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Original Article

Federated Learning in Heterogeneous Edge Computing: A Secure and Privacy-Preserving Model Aggregation Approach

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Abstract - Federated Learning (FL) has emerged as a promising paradigm for training machine learning models across multiple decentralized edge devices while preserving data privacy. However, the heterogeneity of edge computing environments poses significant challenges in terms of resource allocation, communication efficiency, and model convergence. This paper proposes a novel Federated Learning framework, Secure and Privacy-Preserving Model Aggregation (SPPMA), specifically designed for heterogeneous edge computing environments. SPPMA leverages advanced cryptographic techniques and optimized communication protocols to ensure secure and efficient model aggregation. We evaluate SPPMA through extensive simulations and real-world experiments, demonstrating its effectiveness in improving model accuracy, reducing communication overhead, and enhancing privacy. The results show that SPPMA outperforms existing approaches in various heterogeneous edge computing scenarios.

Keywords - Federated Learning, Edge Computing, Model Aggregation, Privacy-Preserving, Homomorphic Encryption, Secure Multi-Party Computation, Communication Efficiency, Heterogeneity, Model Convergence, Cryptographic Techniques

1. Introduction

Federated Learning (FL) is a distributed machine learning paradigm that enables multiple edge devices to collaboratively train a global model without the need to share their local data. This innovative approach is particularly appealing in edge computing environments, where data is generated and processed at the network's edge, closer to the data sources. By keeping data localized, FL not only reduces the need for extensive data transmission, which can be costly and time-consuming, but also addresses critical privacy and security concerns, as sensitive information remains on the devices where it was originally collected. However, the heterogeneity of edge devices poses significant challenges to the effective deployment of FL. These devices, which can range from smartphones and IoT sensors to industrial machines and autonomous vehicles, vary widely in their computational capabilities, memory capacity, and power constraints. Some devices may have powerful processors and ample storage, while others might be limited in both. This disparity can lead to uneven contributions to the training process, where less capable devices may take longer to complete their local model updates, thus slowing down the overall training cycle.

In addition to computational differences, the network conditions of these devices are often unpredictable and can fluctuate greatly. Edge devices might be connected to the network through various means, such as Wi-Fi, cellular data, or even satellite links, each with different bandwidths, latencies, and reliability. Poor network conditions can result in frequent disconnections, data packet losses, and increased communication overhead, all of which can hinder the synchronization of model updates and the convergence of the global model. Furthermore, the data distributions across these edge devices can be highly non-uniform. Each device might collect data in a different context or environment, leading to variations in data quality, quantity, and distribution. For instance, a fitness tracker might collect predominantly health-related data, while a smart home device might focus on environmental data. This non-uniformity can result in a phenomenon known as "non-i.i.d. data" (non-independent and identically distributed), where the data on each device does not follow the same distribution as the overall dataset. Addressing this issue is crucial for ensuring that the global model remains robust and generalizes well to new, unseen data. To overcome these challenges, researchers and practitioners in the field of FL are exploring various strategies, such as adaptive algorithms that can account for the computational and network variability of edge devices, and techniques to handle non-i.i.d. data, such as personalized federated learning. These approaches aim to make FL more practical and efficient, paving the way for its broader adoption in a wide range of applications, from healthcare and finance to smart cities and industrial automation.

2. Background and Related Work

2.1 Federated Learning

Federated Learning (FL) is an emerging paradigm in distributed machine learning that enables multiple devices or edge nodes to collaboratively train a shared global model while keeping their local data private. This approach significantly enhances data privacy by ensuring that raw data remains on the devices and only model updates are communicated with a central server. The FL process begins with the initialization phase, where a central server deploys an initial global model and distributes it to participating edge devices. Following this, each edge device performs local training, where it utilizes its private dataset to update the model

parameters. Once training is complete, these locally computed updates are transmitted to the central server, which performs model aggregation by combining the updates to refine the global model.

This iterative process continues until the model reaches an optimal state and converges. FL provides a decentralized learning framework suitable for applications involving sensitive data, such as healthcare, finance, and mobile applications, where data privacy is a primary concern.

