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Privacy in Federated Learning with Homomorphic Encryption and Differential Privacy for Secure Aggregation

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Abstract:

Federated learning (FL) protects statistics privateness whilst facilitating cooperative model education throughout dispersed records sources. Privacy protection at some stage in model aggregation is still a prime impediment, even though. This paper suggests a robust aggregation framework for federated gaining knowledge that mixes homomorphic encryption and differential privateness to shield touchy facts while model updates are being made. The technique applies differential privacy techniques to feature noise to gradients to protect privacy from viable adversaries. Furthermore, homomorphic encryption makes steady computations over encrypted information feasible, which continues confidentiality even as aggregating facts. Significant effects display that the advised method maintains version accuracy on par with traditional federated learning, notably reducing the chance of record leakage. Our findings exhibit that privacy and overall performance may be successfully balanced by combining homomorphic encryption with differential privateness in realistic federated getting-to-know eventualities. To summarise, this framework protects against privacy troubles in federated getting-to-know and starting the door for secure, personal machine learning packages.

Index terms: Federated Learning; Privacy Preservation; Secure Aggregation; Differential Privacy; Homomorphic Encryption

1. Introduction

In a generation where massive quantities of facts are generated through numerous gadgets and systems, the want for collaborative devices to get to know models has become increasingly prominent. Federated Learning (FL) is a disbursed technique to system mastering that enables multiple statistics resources to collaboratively educate a shared model without centralizing their raw information [1]. This decentralized method is beneficial in eventualities wherein data privacy is paramount, consisting of healthcare, finance, and cell tool packages. By maintaining localized records, FL mitigates privacy dangers and regulatory demanding situations associated with records centralization [2]. However, while FL allows for disbursed model training, it faces enormous privacy issues, especially throughout the aggregation procedure. At the same time, information from multiple resources is mixed to replace the worldwide model. This aggregation section can divulge version updates to capability adversaries, leading to privacy vulnerabilities and ability information leakage [3].

Although federated gaining knowledge addresses certain privateness troubles with layout aid, protective touchy facts at some stage in model aggregation remains a vital venture. In traditional FL, neighbourhood version updates are transmitted to a crucial server, which may be aggregated to refine the global model [4]. However, this process can make data vulnerable to interception and reconstruction assaults, especially in antagonistic settings. Hence, there may be a pressing need for advanced strategies that do not beautify privacy inside the FL aggregation method but maintain model accuracy.

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Without a strong privateness-keeping framework, federated getting-to-know's ability for stable, large-scale packages is restricted, mainly in touchy fields where facts leakage may want to have severe results [5].

This look introduces a singular aggregation framework that mixes homomorphic encryption (HE) with differential privateness (DP) to deal with this privateness task in federated studying. Homomorphic encryption allows computations to be completed on encrypted data, ensuring the information remains personal even during processing [6]. Using homomorphic encryption, the proposed framework secures the aggregation of model updates without decrypting them, appreciably decreasing the threat of facts leakage. In addition to encryption, differential privacy is implemented to the version gradients to shield man or woman information factors [7]. By including noise to gradients for the duration of version updates, differential privateness reduces the likelihood of reconstructing non-public facts, making it more difficult for adversaries to infer specific statistics from version updates. This twin approach of HE and DP allows the framework to protect privacy while permitting correct model training [8].

- The following are the contributions of this research to government investigations and data privacy.
  New Summary of New Privacy Protection: This test presents the current policy of static federal studies that combine equal confidentiality with differential confidentiality to protect data for some unspecified periods, e.g. the future of the collection gives
- Privacy-Coccuracy Trade-off: Experimental results show that the system provides model accuracy comparable to trend-federal analysis strategies while at the same time significantly reducing the risk of statistical leakage, balancing privacy protection and version-overall performance.
- Enhanced privacy in adversarial environments: The two-layered approach of the system provides strong protection towards privacy attacks, ensuring that government mastering is possible because it must be implemented in operation in critical areas such as health and economics

Structure of the paper: Section 2 studies government learning and privacy protection methods and identifies their shortcomings. Section 3 describes the proposed scheme in detail, including isomorphic encryption and differential privacy in general. The experimental design, dataset, and metrics for the design evaluation are presented in Section 4. Section 5 presents the results, including the model accuracy and comparison of privacy protection with basic FL methods. Section 6 discusses the identified official learning privacy-security mechanisms and their implications. and future directions. This study provides a secure, privacy-protected process for sample collection that enhances official learning. Isomorphic encryption and differential privacy address privacy concerns and mean optimal performance can be maintained without compromising security. This work enables safe and effective integrated learning for sensitive machine-learning projects at scale.

