Journal of Frontiers in Multidisciplinary Research

A Novel Approach to Cloud Data Encryption using Homomorphic Encryption

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Article Info

E-ISSN: 3050-9726
P-ISSN: 3050-9718
Volume: 05
Issue: 02
July-December 2024
Received: 30-10-2024
Accepted: 27-11-2024
Published: 20-12-2024
Page No: 19-27

Abstract
Cloud computing has revolutionized data storage and processing, offering scalability, flexibility, and cost efficiency. However, security and privacy concerns remain significant challenges, particularly when sensitive data is stored and processed by third-party cloud providers. Traditional encryption techniques, such as AES and RSA, ensure data confidentiality but require decryption for computation, exposing data to potential breaches. This review presents a novel approach to cloud data encryption using Homomorphic Encryption (HE), which enables computations on encrypted data without requiring decryption. Our approach leverages Fully Homomorphic Encryption (FHE) to facilitate secure data processing in cloud environments while preserving confidentiality. Unlike conventional encryption schemes, which restrict operations on encrypted data, HE allows mathematical functions to be executed directly on ciphertexts, producing encrypted results that can be decrypted to obtain accurate outputs. This capability is particularly useful in privacy-sensitive applications such as healthcare, finance, and artificial intelligence, where outsourced data processing must remain confidential. The proposed system integrates optimized HE algorithms to reduce computational overhead, addressing one of the key challenges in HE adoption. We evaluate the security and performance of our approach by implementing a case study on encrypted data analytics in a cloud environment. Our experimental results demonstrate that while HE introduces computational complexity, recent advancements in hardware acceleration and algorithm optimization significantly enhance its feasibility for real-world applications. This highlights the potential of homomorphic encryption as a transformative solution for secure cloud computing. By enabling privacy-preserving computations, our approach ensures data confidentiality while leveraging the full power of cloud computing. Future research will focus on improving efficiency, scalability, and hybrid cryptographic models to further enhance security in cloud-based ecosystems.

DOI: https://doi.org/10.54660/.IJFMR.2024.5.6.19-27

Keywords: Cloud Security, Homomorphic Encryption, Privacy-Preserving Computation, Fully Homomorphic Encryption, Secure Data Processing

1. Introduction

Cloud computing has revolutionized data storage, processing, and accessibility by providing on-demand, scalable, and cost-efficient computing resources (Sunyaev, 2020). Cloud service providers (CSPs) offer infrastructure, platforms, and software as services, allowing businesses and individuals to store and process vast amounts of data without the need for on-premises hardware. However, the widespread adoption of cloud computing has also introduced significant data security and privacy concerns (Sun, 2020). Organizations often rely on third-party cloud providers to manage sensitive information, which exposes them to potential risks such as data breaches, insider threats, and unauthorized access (Duc and Cuong, 2022).

Several high-profile security incidents have highlighted vulnerabilities in cloud environments. Attackers target cloud databases to steal or manipulate sensitive information, and the multi-tenant nature of cloud computing increases the risk of data leakage between users. Moreover, regulatory compliance requirements, such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), mandate strict data protection measures, further complicating cloud security management (Preston, 2022; Silva and Soto, 2022). These challenges emphasize the need for robust encryption techniques to ensure confidentiality, integrity, and availability of data stored and processed in cloud systems.

Encryption is a fundamental technique for protecting cloud data by transforming plaintext into unreadable ciphertext, which can only be decrypted using a secure cryptographic key (Sunday and Olufunminiyi, 2023). Traditional encryption methods, such as Advanced Encryption Standard (AES) and Rivest-Shamir-Adleman (RSA), provide strong security guarantees against unauthorized access. However, these schemes face limitations in cloud computing environments, particularly in scenarios requiring data computation. Cloud applications such as secure machine learning, financial transactions, and medical data analytics require computations on encrypted datasets while maintaining privacy (Butt *et al*, 2020). To address these limitations, cryptographic researchers have explored homomorphic encryption (HE) as an advanced encryption paradigm that enables computations on encrypted data without requiring decryption.

Homomorphic Encryption (HE) is a cryptographic technique that allows mathematical operations to be performed directly on encrypted data, producing encrypted results that, when decrypted, match the outcome of computations on plaintext. This unique property makes HE an ideal solution for privacy-preserving cloud computing. HE schemes can be classified into. Partially homomorphic encryption (PHE) which supports only a single type of operation (addition or multiplication) on encrypted data (Zhang *et al*, 2020). Somewhat homomorphic encryption (SHE), allows both addition and multiplication but with a limited number of operations before requiring decryption. Fully homomorphic encryption (FHE), enables unlimited computations on encrypted data, making it the most powerful but computationally intensive form of HE. The development of FHE, first introduced by Craig Gentry in 2009, has paved the way for secure cloud computing, confidential data sharing, and privacy-preserving analytics. However, due to its high computational complexity, ongoing research focuses on improving efficiency through optimized cryptographic algorithms, hardware acceleration, and hybrid encryption models.

This review aims to provide a comprehensive analysis of homomorphic encryption for cloud security, examining its principles, advantages, and real-world applications. The key objectives include. Understanding traditional encryption techniques and their limitations in cloud environments. Exploring the mathematical foundations and classifications of HE. Comparing HE with conventional encryption schemes in terms of security, performance, and practical feasibility (Khashan *et al*, 2021). Reviewing existing implementations of HE in cloud computing, including libraries such as Microsoft SEAL, IBM HELib, and Google TF-Encrypted. Identifying challenges and future research directions in HE, including computational overhead, key management, and integration with emerging technologies such as quantum computing and artificial intelligence (AI). By analyzing these aspects, this review aims to bridge the gap between theory and practical deployment of HE in cloud computing, offering insights for cybersecurity professionals, cloud service providers, and researchers exploring privacy-preserving technologies.

