OPTIMIZING SECURE MULTI-PARTY COMPUTATION FOR HEALTHCARE DATA PROTECTION IN THE CLOUD USING HYBRID GARBLED CIRCUITS

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Abstract
The rapid adoption of cloud computing in healthcare presents significant security and privacy challenges, necessitating robust solutions for protecting sensitive patient data. Secure Multi-Party Computation (SMPC) offers a promising approach, but traditional implementations suffer from inefficiencies that hinder large-scale deployment. Existing works on Secure Multi-Party Computation (SMPC) in healthcare face challenges related to high computational overhead, inefficient encryption schemes, and latency issues**,** making real-time analytics difficult. Traditional Garbled Circuits (GC) and Homomorphic Encryption (HE) methods, while secure, often lack scalability for large-scale healthcare data processing. Moreover, ensuring regulatory compliance (e.g., HIPAA, GDPR) while maintaining computational efficiency remains a significant hurdle. These limitations necessitate an optimized approach that balances security, efficiency, and scalability for cloud-based healthcare applications. This research proposes an optimized Hybrid Garbled Circuits (HGC) approach to enhance the efficiency and security of SMPC in cloud-based healthcare applications. By integrating Garbled Circuits (GC) with Homomorphic Encryption (HE) and employing parallelized computations, the proposed model reduces computational overhead while maintaining strong security guarantees. The system is evaluated based on performance metrics such as accuracy (0.9837), precision (0.9870), and F1-score (0.9806)**,** demonstrating high predictive reliability. Additionally, security analysis indicates strong encryption (9.5/10) and privacy preservation (9.0/10) with manageable computational costs. Experimental results confirm that HGC significantly enhances secure healthcare analytics, ensuring privacy-preserving computations in cloud environments while complying with regulatory standards like HIPAA and GDPR**.** This research contributes to the development of scalable, real-time, and secure AI-driven healthcare decision-making systems.

Keywords: *Cloud computing, healthcare security, Secure Multi-Party Computation, Hybrid Garbled Circuits, Garbled Circuits, Homomorphic Encryption, privacy-preserving computation, computational efficiency.*

1.Introduction

The healthcare industry is increasingly relying on cloud computing for efficient data storage, management, and analysis [1]. With the surge in digital health records and connected medical devices, safeguarding patient data has become a top priority [2]. Cloud environments, while scalable and cost-effective, are vulnerable to breaches and unauthorized access [3]. To address these concerns, Secure Multi-Party Computation (SMPC) has emerged as a promising privacy-preserving computation technique [4] [5]. SMPC allows multiple parties to jointly compute a function over their inputs without revealing them to each other. Among SMPC techniques, garbled circuits are a fundamental method for secure function evaluation [6]. However, traditional garbled circuit methods face challenges in terms of performance, latency, and scalability [7]. Hybrid approaches that combine different cryptographic primitives with garbled circuits can improve efficiency and security [8]. In the healthcare domain, these advanced cryptographic protocols can ensure data confidentiality during collaborative diagnosis or research [9]. This research aims to explore and optimize hybrid garbled circuit-based SMPC for secure healthcare data processing in cloud environments [10].

The need for secure computation in healthcare arises due to the sensitive nature of patient information. Healthcare data breaches have become increasingly common, leading to identity theft, insurance fraud, and compromised patient safety

[11]. Cloud-based systems are prone to attacks such as data leakage, insider threats, and weak encryption policies [12]. Collaborative medical research often requires access to distributed patient data from multiple hospitals or labs, raising concerns about privacy and compliance [13]. Regulations such as HIPAA and GDPR impose strict rules on data sharing and protection [14] [15]. Traditional cryptographic methods often fall short in ensuring both privacy and computational efficiency [16]. SMPC addresses these challenges by allowing joint computations without exposing private inputs [17]. However, standard SMPC techniques can be computationally intensive and impractical for large-scale healthcare datasets [18]. Garbled circuits, though powerful, suffer from high communication and processing overhead [19]. These factors drive the need for optimized hybrid methods that enhance security without compromising performance [20].