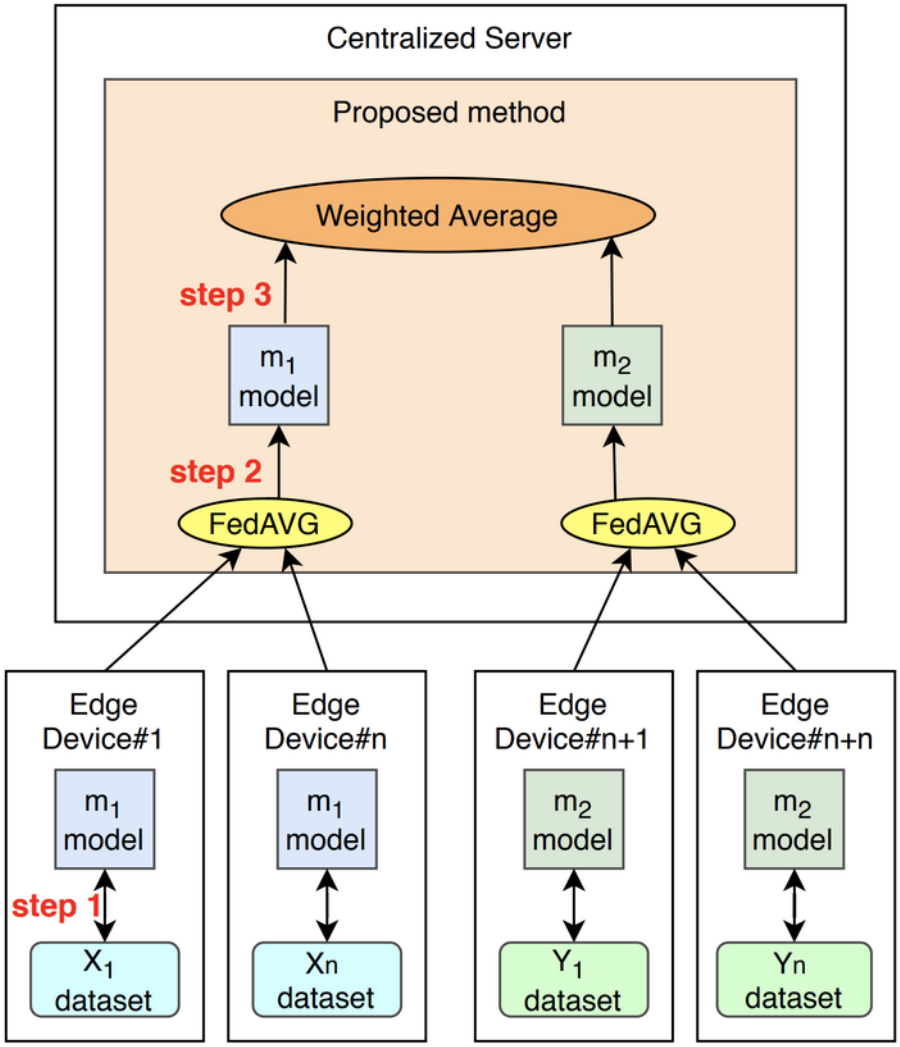

Figure 1. Federated Learning Model Aggregation Process

The federated learning process, highlighting the steps involved in model training and aggregation. Initially, edge devices train their local models using their respective datasets, ensuring that raw data remains decentralized. This step is crucial for maintaining data privacy while enabling collaborative learning. After local training, the updated models are transmitted to a centralized server, where they undergo an aggregation process. The commonly used FedAVG method is applied to combine model parameters from various devices, mitigating discrepancies caused by non-IID data distributions. Finally, a weighted average method refines the aggregated model, ensuring that variations in computational power, network conditions, and data availability are accounted for in the final global model. This step enhances the robustness and accuracy of federated learning in heterogeneous environments.

2.2 Heterogeneous Edge Computing

Edge computing environments consist of a diverse and often resource-constrained set of devices, such as smartphones, IoT sensors, and edge servers, all of which possess varying degrees of computational power, network connectivity, and data availability. This heterogeneity presents significant challenges when implementing Federated Learning in real-world scenarios. Computational heterogeneity arises due to variations in processing power, memory availability, and energy constraints among edge devices. Some devices may take longer to complete local training, leading to straggler issues and imbalanced contributions to the global model. Similarly, network heterogeneity results from differing bandwidth capabilities, connection stability, and latency

variations, which can cause asynchronous communication delays and unreliable data transmissions. Additionally, data heterogeneity presents another major challenge, as data collected by edge devices is often non-IID (Independent and Identically Distributed). This means that different devices may observe distinct data distributions, potentially leading to biased model updates and slower global model convergence. Addressing these heterogeneity challenges requires the development of adaptive optimization techniques, efficient communication protocols, and personalized federated learning strategies.