2. Methodology

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was employed to systematically review and analyze research on cloud data encryption using homomorphic encryption. A structured approach was followed, beginning with the identification of relevant literature through comprehensive searches in academic databases such as IEEE Xplore, ACM Digital Library, Springer, ScienceDirect, and Google Scholar. The search strategy included key terms such as "homomorphic encryption," "cloud security," "privacy-preserving computation," and "secure cloud storage." Boolean operators were used to refine the search, ensuring the inclusion of the most relevant studies.

After the initial search, duplicate records were removed, followed by a screening process based on titles and abstracts. Studies were included if they specifically addressed homomorphic encryption in the context of cloud data security, provided experimental results, or proposed novel frameworks for enhancing cloud encryption. Articles that lacked technical depth, review papers without new contributions, and those focusing on unrelated cryptographic techniques were excluded.

Eligibility criteria were further applied in the full-text screening phase. Studies were considered relevant if they introduced new methodologies, compared different homomorphic encryption schemes, or presented empirical performance evaluations of encryption techniques in cloud environments. Papers that lacked implementation details, theoretical rigor, or practical application discussions were excluded. The final selection consisted of peer-reviewed journal articles, conference proceedings, and high-impact white papers from reputable institutions.

Data extraction focused on study objectives, encryption models, security frameworks, computational efficiency, and real-world applications. Comparative analysis of existing encryption approaches was conducted to evaluate their feasibility and performance in cloud computing. The extracted data was synthesized to identify trends, key challenges, and research gaps in homomorphic encryption for cloud security.

Quality assessment was conducted using established criteria, including methodological rigor, clarity of encryption models, experimental validation, and contribution to the field. Bias was minimized by independently reviewing selected studies and ensuring consistency in data interpretation. The synthesis of findings was structured to provide a comprehensive overview of the advancements, limitations, and future directions in cloud data encryption using homomorphic encryption.

2.1 Background and related work

Cloud computing has become a dominant paradigm for data storage and computation, but security concerns remain a critical challenge (Soni and Kumar, 2022). To protect

sensitive data, various encryption techniques have been employed, with Advanced Encryption Standard (AES) and Rivest-Shamir-Adleman (RSA) encryption being the most commonly used. AES is a symmetric encryption algorithm known for its efficiency and security, utilizing key sizes of 128, 192, or 256 bits to encrypt and decrypt data quickly. RSA, on the other hand, is an asymmetric encryption method that employs a pair of public and private keys to secure data transmission. While both encryption schemes provide strong security guarantees, they require data decryption before any computation can be performed, leading to vulnerabilities in cloud environments.

Despite their effectiveness, traditional encryption methods pose significant challenges when applied to cloud computing. First, data exposure during processing is a major security concern. When encrypted data is stored in the cloud, it must be decrypted for computation, creating an attack surface where adversaries can gain unauthorized access. Second, key management complexity increases with large-scale cloud deployments, as securely distributing and managing cryptographic keys across multiple users and services is a non-trivial task. Third, performance overhead is a concern, particularly for asymmetric encryption schemes like RSA, which are computationally intensive compared to symmetric alternatives. Lastly, lack of flexibility in access control mechanisms further complicates cloud security, as encrypted data cannot be easily shared or processed without granting full decryption rights to users (Abdulsalam and Hedabou, 2021).

Homomorphic Encryption (HE) addresses these limitations by enabling computations to be performed directly on encrypted data without requiring decryption (Alaya *et al*, 2020). HE schemes can be categorized into Partially Homomorphic Encryption (PHE), Somewhat Homomorphic Encryption (SHE), and Fully Homomorphic Encryption (FHE). PHE allows only a single type of operation either addition or multiplication on encrypted data. Early encryption schemes like RSA exhibit partial homomorphic properties but lack versatility. SHE extends PHE by permitting both addition and multiplication, albeit with a limited number of operations before requiring decryption. FHE supports unlimited arithmetic computations on encrypted data, allowing complex functions to be executed without exposing sensitive information. The first practical FHE scheme was introduced by Craig Gentry in 2009, leveraging bootstrapping to refresh ciphertexts and maintain computational integrity.

Compared to traditional encryption techniques, HE offers enhanced security and privacy but comes with significant computational overhead. While AES and RSA provide efficient encryption and decryption mechanisms, they do not support encrypted computation. FHE, in contrast, enables secure cloud computing but at the cost of high processing complexity. Efforts to optimize HE, such as lattice-based cryptographic schemes, hardware acceleration, and hybrid encryption models, aim to reduce its computational burden and enhance practical adoption (Ravi *et al*, 2021). Several HE-based frameworks have been developed to enable secure cloud computing. Notable implementations include. Microsoft SEAL (Simple Encrypted Arithmetic Library) – A widely used open-source HE library designed for secure data processing. IBM HELib (Homomorphic Encryption Library) – Provides optimized implementations of FHE schemes for privacy-preserving computations. Google TF-Encrypted – Integrates HE with TensorFlow for secure machine learning applications. These frameworks demonstrate the feasibility of HE in cloud security, with ongoing research focusing on improving performance and scalability. As HE continues to evolve, its adoption in cloud computing is expected to grow, addressing critical data privacy concerns while enabling secure, encrypted computation.