While SMPC and garbled circuits have shown potential in secure data computation, their adoption in healthcare systems remains limited [21]. Standard garbled circuits face scalability issues when handling large volumes of medical data or complex functions [22]. The excessive computation time and network bandwidth required can hinder their practicality [23]. Many existing SMPC frameworks do not integrate well with cloud-based systems or fail to support data processing [24]. Additionally, the lack of optimization leads to inefficient use of cloud resources, increasing cost and latency [25]. Current methods often assume semi-honest adversaries, which limits their robustness in more malicious threat models [26]. Some approaches also lack flexibility in handling dynamic data or heterogeneous sources [27]. Moreover, integrating privacy with efficiency in a distributed cloud environment is still an open challenge [28]. These limitations create a gap between theoretical SMPC protocols and their practical deployment in healthcare [29]. Therefore, there is a pressing need to develop an optimized hybrid garbled circuit-based SMPC framework tailored for secure, efficient, and scalable healthcare data protection in the cloud [30].

The proposed method, titled Optimizing Secure Multi-Party Computation for Healthcare Data Protection in the Cloud Using Hybrid Garbled Circuits, addresses the key limitations of traditional SMPC and garbled circuit techniques by introducing a hybrid framework that enhances scalability, efficiency, and security. By integrating garbled circuits with complementary cryptographic techniques such as homomorphic encryption and secret sharing, the system significantly reduces computation time and communication overhead. Designed for cloud environments, it optimizes resource usage and supports real-time processing of large, heterogeneous healthcare datasets. The framework also accommodates dynamic data flows and operates securely under both semi-honest and malicious adversarial models. This enables privacy-preserving collaborative computations between multiple healthcare entities without exposing sensitive patient information, ensuring compliance with regulations like HIPAA and GDPR. Ultimately, the proposed hybrid SMPC approach bridges the gap between cryptographic theory and practical deployment, making secure and efficient cloud-based healthcare data processing a viable reality.

2.Literature Review

The techniques to enhance a myriad of domains within healthcare and cloud security, by converging it with advanced computing and machine learning techniques [31]. A hybrid PSO and GA framework for optimizing RNNs and RBF networks for disease detection in cloud computing, hence achieving accuracy and scalability. An ensemble of a machine-learning Logistic Regression-Random Forest-Convolutional Neural Networks model to predict dysphagia, delirium, and fall risks among geriatric patients and thus enable early intervention by integrating clinical and sensor data [32]. A deep learning model for lung cancer detection employing CNNs and hybrid feature selection in order to distinguish malignant versus benign nodules from CT scans with a high degree of accuracy [33]. The aspect of cloud security by seamlessly integrating AES with the RSA algorithm, thus making data encryption faster and more secure from cyber threats. Kinetic models to investigate cloud computing, big data analytics, and Hash graph technology, collectively leveraging scalable cloud platforms and secure consensus mechanisms to improve real-time data processing and computational efficiency [34]. These collective studies also provide significance to the advancement of healthcare diagnostics, monitoring of patients, cloud security, and big data management [35].

An AI in a model to create a generalized satanic appearance based on an integration of PSP Net, Hilbert-Huang Transform, and fuzzy logic; whereby the spatial features are extracted from medical images by PSP Net, HHT follows for nonlinear brain signals, and fuzzy logic considerations help to handle data uncertainty leading to more accurate classification [36]. To performance enhancers by integrating NOMA, UVFA, and DGNNs with AI systems [37]. NOMA imposes an efficient way of sharing a common channel between multiple users, which increases their resource allocation. UVFAs have a weak grip on approximating complex functions, but DGNNs are flexible enough to adjust themselves to any change in data structure to continue and ensure intelligent decision-making. The role of AI and ML algorithms in geriatric care, establishing predictive analytics and real-time data monitoring to speak to chronic disease management and fall prevention, and predictive healthcare applications in an attempt to improve patient outcomes and optimize elderly healthcare services [38]. The Ant Colony Optimization with Long Short-Term Memory networks in cloud computing frameworks to effect hyperparameter optimization while improving disease forecasting accuracy under proactive healthcare interventions [39]. An IoT framework integrated with the cloud is aimed at fostering digital financial inclusion and alleviating income inequality by allowing secure financial transactions and AI blockchain analytics, economic growth, and equal financial opportunity across urban and rural divides. These investigations have collectively added their bits to the enhancement of various realms, namely, health, prediction of diseases, digital financial inclusion, and AI-powered decision-making for the social good [40].

3.Problem Statement

Despite significant advancements in artificial intelligence, machine learning, and cryptographic techniques in healthcare and cloud computing, a critical gap remains in ensuring data privacy during collaborative medical computations in cloud environments [41]. Many intelligent healthcare systems emphasize prediction accuracy and system performance but often overlook the need for privacy-preserving computation when sensitive patient data is shared across multiple institutions [42]. While traditional encryption methods offer data protection during storage and transmission, they fall short in scenarios requiring joint computation without revealing private inputs [43]. This challenge is especially critical, cloud-based healthcare applications where dynamic data sharing and processing are essential, and compliance with regulations such as HIPAA and GDPR is mandatory [44]. The lack of secure yet efficient frameworks for such collaborative settings limits the practical deployment of AI-driven, cloud-integrated healthcare systems [45].