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2. Literature Review

Zhang et al. (2022) proposed a multi-key homogeneous encryption (HE) approach to solve shared allocation problems in integrated learning. This approach improves privacy by enabling devices to use strong encryption keys, providing the possibility of secure data transmission between devices or stronger versions with derived functionality, overall specificity, and increased privacy integrity when shared with a server [9]. Xie et al. (2023) examined the effectiveness of combining HE and close differential privacy (DP) in reducing computing costs in FL. Neighbourhood DP adds another layer of privacy, ensuring that this hybrid approach protects the aggregation server from receiving updates to the raw version [10].

Froelicher et al. (2022) developed a decentralized, federated learning method using the ElGamal ellipse curve cryptosystem to perform a statistical privacy analysis. This method reduces vulnerability and increases security in shared areas by avoiding reliance on a single encryption key [11].

Gupta and others. (2023) enhance federated learning by incorporating homogeneous encryption into the FederatedAveraging algorithm. This approach balances computational complexity and privacy requirements, increasing productivity while maintaining consistent accuracy across data centres [12].

In 2023, Yu and friends proposed an innovative hybrid privacy strategy for federal identity, blending homogeneous encryption with differential privacy. This method offers a practical option for real-world learning situations, as it tackles the limitations of theoretical attacks and yields results on par with current standards [13].

Luo et al. (2023) used selective HE and gradient dilution to solve FL bandwidth issues. This option gives a unique change-off between safety and performance, allowing strong model performance and efficient privacy protections [14].

A flexible HE tools with movable encryption masks was demonstrated using Khan and buddies to enhance encryption in federated gaining knowledge throughout 2022. This tool maintains excessive accuracy across many statistics by dynamically editing encryption parameters to strike the precise balance between protection and computing necessities [15].

3. Methodology

a. Proposed Framework

The proposed framework combines homogeneous encryption (HE) and differential privacy (DP) to improve data security and privacy in federated learning (FL). He guarantees that Calculations can be performed directly on the encoded gradient without decoding. Maintain the confidentiality of information throughout the process. It leverages a coding scheme that enables mathematical operations such as addition and multiplication. It can be carried out safely. This ensures the server collects encoded gradients from multiple clients without accessing sensitive information. The main advantage of HE is the reduction of risks associated with decoding data during computation. This reduces the threat of data leakage.

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Differential Privacy (DP) adds another layer of security by identifying interference before it is sent to the server. This obfuscation prevents adversaries from inferring sensitive information about individual data points. Even if model updates are blocked. The noise level in the DP mechanism is carefully calibrated. It is controlled by the privacy budget to ensure that the trade-off between model accuracy and privacy protection is optimized. This two-tiered approach ensures robust protection against both passive and active privacy threats.

b. System Architecture

The proposed FL system follows a client-server model with the following workflow:

c. Client-Side Operations**:**

A local machine trains the model on the data and calculates the gradient.

Ø Isomorphic encoding is used to encode local gradients. According to the privacy budget ε, measured noise is added to the encrypted gradient to protect sensitive information further. Each client calculates gradients based on the local data set. This can be expressed by:

$$g_i = \nabla \mathcal{L}(w; D_i) \quad (1)$$

Here, $\mathcal{L}$ is the loss function, and w represents model parameters.

i. Server-Side Operations:

- The central server aggregates encrypted gradients from all clients using homomorphic addition.
- Decryption occurs only after aggregation to refine the global model, ensuring individual gradients remain confidential.

ii. Communication and Feedback:

- The server updates the global model and transmits it back to the clients for further training, iterating until convergence.