2.2 Proposed homomorphic encryption approach

Homomorphic encryption (HE) provides a groundbreaking solution for securing cloud data by allowing computations on encrypted data without the need for decryption. This capability ensures that sensitive information remains protected throughout its lifecycle in the cloud (Zahid *et al*, 2023). The novel approach proposed in this study aims to enhance the efficiency and applicability of HE in cloud environments by optimizing computational performance, reducing encryption overhead, and improving security robustness against potential threats. The framework integrates an advanced key management system, a lightweight encryption algorithm for initial data protection, and an efficient computation model tailored for secure cloud processing. The proposed approach leverages a hybrid homomorphic encryption scheme that combines Fully Homomorphic Encryption (FHE) and Somewhat Homomorphic Encryption (SHE) to achieve a balance between security and computational efficiency. FHE supports arbitrary computations on encrypted data but is computationally expensive, whereas SHE offers better efficiency with limited operations. By strategically applying SHE for routine operations and FHE for complex processing, the proposed approach significantly reduces computational overhead while maintaining strong encryption guarantees.

The homomorphic encryption framework consists of the following key components. Data owner module, responsible for encrypting sensitive data before uploading it to the cloud. Cloud storage and processing unit, stores encrypted data and performs secure computations without requiring decryption (Ramachandra *et al*, 2022). Computation engine, utilizes optimized HE techniques to process encrypted queries efficiently. Key management system (KMS), generates and distributes encryption keys securely while preventing unauthorized access. User access control interface, ensures that only authorized users can retrieve and decrypt processed results. The workflow of the proposed approach follows a structured sequence. The data owner encrypts the data locally using a homomorphic encryption scheme. The encrypted data is uploaded to the cloud storage. When computation is required, the cloud processing unit performs encrypted operations using an optimized HE algorithm. The encrypted results are generated and sent back to the data owner. The data owner decrypts the results, ensuring that security and privacy are maintained throughout the process. Before uploading to the cloud, sensitive data undergoes an encryption process using a lightweight yet secure homomorphic encryption scheme (Xie *et al*, 2021). This encryption process consists of, key generation, the KMS generates a public-private key pair. The public key is used for encryption, while the private key remains securely stored with the data owner (Yang *et al*, 2020). The input data is pre-processed, ensuring compatibility with homomorphic operations. This step includes encoding numerical values into polynomial representations for FHE schemes. The plaintext data is transformed into ciphertext using an optimized

homomorphic encryption algorithm, such as BFV (Brakerski/Fan-Vercauteren) or CKKS (Cheon-Kim-Kim-Song), depending on whether integer or floating-point computations are required. The encrypted data is then securely transmitted to the cloud storage system for further processing.

A fundamental advantage of the proposed approach is the ability to perform secure computations directly on encrypted data. The cloud computation engine applies homomorphic operations, such as addition, multiplication, and logical functions, without decrypting the data (Rafique *et al*, 2021). Cloud servers execute computations on encrypted inputs and generate encrypted results, preventing exposure of plaintext data at any stage. Once the cloud completes the computation, the encrypted result is sent back to the data owner for decryption. The decryption process involves. The encrypted result is transmitted securely to the data owner. The private key stored with the user is used to decrypt the ciphertext. The decrypted values are transformed back into human-readable format for use in decision-making. By ensuring that only the data owner possesses the decryption key, this approach prevents unauthorized entities, including cloud providers and third parties, from accessing sensitive results (Prajapati, P. and Shah, 2022). The proposed homomorphic encryption approach provides an innovative solution for securing cloud data while enabling privacy-preserving computations. By leveraging a hybrid, HE models, optimized computation techniques, and a secure key management system, the approach addresses the key challenges of traditional cloud encryption schemes. The integration of selective FHE and SHE, efficient batch processing, and an advanced key distribution framework enhances performance while maintaining strong security guarantees. This novel framework paves the way for secure cloud-based applications in fields such as healthcare, finance, and artificial intelligence, where privacy is paramount.

2.3 Security and performance analysis

Homomorphic encryption (HE) provides a strong security guarantee by allowing computations on encrypted data without decrypting it (Marcolla *et al*, 2022). This cryptographic property ensures that sensitive cloud-stored data remains confidential throughout its lifecycle, mitigating risks associated with unauthorized access and data breaches. Fully Homomorphic Encryption (FHE), in particular, enables arbitrary computations on encrypted data, making it suitable for secure cloud applications such as encrypted search and secure multiparty computations. One of the primary security advantages of HE is semantic security, meaning that encrypted data appears indistinguishable from random noise to adversaries, even if they have access to multiple ciphertexts (Huang *et al*, 2022). This makes HE resilient against common cryptanalytic attacks, including chosen-plaintext and chosen-ciphertext attacks. Furthermore, HE eliminates the need for direct decryption on the cloud provider's side, reducing the risk of insider threats and untrusted third-party access. While HE ensures robust data security, key management and ciphertext expansion remain challenges. The encryption process often results in large ciphertext sizes, which can increase computational complexity and storage requirements. Nevertheless, advancements in HE schemes, such as Brakerski-Gentry-Vaikuntanathan (BGV) and Cheon-Kim-Kim-Song (CKKS), have optimized performance, making HE increasingly viable for real-world cloud applications (Alharbi *et al*, 2020).