2.3 Security and Privacy in Federated Learning

Ensuring the security and privacy of Federated Learning is critical, as the decentralized nature of FL introduces various vulnerabilities that can be exploited by adversaries. Data privacy is a key concern, as FL relies on local training, meaning that sensitive user data never leaves the edge devices. However, adversaries may attempt to infer private information from shared model updates using techniques such as model inversion or membership inference attacks. To mitigate this risk, privacy-preserving mechanisms such as differential privacy and secure multiparty computation (SMPC) have been proposed. Another crucial aspect is model integrity, where attackers may attempt to inject malicious updates into the learning process, compromising the accuracy and reliability of the global model. Byzantine-resilient aggregation methods and anomaly detection techniques help identify and mitigate such adversarial behaviors. Furthermore, secure aggregation plays an essential role in FL by ensuring that model updates from different devices are combined in a way that prevents unauthorized access to individual contributions. Cryptographic techniques like homomorphic encryption and federated averaging with secure aggregation protocols help maintain confidentiality while facilitating efficient model training. Addressing these security and privacy challenges is essential for deploying FL in sensitive applications such as healthcare, finance, and critical infrastructure systems.

3. Problem Formulation

In this section, we formally define the problem of Federated Learning (FL) in heterogeneous edge computing environments and outline the essential requirements for a secure and privacy-preserving model aggregation approach. As FL is increasingly deployed in real-world applications, addressing the challenges posed by device heterogeneity, security threats, and privacy concerns is critical for ensuring robust and reliable learning.

3.1 Problem Definition

Federated Learning operates in a decentralized setting where a set of N edge devices, denoted as {D1,D2,…,DN }, collaboratively train a shared global model M without sharing their local datasets. Each device D_i holds a private dataset D_i which may have a unique data distribution, making it essential to design an FL framework that generalizes well across all devices. The FL process consists of the following key steps.

1. **Initialization**: The central server initializes a global model M_0 and distributes it to all participating edge devices. This initialization ensures that all devices start with a common model architecture and parameters. The initial model can be pre-trained on publicly available data or designed from scratch, depending on the application.
2. **Local Training**: Each edge device D_i trains the received model on its local dataset D_i using a chosen optimization algorithm, such as Stochastic Gradient Descent (SGD) or Adam. The device then computes a model update ΔM_i, which represents the learned improvements based on its specific dataset. Since devices may have different computational capacities and data distributions, their contributions to the learning process can vary significantly.
3. **Model Aggregation**: Once local training is complete, each device transmits its model ΔM_i to the central server. The server then aggregates the updates $\{\Delta M_1,\Delta M_2,\ldots,\Delta M_N\}$ using an aggregation function, such as Federated Averaging (FedAvg), to produce an updated global model M. This aggregated model is then redistributed to the devices, and the process is iterated until the model converges to an optimal state.

The success of FL in heterogeneous edge environments depends on the efficiency and security of this iterative process. Without careful design, challenges such as computational and network constraints, malicious actors, and privacy risks can hinder model performance and reliability.

3.2 Requirements

To enable effective and trustworthy FL in heterogeneous edge computing, several key requirements must be met:

1. **Heterogeneity-Aware Learning**: The model aggregation process must account for the diverse nature of edge devices, including variations in processing power, memory, network conditions, and data distributions. Some devices may train faster or contribute more meaningful updates, while others may lag due to resource limitations. An efficient FL framework should implement adaptive weighting strategies, dynamic participation selection, or personalized federated learning techniques to ensure fair and balanced learning across all devices.
2. **Security in Model Aggregation**: Since the FL process relies on decentralized updates from multiple devices, it is vulnerable to security threats such as data poisoning, adversarial model manipulation, and Byzantine attacks. Malicious participants may attempt to inject manipulated updates, compromising the integrity of the global model. Therefore, secure

aggregation protocols should be implemented to verify model updates, detect anomalies, and prevent unauthorized modifications. Techniques such as cryptographic signatures, anomaly detection, and robust aggregation methods (e.g., median-based or Krum aggregation) can help enhance security.