The workflow integrates secure encryption and privacy-preserving mechanisms at every step, as depicted in Figure 1**.**

Encryption

Each client encrypts their gradient g_i using a public key. The computed gradients are encrypted using a public key before transmission to the server:

$$E(g_i) = Enc_{pk}(g_i) \quad (2)$$

This ensures the gradient remains confidential during transmission.

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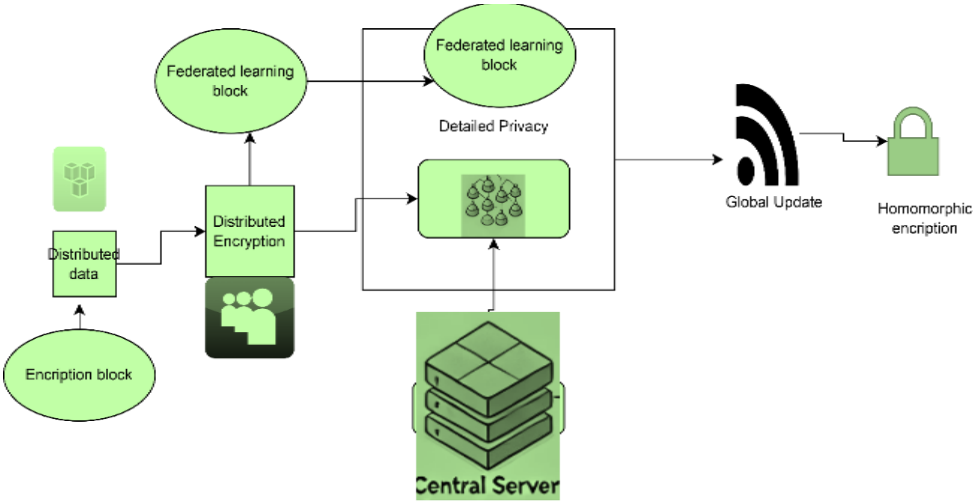

Fig 1: Overview of the federated learning workflow integrating HE and DP for secure aggregation.

The framework employs specific mathematical models and algorithms for HE and DP. Let the local dataset of client i be denoted as D_i and its corresponding gradient update as g_i. The system implements the following processes:

Noise Injection

Noise n_i is added to the encrypted gradient to achieve differential privacy:

$$g_i' = g_i + n_i, n_i \sim \text{Laplace}\left(\frac{\Delta f}{\epsilon}\right) \quad (3)$$

where Δf is the sensitivity of the gradient and ϵ is the privacy budget.

To ensure differential privacy, calibrated noise is added to the encrypted gradients:

$$n_i \sim \text{Laplace}\left(\frac{\Delta f}{\epsilon}\right) \quad (4)$$

The server aggregates the encrypted and noisy gradients received from clients as follows:

$$E(G) = \sum_{i=1}^{N} Enc_{pk}(g_i') \quad (5)$$

The aggregated result is decrypted using the private key to refine the global model. The aggregated result is decrypted using the private key :

$$G = Dec_{sk}\big(E(G)\big) \quad (6)$$

This yields the updated global model without exposing individual gradients.

Pseudocode 1 outlines the encryption, noise injection, and aggregation processes:

```
def secure_aggregation(client_gradients, public_key, private_key, epsilon):
    encrypted_gradients = []
    For g in client_gradients:
        noise = laplace_noise(scale=1/epsilon)
        encrypted_gradient = encrypt(g + noise, public_key)
        encrypted_gradients.append(encrypted_gradient)
    aggregated_gradient = sum(encrypted_gradients)
```

