A Privacy-Preserving Federated Learning Framework for Secure Distributed Model Training Using Differential Privacy and Homomorphism Encryption

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Abstract: With the rapid growth of distributed data generation, traditional centralized machine learning approaches face serious challenges related to data privacy and security. Federated Learning (FL) has emerged as a promising solution by enabling collaborative model training without sharing raw data among participants. However, recent studies have shown that sensitive information can still be inferred from model updates, making privacy preservation a critical concern in federated learning systems. This paper proposes a privacy-preserving federated learning framework that integrates Differential Privacy, Secure Aggregation, and homomorphic Encryption to enhance data confidentiality during distributed model training. In this work, local models are trained on client devices using private datasets, and controlled noise is added to the model gradients to prevent data leakage. The privacy-preserved updates are then encrypted and securely aggregated at the central server, ensuring that individual client contributions remain confidential. An adaptive privacy budget mechanism is incorporated to balance the trade-off between model accuracy and privacy protection.

Keywords— *Federated Learning, Privacy Preservation, Differential Privacy, Secure Multiparty Computation, Homomorphic Encryption*

I. INTRODUCTION

In recent years, the rapid growth of data generated by mobile devices, Internet of Things (IoT) systems, healthcare applications, and online services has significantly increased the demand for intelligent data-driven solutions. Traditional machine learning approaches rely on centralized data collection, where data from multiple sources is aggregated and processed on a single server. Although effective, this centralized paradigm raises serious concerns related to data privacy, security, regulatory compliance, and communication overhead, especially when dealing with sensitive information such as medical records, financial data, and personal user behavior. Federated Learning (FL) has emerged as a promising distributed machine learning paradigm that enables multiple clients to collaboratively train a shared global model without directly sharing their raw data. In federated learning, each client performs local model training using its private dataset and only transmits model updates, such as gradients or weights, to a central aggregation server. This approach significantly reduces privacy risks and communication costs while allowing knowledge sharing across distributed participants.

Despite its advantages, federated learning is not inherently secure. Recent studies have demonstrated that sensitive information can still be inferred from shared model updates through attacks such as model inversion, membership inference, and gradient leakage. These vulnerabilities highlight the need for robust privacy preservation mechanisms within federated learning frameworks to ensure complete data confidentiality and trust among participants. To address these challenges, privacy-preserving techniques such as Differential Privacy, Secure Aggregation, and cryptographic methods have gained significant attention. Differential Privacy introduces controlled noise into model updates to limit the exposure of individual data points, while secure aggregation ensures that the central server can only access aggregated information rather than individual client updates. Additionally, encryption techniques such as homomorphic encryption allow computations to be performed on encrypted data, further enhancing security during communication and aggregation.

This thesis focuses on designing and implementing a privacy-preserving federated learning framework that integrates these advanced privacy protection mechanisms. The proposed approach aims to achieve an optimal balance between privacy preservation and model performance, ensuring secure and efficient collaborative learning. The effectiveness of the framework is validated through experimental evaluation using benchmark datasets, making it suitable for real-world applications requiring strict data privacy guarantees.

Figure 1. Federated Learning & Privacy Preserving

II. LITRETURE REVIEW

The literature survey provides an extensive review of existing research on privacy preservation in federated learning, examining a range of techniques such as differential privacy, secure multiparty computation, and homomorphic encryption. It highlights the strengths and limitations of these methods, offering insights into their practical applicability and performance. Additionally, the survey identifies emerging trends and key challenges, setting the stage for future advancements in the field.

This paper [1] presents a privacy-preserving federated learning framework specifically designed for resource-constrained mobile health and wearable IoT devices. The proposed framework effectively addresses key challenges such as limited computation power, communication bandwidth, and energy efficiency in edge environments. Furthermore, the study implements and evaluates the framework on Amazon AWS cloud infrastructure, using a seizure detection application for epilepsy monitoring as a case study.

Author [2] proposed a framework functions with arbitrary types of input features that emphasize its usability with natural language data. The text input on the client-side is encoded using a rolling hash-based representation, which provides a combined solution for the high resource demands of embedding algorithms and the privacy concerns of sharing sensitive data. Authors evaluate method in a sentiment analysis task using the IMDB Movie Reviews dataset as well as a rating prediction task with the Movie Lens dataset augmented with additional movie keywords.

In this work [3] is dedicated to surveying of state-of-the-art privacy-preservation techniques in FL in relations with GDPR requirements. Furthermore, insights into the existing challenges are examined along with the prospective approaches following the GDPR regulatory guidelines that FL-based systems shall implement to fully comply with the GDPR.

In [4] result suggests that proposed algorithm is an effective method of implementing differential privacy with federated learning, and clinical data scientists can use our general framework to produce differentially private models on federated datasets.

In [5] conduct a detailed study on FL, the categorization of FL, the challenges of FL, and various attacks that can be executed to disclose the users' sensitive data used during learning. In this survey, authors review and compare different privacy solutions for FL to prevent data leakage and discuss secret sharing (SS)-based security solutions for FL proposed by various researchers in concise form. Authors also briefly discuss quantum federated learning (QFL) and privacy-preservation techniques in QFL.

In this [6] paper, we reiterate the concept of federated learning and propose secure federated learning (SFL), where the ultimate goal is to build trustworthy and safe AI with strong privacy-preserving and IP-right-preserving. We provide a com- prehensive overview of existing works, including threats, attacks, and defenses in each phase of SFL from the lifecycle perspective.