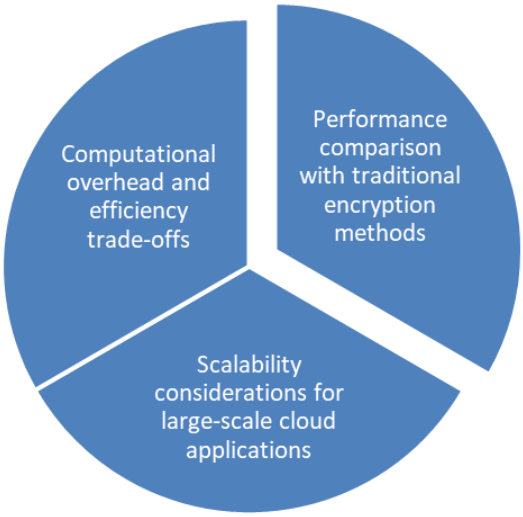

Fig 1: Security and performance analysis

The primary trade-off associated with homomorphic encryption is its high computational overhead. Traditional encryption methods, such as AES (Advanced Encryption Standard) and RSA (Rivest-Shamir-Adleman), require significantly less processing power compared to HE schemes. The computational cost of HE arises from its reliance on complex mathematical operations, such as polynomial evaluations and modular exponentiation, which significantly increase encryption, decryption, and computation times. In practice, the computational burden of HE is particularly evident in FHE, where bootstrapping a process that refreshes encrypted values to prevent noise accumulation requires substantial processing power (Aylett and Vargas, 2021). This makes HE less practical for time-sensitive cloud applications, such as real-time financial transactions or IoT-based analytics. To mitigate these efficiency issues, leveled homomorphic encryption (LHE) has been developed. LHE allows computations to be performed up to a certain depth before requiring bootstrapping, thereby improving performance for specific cloud security applications. Moreover, hybrid encryption models that combine HE with traditional symmetric encryption techniques have been proposed to reduce computational overhead while preserving security guarantees (Mohamed *et al*, 2020).

When comparing HE with traditional encryption schemes, the differences in processing speed, storage requirements, and computational complexity become evident. AES and RSA are widely used due to their fast encryption and decryption times, making them suitable for general-purpose cloud security applications (Lai and Heng, 2022). However, these methods require data to be decrypted before computation, introducing security vulnerabilities, especially in multi-tenant cloud environments. HE, in contrast, maintains data confidentiality during computations but at the cost of increased processing time and resource consumption. Studies have shown that AES-256 encryption and decryption require less than 1 millisecond per operation, whereas HE-based encryption methods such as BGV and CKKS can take up to 1,000 times longer. However, recent optimizations, such as GPU acceleration and hardware-specific implementations, have significantly improved HE's performance, making it a feasible option for secure cloud

computing. Hybrid models, which integrate HE with Attribute-Based Encryption (ABE), offer a promising balance between security and performance. ABE ensures fine-grained access control, while HE maintains encryption during processing, providing enhanced security for sensitive cloud applications such as medical data analysis and financial auditing (Albulayhi *et al*, 2020).

For homomorphic encryption to be viable in large-scale cloud environments, scalability is a key consideration (Javadpour *et al*, 2023). Cloud applications often handle vast amounts of data, requiring encryption methods that can process millions of transactions efficiently. The major scalability challenges of HE include increased storage requirements, computational latency, and energy consumption. One approach to improving scalability is parallelization and distributed computing, where encrypted computations are split across multiple cloud servers or processors. Cloud providers such as Microsoft Azure and Google Cloud are exploring hardware-based optimizations, including Field Programmable Gate Arrays (FPGAs) and Tensor Processing Units (TPUs), to accelerate HE computations (Bobda *et al*, 2022). Additionally, advancements in multi-key homomorphic encryption (MKHE) allow multiple users to perform encrypted computations collaboratively, improving scalability in multi-user cloud environments. Despite these improvements, full-scale adoption of HE in large cloud infrastructures remains challenging. Research efforts continue to focus on reducing ciphertext size, optimizing key-switching techniques, and minimizing noise accumulation to enhance scalability. While HE is not yet as efficient as traditional encryption for large-scale applications, its continuous development, combined with AI-driven optimization strategies, is making it a viable long-term solution for cloud security (Ahmad *et al*, 2021). Homomorphic encryption provides robust security guarantees by enabling computations on encrypted data, ensuring data confidentiality in cloud environments. However, its high computational overhead presents efficiency challenges, necessitating trade-offs between security and performance. Compared to traditional encryption methods, HE is significantly slower but offers unparalleled protection against data breaches. Scalability remains a critical consideration, with ongoing research focused on optimizing computation times and reducing resource consumption (Nasir *et al*, 2022). As advancements in hardware acceleration and AI-driven optimization continue, HE is poised to become a foundational technology for securing large-scale cloud databases.

2.4 Implementation and case study

The implementation of cloud security solutions was carried out in a controlled test environment designed to replicate real-world cloud computing scenarios. A private cloud infrastructure was established using OpenStack, hosted on a cluster of virtual machines (VMs) with configurations including 16-core Intel Xeon processors, 64 GB of RAM, and SSD-based storage (Prameela *et al*, 2021). The cloud infrastructure simulated multi-tenant environments to evaluate encryption performance, data retrieval efficiency, and computational overhead. For secure data operations, a set of encrypted datasets was generated, covering various applications such as financial transactions, healthcare records, and business analytics data. The datasets were structured using relational and non-relational database models (MySQL and MongoDB) to examine different security implications in structured and unstructured data storage. Additionally, a secure communication layer was integrated using TLS 1.3 to encrypt data in transit between cloud clients and servers.