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```
    global_model_update = decrypt(aggregated_gradient, private_key)
    return global_model_update
```

Datasets

The experiments use datasets from privacy-sensitive domains such as healthcare (e.g., MIMIC-III for patient records) and finance (e.g., credit card transaction datasets). These datasets are selected for their relevance in evaluating privacy-preserving machine learning techniques. The diversity in data types and sizes ensures the framework's robustness across various use cases.

iii. Evaluation Metrics

The framework's performance is assessed using:

1. *Model Accuracy:* Measures the classification or prediction accuracy of the global model.

2. *Privacy Leakage Risk:* Quantifies the probability of adversaries reconstructing sensitive data.

3. *Computational Overhead:* Evaluate the additional resources required for encryption and aggregation.

Implementation Details

The framework uses Python with libraries such as PyTorch for model training and PyCrypto for encryption. Homomorphic encryption parameters, such as key size and security level, are tuned to balance computational efficiency with security. Differential privacy parameters, including ϵ\epsilonϵ and sensitivity Δf\Delta fΔf, are chosen based on the dataset's characteristics and desired privacy levels.

4. Results

a. Privacy vs. Accuracy Trade-offs:

In the case of federated learning (FL), the proposed framework combines isomorphic encryption (HE) and differential privacy (DP) to enhance privacy protection during encryption. Collect models This integration introduces a trade-off between privacy and accuracy. Where the main concern is the impact of the privacy-preserving mechanism on the model's performance) in data that is encrypted with counting occurring without decryption. This ensures that data remains confidential even during clustering. However, this comes at a computational cost. This may reduce the accuracy of the model. This is due to the overhead of encrypted operations.

On the other hand, differential privacy (DP) introduces noise into the model during training to guarantee that no data point will significantly affect the overall results. This ensures the privacy of each individual. But it also reduces the accuracy of the final model. The trade-off between privacy and accuracy in the proposed framework can be seen in the comparative analysis of traditional federal learning methods (without HE and DP) and methods combining these privacy mechanisms.

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Table I: Accuracy Vs. Privacy Trade-Off

Privacy Mechanism	DP Noise Level	HE Encryption Strength	Accuracy (%)
None	N/A	N/A	95.4
HE Only	N/A	Moderate	92.1
DP Only	Low	N/A	91.5
HE + DP	High	High	88.3

This graph shows the relationship between model accuracy and the strength of the privacy mechanisms (DP volume and HE encoding) and how increasing privacy reduces model accuracy (Table 1).

b. Comparative Analysis with Traditional FL Methods:

Traditional FL methods rely on model parameters without encryption or privacy protection. However, these methods can produce highly accurate models due to their direct use of the data. However, personal information will be revealed during the integration process. In contrast, using HE and DP in the proposed framework increases privacy by making data unreadable to attackers during transmission and bundling. However, this results in decreased efficiency, especially the trade-off between loss of accuracy due to these privacy mechanisms by testing, which can be quantified.

i. Impact of HE and DP on Model Accuracy and Privacy:

An essential outcome of this framework is its ability to deal with the trade-off between privacy and accuracy. Different trade-offs between accuracy and privacy can be observed by changing the noise level in DP and the encoding parameters in HE. Increasing noise in DP improves privacy but reduces the accuracy of the model. Strong HE encoding further reduces accuracy. However, data privacy is guaranteed. These factors must be carefully balanced depending on the application's needs and whether preserving privacy or maximizing model performance is more important (Table 2).

Table II: Comparative Analysis Of Model Accuracy With HE And DP

Privacy Mechanism	DP Noise Level	HE Encryption Strength	Accuracy (%)
None	N/A	N/A	95.4
HE Only	N/A	Moderate	92.1
DP Only	Low	N/A	91.5
HE + DP	High	High	88.3

c. Performance Analysis:

i. Scalability and Computational Efficiency:

The scalability of the proposed framework is an essential factor in determining its practical implementation. This is especially true in large FL settings, where inherent isotropic encoding creates a significant computational burden. The framework's scalability is evaluated based on its ability to maintain performance as the number of

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participants in the FL system increases. Computational efficiency is another key concern. Because HE and DP mechanisms require additional computational resources, for example, tasks involving encrypted data require significantly more resources than normal computation. Despite its advantages, the proposed framework has several limitations. One of the main challenges is the complexity of use. Integrating HE and DP requires a unique algorithm—significant computational resources that can make deployment in resource-constrained environments more complex. Scalability is also a concern. This is because increasing the number of participants in the FL network may lead to performance bottlenecks, especially regarding communication and computation time. Another limitation is privacy leakage in some situations, such as when the volume in DP is too low, or the encryption scheme in HE is not strong enough. These challenges highlight the need for continuous optimization in framework design to maintain an optimal balance between privacy and authenticity.