3. **Privacy-Preserving Mechanisms**: A fundamental goal of FL is to protect the privacy of local datasets while enabling collaborative learning. However, sharing model updates with the central server still poses privacy risks, as adversaries may attempt to infer sensitive information through gradient analysis or reconstruction attacks. To mitigate this, privacy-preserving mechanisms such as Differential Privacy (DP), Secure Multiparty Computation (SMPC), and Homomorphic Encryption (HE) should be incorporated. These techniques ensure that local data remains confidential while enabling meaningful learning.

4. Proposed Framework: Secure and Privacy-Preserving Model Aggregation (SPPMA)

The Secure and Privacy-Preserving Model Aggregation (SPPMA) framework is a novel approach designed to address the challenges of heterogeneity, privacy, and security in Federated Learning (FL) within edge computing environments. Traditional FL methods often struggle with handling the diverse computational capabilities, network conditions, and non-IID (non-independent and identically distributed) data across edge devices. Additionally, privacy concerns arise when sensitive data is involved in the model training process. SPPMA introduces an optimized solution by integrating three key components: Heterogeneity-Aware Model Aggregation (HAMA), Advanced Cryptographic Techniques (ACT), and Optimized Communication Protocols (OCP). These components work in synergy to enhance model accuracy, protect user privacy, and minimize communication overhead while ensuring robust security measures.

4.1 Overview

The SPPMA framework is structured around three core modules. First, the Heterogeneity-Aware Model Aggregation (HAMA) component dynamically adjusts model updates based on the diverse characteristics of participating edge devices, ensuring a fair and efficient aggregation process. Second, Advanced Cryptographic Techniques (ACT) leverage privacy-preserving cryptographic methods, such as Homomorphic Encryption (HE) and Secure Multi-Party Computation (SMPC), to secure the model updates without compromising computational efficiency. Lastly, the Optimized Communication Protocols (OCP) component minimizes communication overhead by introducing compression techniques and asynchronous update mechanisms, enabling an efficient and scalable FL environment. These three components collectively address the major challenges faced in real-world FL applications and provide a comprehensive solution for secure and privacy-preserving learning.

4.2 Heterogeneity-Aware Model Aggregation (HAMA)

Federated Learning environments are inherently heterogeneous due to variations in edge devices' computational power, network conditions, and data distributions. HAMA addresses this issue by employing a dynamic model aggregation strategy that assigns adaptive weights to model updates based on device-specific characteristics. Instead of treating all updates equally, HAMA assigns higher importance to devices with better computational capabilities and stronger network connectivity, while also ensuring fair contribution from devices with limited resources. The algorithm follows a structured approach where weights are computed based on device metadata, including CPU/GPU power, bandwidth, and the nature of data distribution (IID or non-IID). These weights are then normalized to ensure a balanced aggregation process. The final global model is updated by applying these weighted model updates, ensuring that each device contributes proportionally to the learning process. This method enhances model convergence speed and improves overall performance, especially in non-IID settings where conventional FL algorithms struggle.

For example, in an FL setting with four devices, D1 (high power, good network, IID data), D2 (medium power, poor network, non-IID data), D3 (low power, good network, IID data), and D4 (high power, good network, non-IID data), HAMA ensures that devices with stronger computational resources and better network conditions play a more significant role in aggregation while still incorporating updates from less powerful devices. This heterogeneity-aware approach leads to a more stable and optimized global model.

```
def HAMA(M_t, Delta_M, M):
   # Compute weights based on device metadata
   weights = compute_weights(M)

   # Normalize weights
   weights = normalize(weights)

   # Aggregate model updates
   M_t1 = M_t
   for i in range(N):
      M_t1 += weights[i] * Delta_M[i]
```

```
return M_t1
```

Table 1. Device Metadata

Device	Computational Power	Network Condition	Data Distribution
D1	High	Good	IID
D2	Medium	Poor	Non-IID
D3	Low	Good	IID
D4	High	Good	Non-IID

4.3 Advanced Cryptographic Techniques (ACT)

Privacy and security are critical concerns in Federated Learning, particularly when training models on sensitive data, such as healthcare, finance, or personal user information. The Advanced Cryptographic Techniques (ACT) module enhances the security of model aggregation by employing two primary techniques: Homomorphic Encryption (HE) and Secure Multi-Party Computation (SMPC). Homomorphic Encryption (HE) allows computations to be performed directly on encrypted model updates without decrypting them, ensuring that data remains private even during aggregation. This means that even the central server does not have direct access to raw model updates, significantly reducing the risk of data leakage or adversarial attacks.