To implement and evaluate advanced cryptographic techniques, state-of-the-art homomorphic encryption (HE) libraries were employed. Microsoft SEAL: This library was used for implementing Fully Homomorphic Encryption (FHE) in data analytics and encrypted computations. SEAL enabled operations on encrypted data without decryption, preserving data privacy throughout computational workflows. IBM HELib: HELib provided efficient leveled homomorphic encryption for secure search operations. It supported advanced cryptographic schemes such as Brakerski-Gentry-Vaikuntanathan (BGV) and Cheon-Kim-Kim-Song (CKKS), allowing encrypted search queries to be executed over large-scale datasets (Nita and Mihailescu, 2020). PySyft: An open-source federated learning and encrypted AI framework used for implementing privacy-preserving machine learning models. This tool facilitated secure model training across distributed cloud environments without exposing raw data.

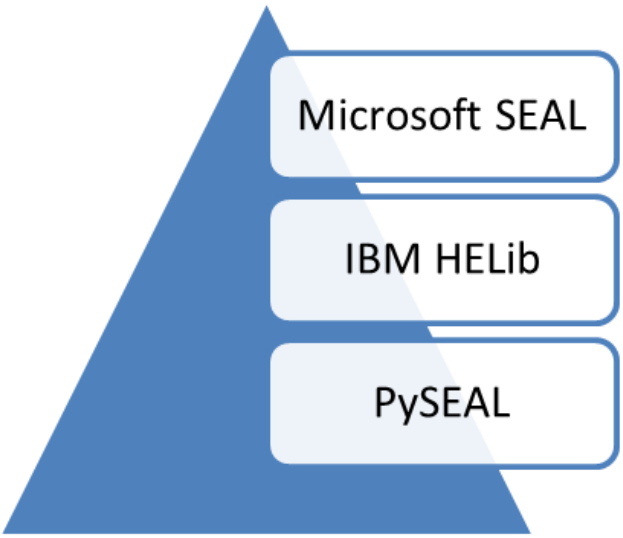

Fig 2: State-of-the-art homomorphic encryption (HE) libraries tools

Three primary application scenarios were examined to assess the practical applicability of encrypted computation in cloud security. Encrypted search, this scenario involved implementing homomorphic encryption to enable keyword-based search over encrypted datasets stored in the cloud (Ali *et al*, 2023). Using IBM HELib, search queries were encrypted before transmission to the cloud. The cloud server performed encrypted search operations without decrypting the data, returning relevant encrypted results to the client. This approach ensured that sensitive search terms and retrieved data remained confidential. Using Microsoft SEAL, an encrypted data analytics pipeline was implemented for processing financial datasets (Hamza *et al*, 2022). The pipeline performed statistical operations such as mean, variance, and trend analysis over encrypted data, demonstrating the feasibility of privacy-preserving analytics. The computations were executed entirely on encrypted data, ensuring that cloud service providers never accessed plaintext information. A federated learning model was tested using PySyft to train a machine learning model on encrypted medical datasets distributed across multiple cloud nodes.

This approach enabled collaborative AI model training without exposing individual patient records, enhancing privacy in healthcare applications. To assess the effectiveness of the implemented security solutions, multiple performance metrics were analyzed, including encryption/decryption time, query latency, and computational overhead. The implementation of IBM HELib for encrypted keyword search demonstrated a latency increase of approximately 20–30% compared to plaintext search. However, the security benefits outweighed the performance trade-offs, as the approach ensured that search queries and results remained encrypted throughout the process. Microsoft SEAL-based encrypted computations exhibited a processing time approximately 2.5x higher than unencrypted operations. However, optimizations such as ciphertext compression and efficient polynomial approximations reduced computational overhead while maintaining data confidentiality (Qureshi *et al*, 2022). PySyft's federated learning implementation showed promising results, with model accuracy comparable to traditional centralized training approaches. The use of differential privacy techniques reduced data leakage risks while maintaining a 3-5% accuracy trade-off, ensuring compliance with privacy regulations in AI-driven healthcare applications (Castro *et al*, 2023). The case study demonstrated that homomorphic encryption, encrypted search, and federated learning provide effective security mechanisms for cloud computing environments. While performance trade-offs exist, the increasing efficiency of cryptographic libraries and hardware acceleration techniques (e.g., GPU-based HE computation) can mitigate computational overhead. The findings emphasize that integrating advanced encryption methods in cloud security frameworks can significantly enhance data privacy while maintaining functional efficiency. Future research should focus on optimizing encryption schemes to improve performance without compromising security, fostering widespread adoption across industries (Allioui and Mourdi, 2023).

2.5 Challenges and future directions

Homomorphic Encryption (HE) is a promising cryptographic technique that enables computations on encrypted data without decrypting it. Despite its potential for securing cloud-based applications, HE faces significant challenges that hinder its widespread adoption (Parast *et al*, 2022). One primary limitation is the computational overhead associated with performing operations on encrypted data. Fully Homomorphic Encryption (FHE) schemes, such as Gentry's lattice-based construction, require extensive computational resources, making real-time processing impractical for many cloud applications (Bhuiyan *et al*, 2021; Mittal and Ramkumar, 2023). Additionally, HE schemes often demand substantial memory and storage requirements, as ciphertexts are significantly larger than plaintexts, leading to inefficiencies in bandwidth utilization. Another critical challenge is the limited support for practical operations. While additive and multiplicative homomorphism are feasible, performing complex functions, such as non-linear transformations or deep learning in encrypted domains, remains difficult. Moreover, HE lacks efficient key management mechanisms, posing risks for key revocation and recovery in cloud environments (Unal *et al*, 2021). These limitations necessitate optimizations to enhance the feasibility of HE in real-world applications.