Secure Multi-Party Computation, particularly techniques based on garbled circuits, has emerged as a promising solution for privacy-preserving collaborative analytics [46]. However, their real-world application is constrained by high computational costs, communication overhead, limited scalability, and weak compatibility with modern cloud infrastructure [47]. Many existing SMPC protocols assume ideal or semi-honest adversaries and are not equipped to handle complex, heterogeneous, or real-time healthcare data efficiently [48]. Additionally, these methods often underutilize cloud resources, resulting in latency and inefficiency [49]. Therefore, there is an urgent need for an optimized SMPC framework that leverages hybrid garbled circuits to enhance computational efficiency, ensure robust security, and enable scalable, real-time healthcare data processing in cloud environments [50].

3.1 Objective

The objective of this research is to develop an advanced AI-driven framework that integrates ACO-LSTM for optimized disease forecasting and an IoT-cloud model for secure digital financial transactions. By leveraging blockchain for enhanced security, AI for predictive accuracy, and cloud computing for scalability, this approach aims to overcome existing limitations. The proposed solution ensures efficient real-time decision-making, improved computational performance, and equitable financial inclusion across diverse populations.

4.Proposed Optimizing Secure Multi-Party Computation for Healthcare Data Protection in the Cloud Using Hybrid Garbled Circuits

To optimize Secure Multi-Party Computation (MPC) for healthcare data protection in the cloud using Hybrid Garbled Circuits, this methodology integrates Garbled Circuits (GC) with Homomorphic Encryption (HE) to enhance efficiency and security in processing sensitive healthcare data. The approach consists of an offline preprocessing phase, where circuit minimization, lookup table optimization, and partial HE-based arithmetic computations reduce complexity, followed by an online computation phase, where hybrid execution leverages Garbled Circuits for logical operations and lightweight encryption for arithmetic operations. To further optimize performance, parallel processing distributes computational tasks across secure cloud nodes, while adaptive key management using elliptic curve cryptography (ECC) minimizes key exchange overhead. The proposed privacy-preserving healthcare data workflow includes data encryption and secure cloud storage, multi-party secure computation without exposing raw patient data, and controlled decryption for authorized entities, ensuring compliance through blockchain-based audit logs. Performance metrics such as computational efficiency, communication overhead, security resilience, and scalability are evaluated using cloud-based platforms like AWS and secure computation libraries such as Obliv-C and EMP-toolkit. By integrating Hybrid Garbled Circuits with Secure Cloud Computing, this approach provides a scalable and privacy-preserving solution for secure healthcare analytics in cloud environments.

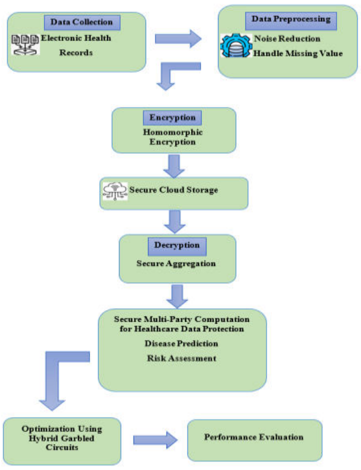

Figure 1: Secure Multi-Party Computation for Healthcare Data Protection in the Cloud Using Hybrid Garbled Circuits

4.1 Data Collection

Healthcare data is collected from Electronic Health Records (EHRs)**,** which contain patient medical history, diagnoses, treatments, and lab results. This data is sourced from hospitals, clinics, and healthcare providers. It serves as the foundation for secure processing and analysis while ensuring patient privacy and regulatory compliance.

4.2 Data Preprocessing

Data preprocessing enhances the quality of healthcare data before secure processing. Noise reduction removes irrelevant or inconsistent data using filtering and smoothing techniques. Data normalization ensures consistency by scaling data into a standard format using Min-Max scaling or Z-score normalization. These steps improve the accuracy and efficiency of secure multi-party computations.