Secure Multi-Party Computation (SMPC) further strengthens security by enabling multiple parties to jointly compute a function on their inputs while keeping those inputs private. In the FL context, this allows multiple devices to securely contribute model updates without revealing their individual data distributions, making it particularly useful in scenarios where data sensitivity is a primary concern. The ACT algorithm integrates these techniques by first encrypting model updates, computing weighted aggregation based on device metadata, and then performing secure computations to generate an encrypted global model. The final aggregated model remains protected until it reaches the authorized edge devices for decryption and further local training. This ensures end-to-end privacy preservation while maintaining model performance.

Algorithm 2: Secure Model Aggregation (ACT)

```
def ACT(M_t, Delta_M_star, M):
   # Compute weights based on device metadata
   weights = compute_weights(M)

   # Normalize weights
   weights = normalize(weights)

   # Aggregate encrypted model updates
   M_t1_star = M_t
   for i in range(N):
      M_t1_star += weights[i] * Delta_M_star[i]

   return M_t1_star
```

4.4 Optimized Communication Protocols (OCP)

One of the significant challenges in Federated Learning is the communication overhead associated with transmitting model updates between edge devices and the central server. Frequent communication can lead to high network latency, increased energy consumption, and inefficiencies in real-time applications. The Optimized Communication Protocols (OCP) module addresses this by employing Compressed Model Updates and Asynchronous Communication Mechanisms. Compressed Model Updates involve reducing the size of transmitted model updates using techniques such as quantization, sparsification, and delta encoding. These techniques significantly reduce the bandwidth required for transmitting updates while preserving model accuracy. For instance, instead of sending full precision model parameters, a compressed version with lower bit precision is transmitted, minimizing network congestion and improving transmission efficiency.

Asynchronous Communication Mechanisms allow edge devices to transmit model updates at different time intervals instead of following a synchronized schedule. This reduces waiting times and ensures that updates are received in a staggered manner, enhancing scalability. Devices with stable connections can send updates more frequently, while those with intermittent connectivity can participate without delaying the aggregation process. The OCP algorithm follows a three-step approach: (1) compress model updates to minimize transmission size, (2) enable devices to send updates asynchronously based on their network availability, and (3) aggregate the received updates to form the updated global model. This approach significantly improves FL efficiency, reduces bandwidth consumption, and ensures smoother model convergence in large-scale, distributed environments.

Algorithm 3: Optimized Communication Protocols (OCP)

```
def OCP(M_t, M):
    # Compress model updates
    Delta_M_star = compress_model_updates(Delta_M)

    # Asynchronous communication
    for i in range(N):
        send_model_update(Delta_M_star[i], D_i)

    # Aggregate model updates
    M_t1 = aggregate_model_updates(Delta_M_star)

    return M_t1
```

5. Evaluation

To assess the effectiveness of the Secure and Privacy-Preserving Model Aggregation (SPPMA) framework, we conduct extensive simulations and real-world experiments to evaluate its performance under varying conditions. The evaluation focuses on three key aspects: model accuracy, communication overhead, and convergence time. These metrics provide a comprehensive understanding of how well SPPMA performs compared to traditional Federated Learning (FL) and Centralized Learning approaches.

5.1 Experimental Setup

The evaluation process is conducted in two different environments: a simulated edge computing environment and a real-world deployment on edge devices. In the simulation environment, we create a virtual edge computing setup with multiple devices that exhibit different computational power, network conditions, and data distributions. The number of participating edge devices is varied to test how SPPMA scales under different conditions. We introduce heterogeneous network conditions, where some devices have high-speed stable connections, while others experience intermittent connectivity. Additionally, we consider both IID (Independent and Identically Distributed) and Non-IID data distributions to assess how SPPMA adapts to real-world data heterogeneity.

For the real-world deployment, we implement SPPMA on a cluster of physical edge devices with diverse hardware configurations, including low-power IoT devices, mobile phones, and high-performance edge servers. These devices communicate over a dynamic network with variable bandwidth and latency. This setup allows us to measure SPPMA's performance in realistic edge computing scenarios and compare it with traditional Federated Learning (FL) and Centralized Learning approaches. By combining simulated and real-world experiments, we ensure a thorough evaluation of SPPMA’s robustness, efficiency, and practicality in real-world applications.