The paper [7] presents a novel privacy-preserving federated learning solution, PPFL-LQDP that addresses the issue of excessive participation of low-quality data in Federated training. By constructing a composite evaluation value for the data, the negative impact of low-quality data on Federated training is reduced, while ensuring privacy and security of participant data through a secure framework.

Author's [8] prevent patient privacy compromise while promoting scientific research on large datasets that aims to improve patient care, the implementation of technical solutions to simultaneously address the demands for data protection and utilization is mandatory. Here we present an overview of current and next-generation methods for federated, secure and privacy-preserving artificial intelligence with a focus on medical imaging applications, alongside potential attack vectors and future prospects in medical imaging and beyond.

III. PROPOSED METHODOLOGY

This paper proposes a privacy-preserving federated learning framework aimed at securing distributed model training while maintaining high learning performance. In the proposed approach, multiple decentralized clients collaboratively train a global model without sharing their raw data, thereby reducing privacy risks associated with centralized data collection. Each client performs local model training using its private dataset and computes model updates in the form of gradients or weights. To prevent sensitive information leakage from model updates, Differential Privacy (DP) is applied at the client side by adding calibrated noise to the computed gradients. This ensures that individual data

records cannot be inferred by adversaries through gradient analysis or model inversion attacks. An adaptive privacy budget mechanism is introduced to dynamically adjust the level of noise based on training iterations, achieving a balanced trade-off between privacy protection and model accuracy.

Furthermore, the proposed framework incorporates secure aggregation to ensure that the central server can only access the aggregated model updates rather than individual client contributions. To enhance security during communication, homomorphic encryption is employed, allowing encrypted model updates to be aggregated without decryption at the server side. This layered security approach effectively protects the system against both external and internal threats.

The central server updates the global model using a federated averaging strategy and redistributes the updated model to participating clients for subsequent training rounds. The proposed model is evaluated using standard benchmark datasets and compared with conventional federated learning approaches in terms of accuracy, convergence speed, communication overhead, and privacy leakage risk. The experimental results demonstrate that the proposed framework achieves improved privacy preservation with minimal degradation in model performance, making it suitable for privacy-sensitive applications such as healthcare, finance, and IoT environments.

IV. RESULT ANALYSIS

The performance of the proposed privacy-preserving federated learning framework is evaluated and compared with conventional federated learning methods that do not incorporate privacy protection mechanisms. The evaluation is carried out using standard benchmark datasets under identical experimental conditions to ensure fair comparison. Key performance metrics such as accuracy, precision, recall, F1-score, convergence speed, communication overhead, and privacy leakage risk are analyzed. The experimental results indicate that the proposed model achieves higher robustness against privacy attacks due to the integration of differential privacy, secure aggregation, and homomorphic encryption. Although the addition of noise slightly affects model accuracy, the impact is minimal and remains within acceptable limits. The adaptive privacy budget mechanism helps maintain a balance between privacy preservation and learning performance. Compared to baseline federated learning, the proposed framework demonstrates improved privacy protection with only a marginal increase in communication overhead. Secure aggregation ensures that the central server cannot infer individual client updates, thereby significantly reducing privacy leakage risk. Furthermore, the convergence behavior of the proposed model remains stable across training rounds, showing effective learning despite privacy constraints. This result confirm that the proposed approach provides a secure, privacy-aware, and efficient federated learning solution, making it suitable for real-world applications involving sensitive and distributed data.

Table 1: Performance of Proposed Framework

Metric	Value
Accuracy (%)	98.5%
Precision	98.3%
Recall	98.3%
F1-Score	98.3%

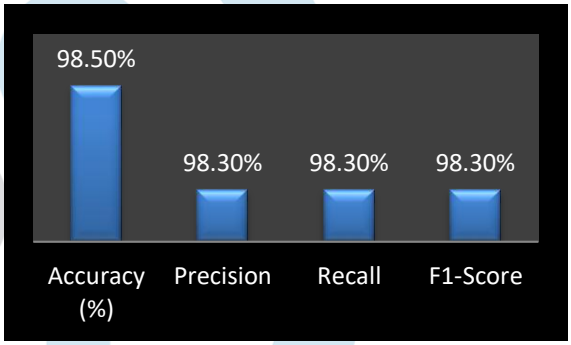

Figure 1: Performance of Proposed Framework

CONCLUSION

This paper presented a privacy-preserving federated learning framework that addresses critical security and confidentiality challenges in distributed machine learning environments. By integrating differential privacy, secure aggregation, and homomorphic encryption, the proposed approach ensures that sensitive client data remains protected throughout the training process. The experimental results demonstrate that the framework effectively reduces privacy leakage risks while maintaining competitive model accuracy and stable convergence behavior. The adaptive privacy budget mechanism further helps balance the trade-off between privacy protection and learning performance, making the proposed solution suitable for real-world applications involving sensitive and decentralized data, such as healthcare, finance, and IoT systems. Despite its effectiveness, there are several directions for future research. Future work can focus on reducing communication overhead through advanced model compression and update sparsification techniques. Additionally, the framework can be extended to handle non-IID data distributions and dynamic client participation more efficiently. Incorporating lightweight encryption schemes and trust-aware aggregation strategies may further improve scalability and robustness. Future studies may also explore the integration of blockchain-based mechanisms for decentralized trust management and auditing in federated learning systems.

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