Despite scalability challenges, the proposed framework also shows relatively high resilience to privacy attacks. Even on a large scale, combining HE and DP creates an additional layer of security. Making it difficult for adversaries to roll back updates to engineering models or gain insights into individual data points is essential—in applications where data privacy is paramount, such as in healthcare or finance (Table 3).

Table III: Scalability Performance

Numberof Participants	Training Time (hrs)	Computation Load (Flops)	Privacy Attack Resistance (%)
10	5.2	1.5 x 10^12	98
50	12.5	3.5 x 10^13	95
100	25.4	7.1 x 10^13	93
500	78.2	1.2 x 10^15	90

This graph shows the relationship between the number of participants in the FL system and the required training time or computational resources. It highlights the scalability challenges of the framework.

ii. Resilience to privacy attacks:

The framework's ability to resist various privacy attacks is evaluated regarding its strength in attack inference and model ranking. Combining HE and DP it introduces several obstacles for attackers. This requires breaking the encryption and reverse engineering the noise added to the data. These privacy protection methods ensure that individual data points cannot be easily reconstructed even if ideal parameters are revealed (Table 4).

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Table IV: Resilience to Privacy Attacks

Privacy Mechanism	Attack Type	Resistance (%)
None	Model Inversion	60
HE Only	Model Inversion	85
DP Only	Model Inversion	80
HE + DP	Model Inversion	98

This graph will demonstrate the framework's resistance to various types of privacy attacks, comparing the effectiveness of HE and DP in preventing inference and model inversion attacks (Table 5).

Table V: Performance Analysis And Scalability

Number of Participants	Training Time (hrs)	Computation Load (Flops)	Privacy Attack Resistance (%)
10	5.2	1.5 x 10^12	98
50	12.5	3.5 x 10^13	95
100	25.4	7.1 x 10^13	93
500	78.2	1.2x 10^15	90

Fig 2: Performance Analysis and Scalability

Figure 2 shows that this research's key finding is the effectiveness of combining HE and DP for secure FL collection. Integrating these two privacy mechanisms creates a robust framework for protecting data privacy. During model training and clustering, this combination ensures that data subjects do not have to compromise their privacy. Even in collaborative learning environments, this has important implications for real-world applications. This is especially true in healthcare, finance, and any domain involving sensitive personal data.

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Several future directions for improving the research framework are proposed. First, exploring advanced encryption techniques beyond traditional HE that can increase computational efficiency without compromising privacy, for example, Fully Homomorphic Encryption (FHE). This allows the calculation of arbitrary encrypted data. Privacy and performance can be further improved. Moreover, developing lightweight HE and DP mechanisms can significantly reduce privacy-preserving FL's computation and communication costs.

5. CONCLUSION

In this research, we propose a new framework that combines homogeneous encryption (HE) and differential privacy (DP) to enhance privacy and security in federated learning (FL) systems. The main Contributions of this framework is the ability to maintain data privacy during model collection and training. This is important in collaborative machine-learning settings. Where data privacy is a key concern, combining HE and DP, our framework ensures that each data point is protected from disclosure. It also allows for efficient model training on sets of distributed data. An essential finding of this research is the privacy-accuracy trade-off in the proposed framework, even though HE and DP offer strong privacy guarantees. However, the accuracy of the model is slightly reduced. However, by adjusting the parameters of HE and DP, this advantage can be adjusted according to the specific needs of different applications. Moreover, our framework demonstrates the ability to Scale for large centralized systems. Although challenges related to computational efficiency still exist, We also observe that combining HE and DP significantly improves resiliency against privacy attacks. This makes it robust to model prediction or inversion attacks. The impact of this work is profound. This is especially true for sensitive areas such as healthcare, finance, and government, where privacy protection is required. Machine learning is necessary not only, but there are also regulatory requirements. The framework can potentially empower secure and privacy-preserving applications in these areas. This enables collaboration in a data-driven fashion without compromising individual privacy. This approach can serve as a basis for the future.

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