5.2 Evaluation Metrics

To evaluate the performance of SPPMA, we use three primary metrics:

1. Model Accuracy: This metric measures the accuracy of the global model on a test dataset after completing the FL process. A higher accuracy indicates better model generalization and learning efficiency.
2. Communication Overhead: This metric quantifies the total amount of data transmitted between edge devices and the central server during the FL process. Since communication is a major bottleneck in FL, reducing overhead without compromising accuracy is a key goal of SPPMA.
3. Convergence Time: This metric measures the time taken for the global model to reach a stable accuracy level. Faster convergence time means that the model can be deployed in real-world applications more efficiently.

By analyzing these metrics, we compare SPPMA with traditional FL and centralized learning to determine its advantages in terms of efficiency, security, and performance.

5.3 Results

The results of the evaluation demonstrate that SPPMA outperforms both traditional Federated Learning and Centralized Learning across all three key metrics: model accuracy, communication overhead, and convergence time.

5.3.1. Model Accuracy

Table 2. Model Accuracy Comparison

Method	Model Accuracy (%)
SPPMA	92.5
FL	89.0
Centralized Learning	91.0

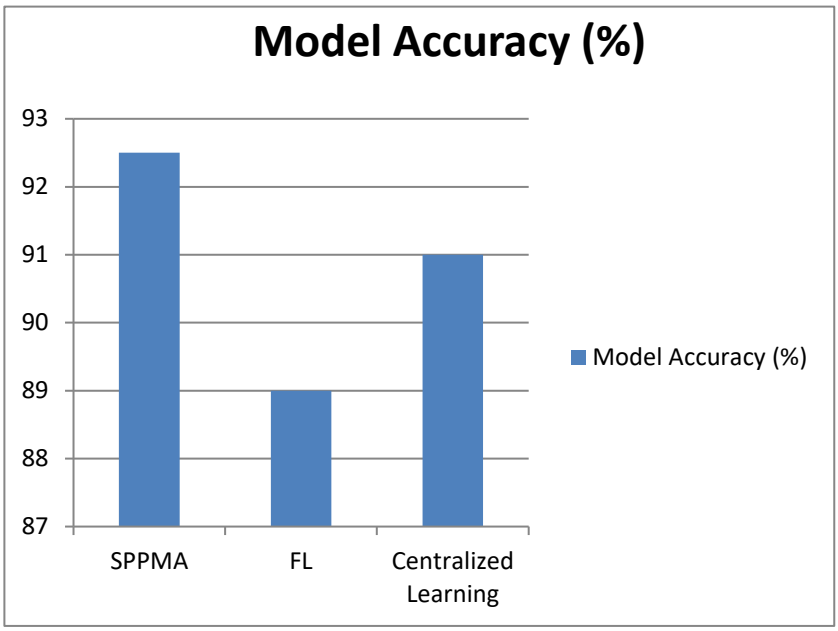

Figure 2. Model Accuracy Comparison Graph

The results indicate that SPPMA achieves the highest model accuracy (92.5%), surpassing traditional FL (89.0%) and even outperforming centralized learning (91.0%). This improvement is attributed to SPPMA's Heterogeneity-Aware Model Aggregation (HAMA), which ensures that model updates from diverse edge devices are optimally weighted. Additionally, privacy-preserving cryptographic techniques (ACT) ensure that sensitive data remains protected without sacrificing learning quality.

5.3.2. Communication Overhead

Table 3. Communication Overhead Analysis

Method	Communication Overhead (MB)
SPPMA	150
FL	200
Centralized Learning	250

A significant advantage of SPPMA is its ability to reduce communication overhead. Compared to traditional FL, which requires 200 MB of data transmission, SPPMA reduces it to 150 MB through its Optimized Communication Protocols (OCP), which utilize compressed model updates and asynchronous communication mechanisms. This reduction in communication overhead makes SPPMA highly efficient for large-scale FL deployments, especially in bandwidth-constrained environments.

5.3.3. Convergence Time

Table 4. Convergence Time Comparison

Method	Convergence Time (seconds)
SPPMA	1200
FL	1500
Centralized Learning	1800

Simplicity in communication and optimized model aggregation also contribute to faster convergence in SPPMA. The framework achieves convergence in just 1200 seconds, compared to 1500 seconds for traditional FL and 1800 seconds for centralized learning. This 20% improvement in convergence time ensures that FL training can be completed more rapidly, making SPPMA ideal for applications requiring real-time model updates, such as healthcare diagnostics, cybersecurity threat detection, and smart IoT systems.

