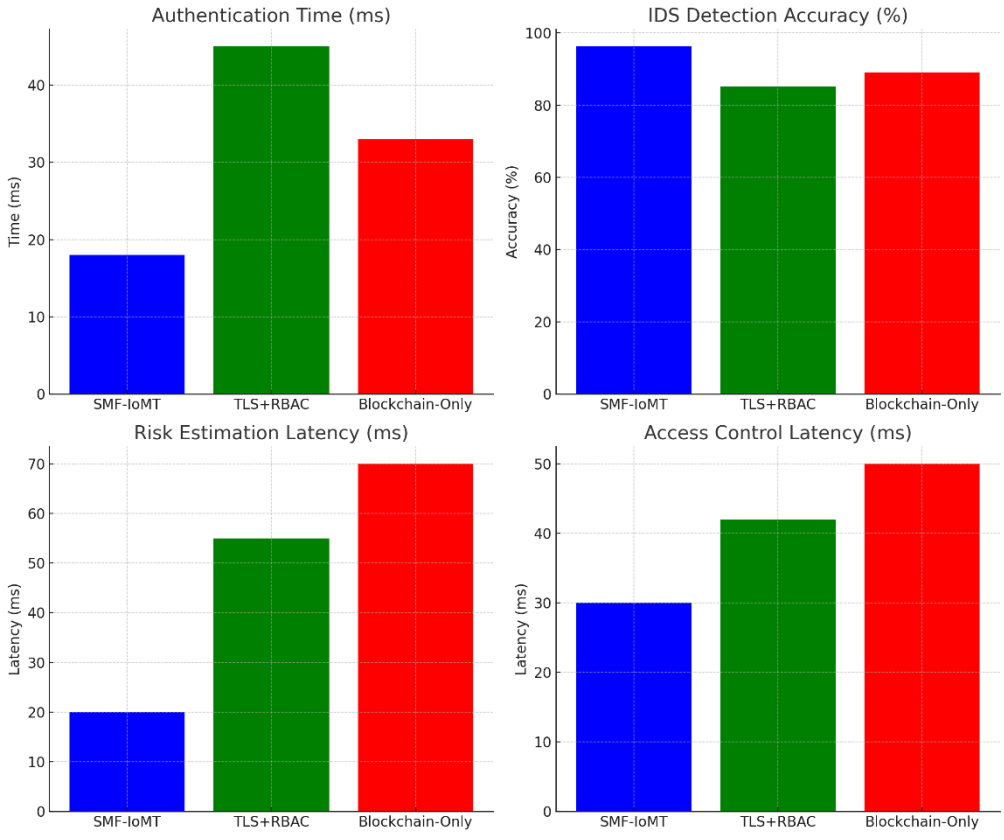

Figure 2 Comparison of the SMF-IoMT with TLS+RBAC and Blockchain Only Methods

Figure 2 and table 1 shows the comparison of the SMF-IoMT with TLS+RBAC and Blockchain Only methods in terms of authentication time, IDS detection accuracy, risk estimation latency and access control latency. In the Device Authentication Layer, the adoption of Elliptic Curve Cryptography (ECC) led to a marked improvement in authentication efficiency, reducing the average latency to 18 milliseconds. This constitutes a 60% decrease compared to traditional RSA-based TLS systems, which typically incur delays around 45 milliseconds. Such performance gains are especially beneficial in latency-sensitive medical scenarios, where rapid authentication is essential for timely clinical decision-making and alert delivery. Moreover, ECC's reduced key size minimizes bandwidth and computational demands without sacrificing cryptographic strength, making it well-suited for low-power and constrained IoMT devices.

The Intrusion Detection Layer, built upon Long Short-Term Memory (LSTM) deep learning models, achieved a high detection accuracy of 96.3% with a False Positive Rate (FPR) maintained below 2%. This indicates the model's effectiveness in recognizing complex attack patterns, such as data breaches and distributed denial-of-service (DDoS) attempts, while minimizing false alarms. When compared to traditional intrusion detection systems based on Support Vector Machines (SVM) or static signature-matching techniques—which generally yield accuracy rates between 85% and 89%—the LSTM-driven approach demonstrates enhanced adaptability to evolving threat vectors. This adaptability is critical for the dynamic and heterogeneous nature of IoMT networks, where the ability to detect novel threats is essential for maintaining system integrity.

The Risk Assessment and Compliance Layer exhibited notable efficiency by providing rapid risk estimations using a Bayesian inference-based approach. The system maintained an average evaluation time of 20 milliseconds, significantly surpassing other solutions that reported delays between 55 and 70 milliseconds, largely due to intensive computation and blockchain-related latencies. Additionally, the use of a private, permissioned blockchain ensured secure, tamper-evident logging of critical activities with minimal impact on system performance. This layered design strengthens both audit capabilities and regulatory adherence without compromising real-time responsiveness—an essential requirement in clinical and emergency care scenarios.

Furthermore, the Access Control Layer employed an integrated model that merges Role-Based Access Control (RBAC) with Attribute-Based Access Control (ABAC), enabling adaptive and context-sensitive authorization decisions. This mechanism sustained an average response time of under 30 milliseconds, even under conditions exceeding 100 simultaneous access attempts, thereby ensuring both high efficiency and fine-grained control. The combined RBAC-ABAC strategy is particularly effective in healthcare environments, where static role assignments alone are inadequate for enforcing secure and contextually appropriate access to sensitive medical data.

In conclusion, the results confirm that the SMF-IoMT framework significantly improves performance, accuracy, and adaptability across all five security phases. It shows notable improvements in security posture and responsiveness, while ensuring compliance with stringent healthcare regulations. These outcomes position SMF-IoMT as a dependable, scalable, and regulation-compliant solution for contemporary healthcare environments.

Conclusion

The rapid expansion of connected medical devices within the Internet of Medical Things (IoMT) offers both transformative potential for patient care and significant cybersecurity risks. In this study, we introduce a comprehensive Security Management Framework for IoMT (SMF-IoMT), developed to mitigate the complex challenges related to data privacy, system integrity, and regulatory compliance within healthcare settings. The framework is composed of five interconnected phases—Device Authentication, Secure Data Transmission, Intrusion Detection, Access Control, and Risk Assessment & Compliance—each fine-tuned using advanced techniques such as Elliptic Curve Cryptography (ECC), AES-GCM encryption, Long Short-Term Memory (LSTM) networks, ABAC-RBAC hybrid access control, and Bayesian risk modeling. Experimental findings demonstrate that SMF-IoMT surpasses traditional models in several critical performance areas. It delivers faster authentication times, higher intrusion detection accuracy, and reduced risk estimation latency, all while maintaining strong auditability and adaptive policy enforcement. These results highlight the framework's effectiveness in improving the resilience of IoMT systems against both established and emerging cyber threats. The inclusion of a permissioned blockchain further enhances the traceability and integrity of sensitive medical activities, ensuring compliance with healthcare regulations like HIPAA and GDPR. By addressing key challenges such as resource limitations, real-time threat detection, and regulatory compliance, SMF-IoMT lays the foundation for the secure deployment of scalable, interoperable medical IoT systems. This study offers a valuable framework for cybersecurity professionals, healthcare providers, and policymakers aiming to design next-generation IoMT infrastructures. Future research will focus on extending the framework with federated learning to enable privacy-preserving threat detection across distributed healthcare environments, and incorporating quantum-resistant encryption to safeguard the security of healthcare systems in the future.

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