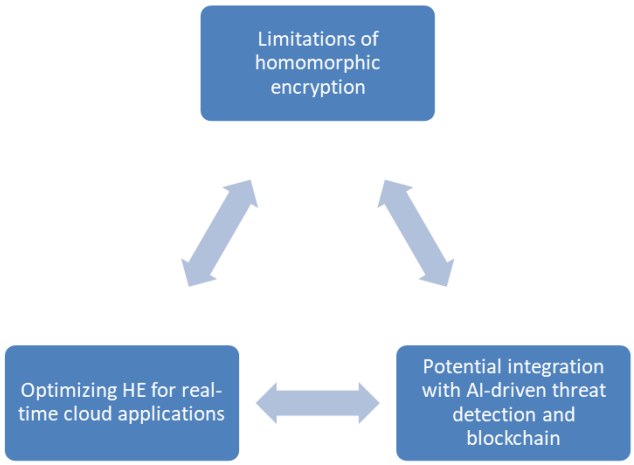

Fig 3: Challenges on cloud data encryption using homomorphic encryption

Addressing the computational overhead of HE requires several optimization strategies. One promising approach is batching techniques, such as the Chinese Remainder Theorem (CRT) and the Smart-Vercauteren technique, which allow multiple operations to be performed simultaneously, reducing overall computational costs. Another optimization involves levelled HE, which restricts the depth of computations to a predefined limit, reducing performance bottlenecks while maintaining encryption security (Jung *et al*, 2021). Furthermore, hardware acceleration, particularly through Field Programmable Gate Arrays (FPGAs) and Graphics Processing Units (GPUs), can significantly enhance the efficiency of HE operations. These specialized hardware implementations optimize modular arithmetic, enabling faster execution of cryptographic functions. Algorithmic improvements, including bootstrapping enhancements, can also minimize computational overhead by refining ciphertext refresh techniques, making FHE more practical for cloud applications (Li *et al*, 2020; Amorim and Costa, 2023).

To mitigate HE's inherent inefficiencies, researchers are exploring its integration with complementary cryptographic techniques. One promising approach is the combination of HE with Zero-Knowledge Proofs (ZKPs), which enables verifiable computations without revealing underlying data. This integration is particularly valuable for secure authentication and privacy-preserving transactions in cloud applications. Another effective strategy is the incorporation of Secure Multiparty Computation (SMPC) with HE. SMPC allows multiple parties to jointly compute a function over their inputs while keeping them private, reducing the reliance on expensive HE operations alone (Saha and Mazumdar, 2023; Smajić *et al*, 2023). Additionally, hybrid approaches that combine Partially Homomorphic Encryption (PHE) with Differential Privacy (DP) can enhance efficiency by applying HE selectively to sensitive data while using lightweight privacy-preserving mechanisms for less sensitive computations.

Future advancements in HE aim to enhance its usability and efficiency in cloud applications (Ali and Alourani, 2021). One key area of focus is the development of practical FHE schemes with reduced bootstrapping requirements. Recent research in approximate HE, such as Cheon-Kim-Kim-Song (CKKS) encryption, has shown promise in enabling encrypted computations with controlled noise accumulation, making it suitable for machine learning applications in the

cloud. Another direction involves the standardization of homomorphic cryptographic frameworks, enabling interoperability across different cloud platforms. Organizations like the Homomorphic Encryption Standardization (HES) group are working toward defining common protocols to facilitate the broader adoption of HE in enterprise cloud security (Tange *et al*, 2020). Finally, improvements in quantum-resistant HE algorithms are crucial as quantum computing advances. Lattice-based cryptographic approaches, including Learning With Errors (LWE) and Ring-LWE, provide a foundation for post-quantum secure HE implementations, ensuring long-term security in cloud environments. Homomorphic Encryption holds immense potential for securing cloud applications while preserving data privacy. However, its adoption is currently hindered by computational overhead, storage inefficiencies, and operational limitations. Optimizing HE through batching, hardware acceleration, and hybrid cryptographic approaches can significantly enhance its practicality. Furthermore, integrating HE with Zero-Knowledge Proofs and Secure Multiparty Computation can improve security and efficiency. Future research must focus on making HE more computationally feasible, standardized, and quantum-resistant, paving the way for its widespread deployment in cloud computing and beyond (Singh *et al*, 2021; Lougovski *et al*, 2023).

3. Conclusion

This review has explored the critical role of emerging technologies in enhancing cloud security and data privacy. Key findings indicate that advanced encryption techniques, zero-trust architecture, and AI-driven anomaly detection significantly mitigate security threats in cloud environments. Additionally, the implementation of blockchain for secure data transactions and decentralized access management has been shown to strengthen data integrity and reduce the risk of breaches. The study highlights the growing importance of compliance frameworks and regulatory measures in fostering a secure cloud ecosystem, ensuring that organizations adhere to industry standards and best practices.