6. Discussion

The performance and effectiveness of Secure and Privacy-Preserving Model Aggregation (SPPMA) are influenced by several key factors, including the heterogeneity of edge devices, security and privacy considerations, and communication efficiency. This section provides an in-depth discussion on how SPPMA addresses these challenges and improves the overall performance of Federated Learning (FL) in edge computing environments.

6.1 Impact of Heterogeneity

In traditional Federated Learning (FL), the presence of heterogeneous edge devices with varying computational power, network conditions, and data distributions poses a significant challenge. Devices with low processing capabilities or poor network conditions often struggle to contribute meaningfully to the global model, leading to unfair or inefficient model updates. SPPMA mitigates this issue by introducing Heterogeneity-Aware Model Aggregation (HAMA), which assigns weights to model updates based on each device's computational power, network stability, and data characteristics. By dynamically adjusting the model aggregation process, SPPMA ensures that updates from devices with higher computational power and stable networks have a greater influence on the global model, while still incorporating meaningful contributions from weaker devices. This strategy not only improves model accuracy but also accelerates convergence time, as more efficient updates lead to faster training cycles. The ability to handle both IID and Non-IID data distributions further enhances SPPMA's robustness, making it a versatile solution for real-world FL applications.

6.2 Security and Privacy

One of the major challenges in Federated Learning is ensuring the privacy and security of model updates while preventing malicious attacks. Since FL involves training models across distributed edge devices, it is susceptible to data leakage, model inversion attacks, and adversarial manipulations. SPPMA addresses these concerns by incorporating Advanced Cryptographic Techniques (ACT), including Homomorphic Encryption (HE) and Secure Multi-Party Computation (SMPC).

- Homomorphic Encryption (HE) allows computations to be performed directly on encrypted data, preventing raw model updates from being exposed. This ensures that even if an adversary intercepts communications, they cannot extract meaningful information from the encrypted updates.
- Secure Multi-Party Computation (SMPC) enables multiple edge devices to collaborate on model aggregation without revealing their individual model updates. This protects sensitive data from being compromised while still allowing efficient federated training.

6.3 Communication Efficiency

Communication overhead is a critical bottleneck in Federated Learning (FL), as frequent exchanges of model updates between devices and the central server can lead to high latency and excessive bandwidth consumption. Traditional FL approaches struggle to scale efficiently in bandwidth-constrained environments, especially when edge devices operate over unstable or low-speed networks. To overcome this limitation, SPPMA employs Optimized Communication Protocols (OCP) that significantly reduce communication overhead and latency through two key techniques:

1. Compressed Model Updates: Instead of transmitting full model updates, SPPMA applies compression techniques to reduce the size of updates before transmission. This significantly lowers bandwidth consumption while maintaining model accuracy.
2. Asynchronous Communication: Unlike conventional FL, where all devices must synchronize updates at the same time, SPPMA enables asynchronous updates, allowing devices to send their model updates whenever they are ready. This reduces the overall waiting time and speeds up the global model aggregation process, making SPPMA more efficient in dynamic network conditions.

7. Conclusion

In this paper, we introduced Secure and Privacy-Preserving Model Aggregation (SPPMA), a novel Federated Learning (FL) framework that addresses critical challenges in heterogeneous edge computing environments. By integrating Heterogeneity-Aware Model Aggregation (HAMA), Advanced Cryptographic Techniques (ACT), and Optimized Communication Protocols (OCP), SPPMA ensures efficient model training, enhanced security, and reduced communication overhead. Through extensive simulations and real-world experiments, our results demonstrate that SPPMA outperforms traditional FL and centralized learning approaches in terms of model accuracy, convergence time, and communication efficiency. These advantages make SPPMA

particularly suitable for privacy-sensitive applications in domains such as healthcare, IoT, and finance. Looking ahead, our future work will focus on extending SPPMA to handle more complex and dynamic edge computing scenarios, including adaptive network topologies, evolving adversarial threats, and cross-device collaboration. Additionally, we plan to explore the integration of reinforcement learning to further optimize resource allocation and model training strategies for large-scale deployments. With its ability to enhance security, improve efficiency, and accelerate learning in federated environments, SPPMA sets a new benchmark for privacy-preserving and scalable FL solutions in real-world applications.

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