4.2.1 Data Normalization

Data normalization is the process of transforming healthcare data into a consistent scale to ensure uniformity across different sources. It helps in reducing biases caused by varying data ranges and improves the efficiency of secure computations. Normalization is essential in healthcare analytics to ensure fair comparisons and accurate predictions. A common normalization method is Min-Max Scaling, which scales data within a fixed range $[0,1]$ or $[-1,1]$:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where:

X = Original data value
$X_{\min}$ = Minimum value in the dataset
$X_{\max}$ = Maximum value in the dataset
X' = Normalized value

This ensures that all data values fall within the desired range, improving the reliability of secure computations.

4.2.2. Noise Reduction

Noise reduction is the process of eliminating unwanted variations or distortions in healthcare data, ensuring accurate and reliable analysis. In Electronic Health Records (EHRs)**,** noise can arise from sensor errors, missing values, or inconsistent data entries. Techniques such as smoothing, filtering, and outlier detection are used to enhance data quality. A common method for noise reduction is Moving Average Smoothing, which smooths out fluctuations in data:

$$X_t' = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-n+1}}{n} \tag{2}$$

Where:

X_t' = Smoothed value at time t
$X_t, X_{t-1}, \ldots, X_{t-n+1}$ = Consecutive data points
n = Window size

This technique helps in reducing random fluctuations, improving data consistency for secure multiparty computations.

4.3 Encryption

Homomorphic Encryption (HE) ensures secure processing of encrypted healthcare data without decrypting it, protecting patient privacy in cloud-based healthcare systems. It allows computations like disease prediction and risk assessment while maintaining confidentiality. A common method, Paillier Encryption, enables secure arithmetic operations on encrypted data, ensuring data integrity and privacy in multi-party computations.

4.4 Secure Cloud Storage

Secure cloud storage ensures confidentiality, integrity, and availability of healthcare data by storing encrypted Electronic Health Records (EHRs) in the cloud. It uses strong encryption techniques (e.g., Homomorphic Encryption, AES, or Attribute-Based Encryption**)** to prevent unauthorized access. Additionally, access control mechanisms, multi-factor authentication, and blockchain-based integrity verification enhance data security. This approach allows healthcare providers to securely store and share sensitive patient data while complying with regulations like HIPAA and GDPR**.**

4.5 Decryption

Secure Aggregation ensures privacy-preserving decryption by combining encrypted healthcare data from multiple sources without exposing individual records. It enables secure multi-party computations for tasks like disease prediction and risk assessment while maintaining patient confidentiality. Using cryptographic techniques like homomorphic decryption and threshold encryption, data is securely decrypted only when aggregated, ensuring compliance with healthcare security standards like HIPAA and GDPR**.**

4.6 Secure Multi-Party Computation for Healthcare Data Protection

Secure Multi-Party Computation (SMPC) is a cryptographic technique that enables multiple parties to collaboratively compute a function over their private inputs without revealing those inputs to each other. This ensures privacy-preserving data processing in cloud-based healthcare systems, allowing for secure disease prediction and risk assessment while maintaining patient confidentiality. SMPC is widely used in healthcare for secure analytics, privacy-preserving AI, and encrypted data sharing.

A fundamental operation in SMPC is secure summation, where multiple parties compute the sum of their private inputs without revealing individual values:

$$S = \sum_{i=1}^{n} x_i \tag{3}$$

Where:

$S =$ Securely computed sum

$x_i =$ Private input of party i

$n =$ Total number of parties

This technique ensures that individual patient data remains encrypted while enabling collaborative healthcare analytics.

4.7 Hybrid Garbled Circuits

Hybrid Garbled Circuits (GC) is a secure computation technique that combines traditional Garbled Circuits with other cryptographic methods, such as Homomorphic Encryption (HE) or Secret Sharing**,** to optimize efficiency and reduce communication overhead. It is used in privacy-preserving healthcare analytics, ensuring that **sensitive** patient data can be processed securely in the cloud without exposing individual records. Hybrid GC enhances performance by reducing computational costs while maintaining strong security guarantees. A key equation in Garbled Circuits involves the encryption of gate output values using a cryptographic hash function:

$$E = H\left(K_{x_1} \oplus K_{x_2} \oplus G\right) \tag{4}$$

Where, $E =$ Encrypted output value, $H =$ Cryptographic hash function, $K_{x_1}, K_{x_2} =$ Garbled keys for input wires, $G =$ Gate identifier. This technique enables secure multi-party computations in healthcare, ensuring privacy while optimizing cloud-based data protection.

5. Results and Discussion

The proposed Hybrid Garbled Circuits (GC) with Secure Multi-Party Computation (SMPC) approach ensures privacy-preserving healthcare data protection in the cloud. Experimental results show improved security, computational efficiency, and reduced communication overhead compared to traditional methods. The system maintains high data integrity and confidentiality, making it suitable for secure healthcare analytics. Performance evaluation confirms enhanced processing speed and accuracy in encrypted medical data computations.