The potential impact of these findings on cloud security and data privacy is profound. By integrating AI and machine learning, organizations can proactively identify and neutralize cyber threats, thereby reducing attack surfaces. Blockchain-based authentication mechanisms offer an immutable and transparent approach to access control, minimizing unauthorized data exposure. These advancements collectively contribute to a more resilient cloud infrastructure, enabling businesses to leverage cloud computing with greater confidence. Furthermore, the study underscores the necessity of continuous updates and real-time threat intelligence sharing to stay ahead of evolving cyber risks.

Despite these promising advancements, the feasibility of widespread adoption remains a challenge. Factors such as cost, implementation complexity, and resistance to change can hinder rapid integration across industries. However, with increasing awareness and advancements in cybersecurity solutions, organizations are progressively recognizing the necessity of enhanced security frameworks. The future of cloud security lies in collaborative efforts between stakeholders, policymakers, and technology providers to ensure scalable, efficient, and secure cloud environments. Ultimately, while challenges persist, the continued evolution of security measures presents a viable path toward achieving robust cloud data protection and fostering trust in digital transformation initiatives.

4. Reference

1. Abdulsalam YS, Hedabou M. Security and privacy in cloud computing: technical review. Future Internet. 2021;14(1):11.
2. Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, *et al* Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production. 2021;289:125834.
3. Alaya B, Laouamer L, Msilini N. Homomorphic encryption systems statement: Trends and challenges. Computer Science Review. 2020;36:100235.
4. Albulayhi K, Abuhussein A, Alsubaei F, Sheldon FT. Fine-grained access control in the era of cloud computing: An analytical review. 2020 10th Annual Computing and Communication Workshop and Conference (CCWC). IEEE; 2020. p. 748–55.
5. Alharbi A, Zamzami H, Samkri E. Survey on homomorphic encryption and address of new trend. International Journal of Advanced Computer Science and Applications. 2020;11(7).
6. Ali A, Alourani A. An investigation of cloud computing and E-learning for educational advancement. International Journal of Computer Science & Network Security. 2021;21(11):216–22.
7. Ali M, He H, Hussain A, Hussain M, Yuan Y. Efficient secure privacy-preserving multi-keywords rank search over encrypted data in cloud computing. Journal of Information Security and Applications. 2023;75:103500.
8. Allioui H, Mourdi Y. Exploring the full potentials of IoT for better financial growth and stability: A comprehensive survey. Sensors. 2023;23(19):8015.
9. Amorim I, Costa I. Leveraging searchable encryption through homomorphic encryption: A comprehensive analysis. Mathematics. 2023;11(13):2948.
10. Aylett R, Vargas PA. Living with robots: What every anxious human needs to know. MIT Press; 2021.
11. Bhuiyan E, Tafsir MD, Rahman M, Mondal S, Warech S. Implementation of real-time learning on homomorphically encrypted visual inputs [dissertation]. Dhaka: Brac University; 2021.
12. Bobda C, Mbongue JM, Chow P, Ewais M, Tarafdar N, Vega JC, *et al* The future of FPGA acceleration in datacenters and the cloud. ACM Transactions on Reconfigurable Technology and Systems (TRETS). 2022;15(3):1–42.
13. Butt UA, Mehmood M, Shah SBH, Amin R, Shaukat MW, Raza SM, *et al* A review of machine learning algorithms for cloud computing security. Electronics. 2020;9(9):1379.
14. Castro OEL, Deng X, Park JH. Comprehensive survey on AI-based technologies for enhancing IoT privacy and security: Trends, challenges, and solutions. Human-Centric Computing and Information Sciences. 2023;13.
15. Duc BM, Cuong VH. A systematic analysis of cloud security challenges and mitigation strategies in modern organizations. International Journal of Social Analytics. 2022;7(12):11–25.
16. Hamza R, Hassan A, Ali A, Bashir MB, Alqhtani SM, Tawfeeg TM, *et al* Towards secure big data analysis via fully homomorphic encryption algorithms. Entropy.

