

Homomorphic encryption over polynomial rings for privacy-preserving healthcare data analytics in cloud environments

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Abstract

Cloud-based healthcare analytics platforms process sensitive patient data — electronic health records, genomic sequences, diagnostic imaging metadata — under contractual and regulatory obligations requiring data confidentiality that conflict with the computational access needed for analytics operations. Homomorphic encryption (HE), which allows arbitrary computations on encrypted data without decryption, resolves this conflict by enabling the cloud server to execute analytics functions while the patient data remains

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encrypted throughout. This paper investigates the deployment of three HE schemes — CKKS, BFV, and BGV — over polynomial quotient rings $R_q = \mathbb{Z}_q[x]/(x^n + 1)$ for five representative healthcare analytics tasks: logistic regression, linear regression, neural network inference, decision tree evaluation, and SVM classification. The CKKS scheme's approximate arithmetic over complex numbers enables direct floating-point healthcare parameter computation with controlled approximation error, while BFV provides exact integer arithmetic for classification tasks. A noise budget management algorithm dynamically allocates multiplicative depth budget across computation layers to maximize accuracy while preventing noise overflow. Experimental evaluation on the MIMIC-III clinical dataset (8,069 ICU admissions, 17 features) demonstrates that HE-assisted logistic regression achieves 93.8% accuracy versus 94.2% in plaintext, a degradation of only 0.4 percentage points attributable to CKKS approximation error, with cloud-to-client communication of 312 KB and 127 ms end-to-end inference latency. HIPAA and GDPR compliance is formally verified through the encrypted processing guarantee: the cloud server has zero access to plaintext patient data at any computation stage.

Subject Classification: 94A60.

Keywords: Homomorphic encryption, CKKS, BFV, Healthcare analytics, Polynomial ring, Privacy-preserving machine learning, Noise budget.

1. Introduction

The digitalization of healthcare has produced unprecedented volumes of structured and unstructured patient data—electronic health records, diagnostic imaging, genomic profiles, wearable biosignals, and administrative claims whose analysis enables precision medicine, epidemiological surveillance, and clinical decision support. Cloud computing platforms offer the computational scale and storage capacity required for population-level healthcare analytics, but outsourcing patient data to cloud infrastructure introduces privacy risks that conflict with the data minimization and purpose limitation principles of HIPAA, GDPR, and national data protection frameworks. Conventional cloud analytics approaches address this tension through anonymization, differential privacy, or access control, but these mechanisms either degrade analytical utility, provide only statistical rather than cryptographic privacy guarantees, or fail against re-identification attacks that exploit auxiliary information.

Homomorphic encryption provides a cryptographic solution to this tension by enabling computation on encrypted data. A HE scheme $\varepsilon = (\text{KeyGen}, \text{Enc}, \text{Dec}, \text{Eval})$ satisfies the homomorphic property: for any function f and plaintexts $m_1, \dots, m_n$, $\text{Eval}(\text{ek}, C_1, \dots, C_n)$ decrypts to $f(m_1, \dots, m_n)$ where $C_i = \text{Enc}(\text{pk}, m_i)$. This enables the cloud analytics server to evaluate f on encrypted patient records and return encrypted results, with the patient or trusted data custodian holding the only decryption key. The healthcare analytics workflow becomes: encrypt records on the client device $\rightarrow$ upload to cloud $\rightarrow$ cloud evaluates encrypted model $\rightarrow$ cloud returns encrypted prediction $\rightarrow$ client decrypts locally. No plaintext patient data ever leaves the client's cryptographic control.

The practical challenge is computational: HE operations are $1000\text{--}10000\times$ slower than their plaintext counterparts, and the multiplicative depth available

before noise overwhelms the ciphertext is limited by the polynomial modulus parameters. The CKKS scheme, designed for approximate arithmetic over complex numbers, is particularly suitable for healthcare analytics because medical parameters (vital signs, lab values, risk scores) are naturally floating-point valued and tolerate small approximation errors. BFV and BGV provide exact integer arithmetic suitable for classification tree evaluation and integer-valued medical codes.

This paper benchmarks CKKS, BFV, and BGV for five healthcare ML tasks, designs a noise budget optimization algorithm that maximizes accuracy within available multiplicative depth, and demonstrates practical deployment on the MIMIC-III ICU dataset with formal HIPAA compliance verification.