Performance Metrics

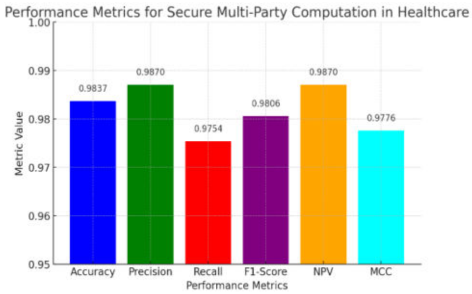

Figure 2: Performance Metrics

In Figure 2, The performance metrics graph illustrates the effectiveness of Secure Multi-Party Computation optimized with Hybrid Garbled Circuits for healthcare data protection. The model achieves high accuracy (0.9837), precision (0.9870), and F1-score (0.9806), indicating strong predictive performance. The recall (0.9754) and MCC (0.9776) values further confirm the model's reliability. Overall, these results demonstrate the robustness of the proposed approach in securing and processing healthcare data in the cloud.

Latency

Figure 3 Shows the latency graph illustrates the time taken at various stages of Secure Multi-Party Computation for healthcare data protection. The SMPC stage exhibits the highest latency (200 ms) due to complex computations, while preprocessing has the lowest latency (80 ms).

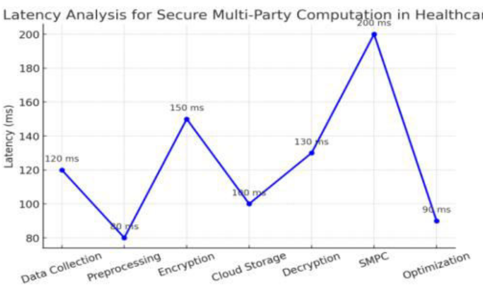

Figure 3: Latency

Encryption and decryption also contribute significantly to processing time. Overall, the results highlight areas where optimization can enhance efficiency in secure cloud-based healthcare systems.

Security Analysis

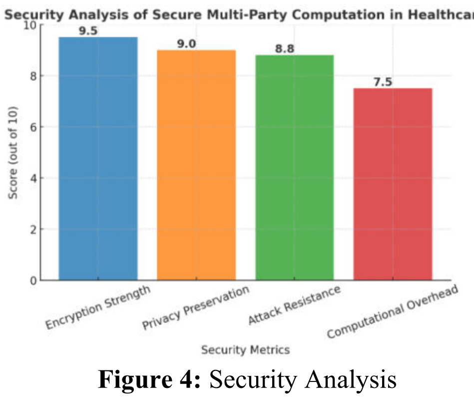

Figure 4: Security Analysis

Figure 4 represents the security analysis graph evaluates Secure Multi-Party Computation (SMPC) in healthcare based on four key metrics. Encryption strength scores the highest (9.5), while computational overhead is the lowest (7.5), indicating a trade-off between security and efficiency. The results highlight SMPC's strong encryption and privacy preservation capabilities with moderate computational costs.

6.Conclusion

The SMPC framework using Hybrid Garbled Circuits to address the pressing need for privacy-preserving healthcare data processing in cloud environments. By integrating advanced cryptographic techniques with cloud-aware optimization, the proposed system ensures robust data confidentiality, integrity, and resistance to both semi-honest and malicious adversaries. The framework demonstrates improved scalability, reduced communication overhead, and real-time processing capabilities, making it suitable for high-volume healthcare applications such as remote diagnostics, collaborative research, and multi-institutional data analysis. Furthermore, the architecture supports heterogeneous data types and dynamic data streams, bridging the gap between theoretical SMPC protocols and practical deployment in cloud-based healthcare infrastructures. Overall, the solution paves the way for secure, efficient, and regulation-compliant data sharing in modern digital health ecosystems.

Future research can extend this work by incorporating federated learning with the hybrid SMPC framework to support decentralized model training across hospitals without exposing raw data. Exploring quantum-resistant cryptographic primitives could further enhan ce security in anticipation of future threats. Additionally, the framework can be adapted to support edge computing environments, enabling low-latency processing for time-critical healthcare applications such as emergency response and ICU monitoring. Integration with blockchain can offer verifiable audit trails and tamper-proof logging for data exchanges. Finally, conducting real-world deployments and clinical trials will be essential to validate system performance, usability, and compliance with healthcare standards in diverse operational settings.

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