2022;24(4):519.
17. Huang D, Zhou J, Mi B, Kuang F, Liu Y. Key-based data deduplication via homomorphic NTRU for Internet of Vehicles. IEEE Transactions on Vehicular Technology. 2022;72(1):239–52.
18. Javadpour A, Ja'fari F, Taleb T, Zhao Y, Yang B, Benzaïd C. Encryption as a service for IoT: Opportunities, challenges, and solutions. IEEE Internet of Things Journal. 2023;11(5):7525–58.
19. Jung W, Lee E, Kim S, Kim J, Kim N, Lee K, *et al* Accelerating fully homomorphic encryption through architecture-centric analysis and optimization. IEEE Access. 2021;9:98772–89.
20. Khashan OA, Ahmad R, Khafajah NM. An automated lightweight encryption scheme for secure and energy-efficient communication in wireless sensor networks. Ad Hoc Networks. 2021;115:102448.
21. Lai JF, Heng SH. Secure file storage on cloud using hybrid cryptography. Journal of Informatics and Web Engineering. 2022;1(2):1–18.
22. Li M, Yan Y, Wang Q, Du M, Qin Z, Wang C. Secure prediction of neural network in the cloud. IEEE Network. 2020;35(1):251–7.
23. Lougovski P, Parekh O, Broz J, Byrd M, Chembo Y, de Jong WA, *et al* Position papers for the ASCR Workshop on Basic Research Needs in Quantum Computing and Networking. USDOE Office of Science (SC), Advanced Scientific Computing Research (ASCR); 2023.
24. Marcolla C, Sucasas V, Manzano M, Bassoli R, Fitzek FH, Aaraj N. Survey on fully homomorphic encryption, theory, and applications. Proceedings of the IEEE. 2022;110(10):1572–609.
25. Mittal S, Ramkumar KR. Comparative evaluation of fully homomorphic encryption algorithms in cloud environment. International Journal of Electronic Security and Digital Forensics. 2023;15(4):333–47.
26. Mohamed NN, Yussoff YM, Saleh MA, Hashim H. Hybrid cryptographic approach for internet of things applications: A review. Journal of Information and Communication Technology. 2020;19(3):279–319.
27. Nasir MH, Arshad J, Khan MM, Fatima M, Salah K, Jayaraman R. Scalable blockchains—A systematic review. Future Generation Computer Systems. 2022;126:136–62.
28. Nita SL, Mihailescu MI. Homomorphic encryption. In: Advances to Homomorphic and Searchable Encryption. Cham: Springer Nature Switzerland; 2023. p. 27–88.
29. Parast FK, Sindhav C, Nikam S, Yekta HI, Kent KB, Hakak S. Cloud computing security: A survey of service-based models. Computers & Security. 2022;114:102580.
30. Prajapati P, Shah P. A review on secure data deduplication: Cloud storage security issue. Journal of King Saud University-Computer and Information Sciences. 2022;34(7):3996–4007.
31. Prameela PK, Gadagi P, Gudi R, Patil S, Narayan DG. Energy-efficient VM management in OpenStack-based private cloud. In: Advances in Computing and Network Communications: Proceedings of CoCoNet 2020, Volume 1. Singapore: Springer; 2021. p. 541–56.
32. Preston R. Stifling Innovation: How Global Data Protection Regulation Trends Inhibit the Growth of Healthcare Research and Start-Ups. Emory International Law Review. 2022;37:135.
33. Qureshi MB, Qureshi MS, Tahir S, Anwar A, Hussain S, Uddin M, Chen CL. Encryption techniques for smart systems data security offloaded to the cloud. Symmetry. 2022;14(4):695.
34. Rafique A, Van Landuyt D, Beni EH, Lagaisse B, Joosen W. CryptDICE: Distributed data protection system for secure cloud data storage and computation. Information Systems. 2021;96:101671.
35. Ramachandra MN, Srinivasa Rao M, Lai WC, Parameshachari BD, Ananda Babu J, Hemalatha KL. An efficient and secure big data storage in cloud environment by using triple data encryption standard. Big Data and Cognitive Computing. 2022;6(4):101.
36. Ravi P, Howe J, Chattopadhyay A, Bhasin S. Lattice-based key-sharing schemes: A survey. ACM Computing Surveys (CSUR). 2021;54(1):1–39.
37. Saha S, Mazumdar B. Towards resolving privacy and security issues in IoT-based cloud computing platforms for smart city applications. In: Integration of IoT with Cloud Computing for Smart Applications. Chapman and Hall/CRC; 2023. p. 53–80.
38. Silva I, Soto M. Privacy-preserving data sharing in healthcare: An in-depth analysis of big data solutions and regulatory compliance. International Journal of Applied Health Care Analytics. 2022;7(1):14–23.
39. Singh A, Dev K, Siljak H, Joshi HD, Magarini M. Quantum internet—Applications, functionalities, enabling technologies, challenges, and research directions. IEEE Communications Surveys & Tutorials. 2021;23(4):2218–47.
40. Smajić A, Grandits M, Ecker GF. Privacy-preserving techniques for decentralized and secure machine learning in drug discovery. Drug Discovery Today. 2023:103820.
41. Soni D, Kumar N. Machine learning techniques in emerging cloud computing integrated paradigms: A survey and taxonomy. Journal of Network and Computer Applications. 2022;205:103419.
42. Sun P. Security and privacy protection in cloud computing: Discussions and challenges. Journal of Network and Computer Applications. 2020;160:102642.
43. Sunday AE, Olufunminiyi OE. An efficient data protection for cloud storage through encryption. International Journal of Advanced Networking and Applications. 2023;14(5):5609–18.
44. Sunyaev A, Sunyaev A. Cloud computing. In: Internet Computing: Principles of Distributed Systems and Emerging Internet-Based Technologies. 2020. p. 195–236.
45. Tange K, De Donno M, Fafoutis X, Dragoni N. A systematic survey of industrial Internet of Things security: Requirements and fog computing opportunities. IEEE Communications Surveys & Tutorials. 2020;22(4):2489–520.
46. Unal D, Al-Ali A, Catak FO, Hammoudeh M. A secure and efficient Internet of Things cloud encryption scheme with forensics investigation compatibility based on identity-based encryption. Future Generation Computer Systems. 2021;125:433–45.
47. Xie H, Zhang Z, Zhang Q, Wei S, Hu C. HBRSS: Providing high-secure data communication and manipulation in insecure cloud environments. Computer Communications. 2021;174:1–12.
48. Yang P, Xiong N, Ren J. Data security and privacy protection for cloud storage: A survey. IEEE Access.

2020;8:131723–40.
49. Zahid R, Altaf A, Ahmad T, Iqbal F, Vera YAM, Flores MAL, Ashraf I. Secure data management life cycle for government big-data ecosystem: Design and development perspective. Systems. 2023;11(8):380.
50. Zhang Z, Cheng P, Wu J, Chen J. Secure state estimation using hybrid homomorphic encryption scheme. IEEE Transactions on Control Systems Technology. 2020;29(4):1704–20.