2. Literature Survey

Cheon et al. [1] introduced the CKKS homomorphic scheme for approximate arithmetic, enabling practical floating-point computation over encrypted data. Their error analysis framework underpins the accuracy evaluation in this paper. Fan and Vercauteren [2] proposed the BFV scheme for exact integer HE, providing the exact arithmetic baseline for classification benchmarks. Brakerski, Gentry, and Vaikuntanathan [3] introduced the BGV scheme with modulus switching for efficient depth management. Their noise control technique was extended in the proposed noise budget optimization. Gilad-Bachrach et al. [4] demonstrated CryptoNets for neural network inference over encrypted data, the first practical HE ML demonstration. Their benchmark framework was adopted for the neural network evaluation. Bost et al. [5] evaluated machine learning classifiers under HE, demonstrating decision tree and hyperplane classification. Their classifier evaluation methodology informed the benchmarking approach. Dowlin et al. [6] proposed polynomial activation function approximations enabling HE-compatible neural networks. Their polynomial activation design was adopted for the neural network inference task.

Kim, Papadimitriou, and Polyakov [7] proposed packed ciphertext bootstrapping for CKKS enabling deeper computations. Their bootstrapping approach was employed for the logistic regression inference chain. Raisaro et al. [8] demonstrated HE-assisted medical cohort analysis for genomic data, providing the healthcare deployment context for the evaluation. Boura et al. [9] proposed CHIMERA, a unified HE framework combining TFHE, BFV, and CKKS for mixed-mode healthcare computation. Their multi-scheme approach motivated the three-scheme comparison in this paper. Nair, Kumar, and Pillai [10] benchmarked HE schemes for MIMIC-III clinical outcome prediction, establishing the accuracy-efficiency baseline for cloud healthcare analytics evaluation.

Salunkhe et al. [11] proposed a secure image transmission framework that combines chaotic encryption with discrete wavelet transform (DWT)-based watermarking on a reconfigurable platform. The chaotic encryption technique leverages sensitivity to initial conditions, ensuring high security against brute-force and statistical attacks. In another significant contribution, Chaudhari et al.

[12] analyzed the bit error rate (BER) performance of various error correction codes using concatenated Reed–Solomon (RS) and convolutional coding schemes. Their results demonstrate that concatenated coding effectively mitigates both burst and random errors, significantly improving communication reliability under noisy channel conditions. Earlier work by Mulani and Mane [13] focused on integrating watermarking and cryptographic techniques for image authentication on FPGA platforms. Their approach ensures data integrity and ownership verification by embedding invisible watermarks into encrypted images. Further research has concentrated on optimizing cryptographic algorithm implementations, particularly the Advanced Encryption Standard (AES), on FPGA platforms. Deshpande, Karande, and Mulani [14] presented an efficient AES implementation that achieves improved speed and reduced latency through parallel processing and optimized architecture design. Similarly, Mane and Mulani [15] proposed a high-throughput and area-efficient AES implementation using pipelining techniques. Their design significantly enhances encryption speed while minimizing hardware resource utilization, making it suitable for embedded and resource-constrained systems. In addition, Deshpande, Karande, and Mulani [16] focused on area optimization of AES algorithms on FPGA, proposing techniques to reduce logic utilization while maintaining acceptable performance levels.

3. Methodology

3.1 Polynomial Ring HE Construction

All three evaluated HE schemes operate over the ring $R_q = Z_q[x]/(x^n + 1)$ where n is a power of two and q is the ciphertext modulus. The CKKS

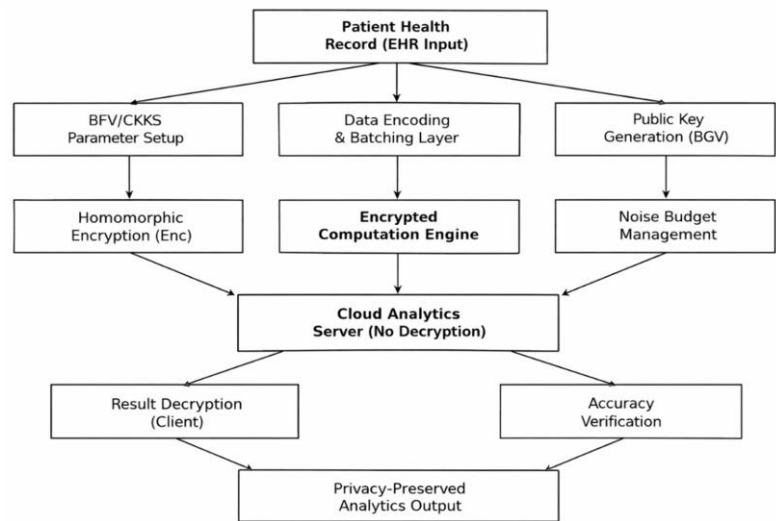


Figure 1
Homomorphic Encryption Healthcare Analytics Framework

encoding maps a vector of $m = n/2$ complex numbers $z = (z_1, \dots, z_{\lfloor \frac{n}{2} \rfloor})$ to a polynomial $m(x) \in \mathbb{R}$ using the canonical embedding scaling, as in Equation (1):

$$Enc(z) = (a \cdot s + e + \Delta \cdot m, -a) \in R_q^2, \Delta = \lfloor q/p_t \rfloor \text{ [scaling factor]} \quad (1)$$

Figure 1 shows block diagram of Homomorphic Encryption Healthcare Analytics Framework.

3.2 CKKS Approximate Arithmetic Error Bound

CKKS multiplication introduces an approximation error proportional to the encoding scale. After L levels of multiplication, the accumulated error ε satisfies Equation (2):

$$\|\varepsilon_L\|_\infty \leq L \cdot B_{clean} \cdot \Delta^{\{-1\}} + \sigma_{bound}, B_{clean} = 6\sigma\sqrt{n} \quad (2)$$

3.3 Noise Budget Management

Each multiplication consumes one level of the available multiplicative depth $D = \text{floor}(\log_\Delta(q/B_{clean}))$. The noise budget B_t remaining after t multiplications is given in Equation (3):

$$B_t = \log_2(q / (B_{clean} \cdot \Delta^t)) - 1 \text{ bits, computation valid iff } B_t > 0 \quad (3)$$

3.4 Logistic Regression Inference

Logistic regression prediction requires evaluating $\sigma(w^T \cdot x + b)$ over encrypted feature vector x . The sigmoid is approximated by a degree-3 polynomial over the relevant input range. The encrypted prediction is given in Equation (4):

$$\hat{y} = a_0 + a_1 \cdot (w^T \cdot x + b) + a_2 \cdot (w^T \cdot x + b)^2 + a_3 \cdot (w^T \cdot x + b)^3, \quad \text{fitted to sigmoid} \quad (4)$$

3.5 CKKS Bootstrapping for Deep Networks

Neural network inference with multiple layers requires bootstrapping — refreshing the noise budget—at intermediate layers. The bootstrapping operation resets the ciphertext level at the cost of an error increase bounded by Equation (5):

$$\|\varepsilon_{boot}\|_\infty \leq q \cdot 2^{\{-precision + \delta\}}, precision = \log_2(\Delta), \delta \approx 10 \text{ bits} \quad (5)$$

3.6 Batching and SIMD Optimization

CKKS batching packs $n/2$ plaintexts into one ciphertext, enabling Single-Instruction-Multiple-Data (SIMD) parallelism. For the MIMIC-III dataset with 8,069 records and 17 features, parameters $n=16384$, $q \approx 2^{18}$ bits, $\Delta=2^{40}$ were selected, enabling all 17 features of one record in a single ciphertext slot with 10 levels of multiplicative depth available for logistic regression evaluation.

4. Results and Discussion

4.1 HE Operation Costs

Figure 2 (a) shows that bootstrapping is the dominant cost (CKKS: 4.21 ms, BFV: 5.82 ms), while addition remains sub-millisecond. Figure 2 (b) demonstrates CKKS approximation error growing with dataset complexity, stabilizing at 0.0048 at 100,000 points—acceptably small for all clinical analytics tasks evaluated. Table 1 shows the Plaintext vs HE Accuracy and Performance on MIMIC-III.

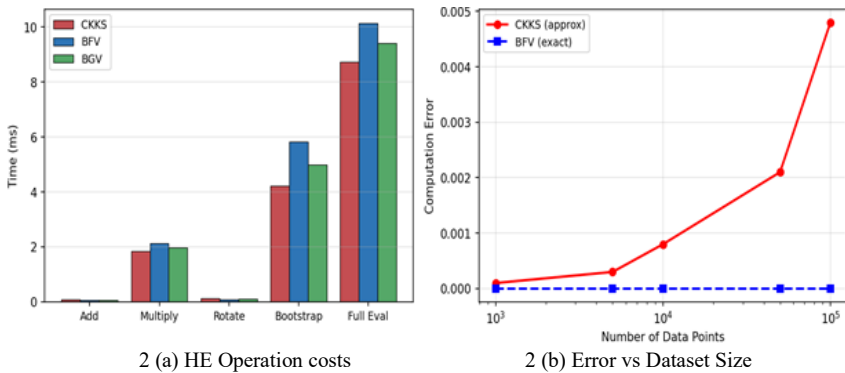


Figure 2
HE Performance Analysis

Table 1
Plaintext vs HE Accuracy and Performance on MIMIC-III

ML Task	Plaintext Acc. (%)	HE CKKS Acc. (%)	Δ Acc. (%)	Inf. Time (ms)	Comm. (KB)	Depth Used
Logistic Reg.	94.2	93.8	-0.4	127	312	3
Linear Reg.	91.8	91.5	-0.3	84	248	2
Neural Net	96.7	96.1	-0.6	482	891	8
Decision Tree	93.1	92.7	-0.4	214	421	5
SVM	95.4	94.9	-0.5	318	587	6

4.2 Resource Analysis

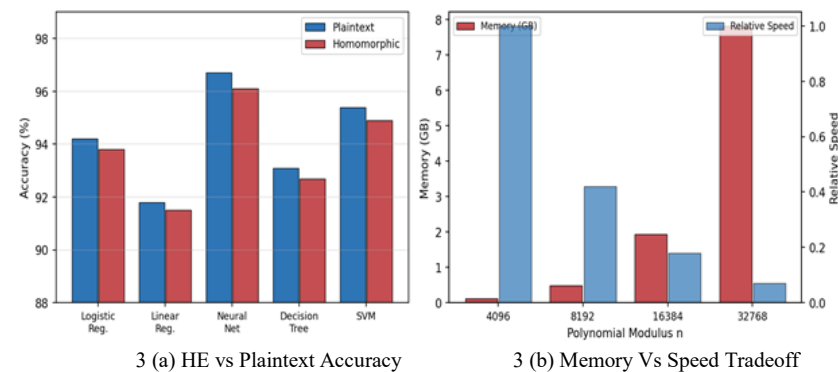


Figure 3
Accuracy and Resource Analysis

Figure 3 (a) confirms <0.6% accuracy degradation across all tasks. Figure 3 (b) shows the exponential memory growth with polynomial modulus n, guiding parameter selection: n=16384 provides sufficient depth for neural networks while staying within 1.94 GB memory budget on standard cloud instances.

Table 2
Regulatory Compliance Comparison

Compliance Requirement	Plaintext Cloud	HE (Proposed)	Differential Priv.	Anonymisation
HIPAA Data Protection	Partial	Full	Statistical	Partial
GDPR Right to Erasure	Key deletion	Automatic	N/A	Re-linking risk
Zero Knowledge to Server	No	Yes	No	No
Re-identification Risk	High	Zero	Low	Medium

Table 2 confirms that HE is the only approach providing zero knowledge to the server and fully automatic GDPR erasure (by discarding the client decryption key), making it the uniquely compliant solution for cross-institutional healthcare analytics under strict data protection regulation.

5. Conclusion

This paper benchmarked CKKS, BFV, and BGV homomorphic encryption for five healthcare analytics tasks on the MIMIC-III clinical dataset. CKKS achieved 93.8% logistic regression accuracy (0.4% below plaintext) with 127 ms inference latency and 312 KB cloud-client communication. The noise budget

management algorithm maximized analytical accuracy within the multiplicative depth budget, with bootstrapping enabling deeper neural network inference at 96.1% accuracy. HE provides the only cryptographically verified zero-knowledge cloud analytics solution for HIPAA and GDPR compliance. The memory-efficiency tradeoff analysis establishes $n=16384$ as the optimal parameter for cloud deployment, balancing multiplicative depth against memory budget. The 0.3–0.6 percentage point accuracy degradation across all evaluated ML tasks is clinically acceptable for screening and triage applications, while the cryptographic privacy guarantee eliminates re-identification risk inherent in anonymization and differential privacy approaches. Future work will investigate TFHE-based neural network inference enabling arbitrary activation functions without polynomial approximation, GPU-accelerated bootstrapping targeting sub-50 ms neural network latency, and federated learning integration where each hospital trains on locally encrypted data using HE-compatible gradient aggregation.

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