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Cloud-based Federated Learning for Distributed IoT Networks

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Abstract

The Internet of Things (IoT) has led to an explosion of connected devices generating massive amounts of data at the network edge. Traditional centralized machine learning approaches face challenges in processing this distributed data due to privacy concerns, communication costs, and latency issues. Federated learning has emerged as a promising paradigm to enable collaborative model training across distributed clients without raw data sharing. This paper presents a comprehensive framework for cloud-based federated learning in IoT networks. We propose a novel architecture that leverages cloud computing for aggregation and orchestration while keeping raw data local on IoT devices. Key techniques are developed for client selection, secure aggregation, and model compression to address the unique challenges of resource-constrained IoT environments. Extensive experiments on real-world IoT datasets demonstrate the effectiveness of our approach in terms of model accuracy, communication efficiency, and privacy preservation. The results show that our federated learning system achieves comparable accuracy to centralized learning while reducing communication costs by up to 95% and protecting data privacy. This work provides important insights into realizing large-scale machine learning across distributed IoT networks.

Keywords: Federated learning, Internet of Things, edge computing, distributed machine learning, privacy-preserving AI

1. Introduction

The proliferation of Internet of Things (IoT) devices has led to an explosion of data being generated at the network edge. It is estimated that there will be over 75 billion connected IoT devices by 2025, generating a staggering 79.4 zettabytes of data (Lueth, 2020). This massive amount of distributed data presents both opportunities and challenges for machine learning and artificial intelligence. On one hand, the rich and diverse data from IoT devices can potentially enable more accurate and robust AI models. On the other hand, traditional centralized machine learning approaches face significant hurdles in leveraging this distributed data due to privacy concerns, communication bottlenecks, and latency issues.

Federated learning has recently emerged as a promising paradigm to address these challenges (McMahan et al., 2017). The key idea is to train machine learning models collaboratively across multiple decentralized edge devices or servers holding local data samples, without exchanging the raw data. This allows the collective benefits of shared models to be reaped while keeping the raw data locally on each device. A typical federated learning process involves the following steps: 1) A central server shares the global model with selected client devices. 2) The clients train the model on their local data. 3) The clients send only the model updates back to the server. 4) The server aggregates the updates to improve the global model. This process is repeated for multiple rounds until the model converges.

While federated learning provides an elegant solution to enable collaborative learning with distributed data, applying it to IoT networks poses unique challenges:

1. Resource constraints: IoT devices typically have limited compute, memory, and energy resources, making it challenging to run complex model training locally.
2. System heterogeneity: IoT networks consist of a wide variety of devices with different capabilities, making it difficult to coordinate training.
3. Unreliable connectivity: IoT devices may have intermittent network connectivity, affecting the reliability of the federated learning process.
4. Scale: IoT networks can involve millions of devices, necessitating efficient client selection and aggregation mechanisms.
5. Privacy and security: IoT data can be highly sensitive, requiring strong privacy guarantees and secure aggregation techniques.

To address these challenges, this paper presents a comprehensive framework for cloud-based federated learning in IoT networks. We leverage cloud computing to provide the necessary computational resources and orchestration capabilities, while keeping raw data local on IoT devices. The main contributions of this work are:

1. A novel cloud-based architecture for federated learning in IoT networks that efficiently distributes computational tasks between cloud servers and edge devices.
2. An adaptive client selection algorithm that considers device capabilities, data quality, and network conditions to optimize training efficiency.
3. A secure aggregation protocol based on homomorphic encryption that enables privacy-preserving model updates in untrusted cloud environments.
4. Model compression and quantization techniques tailored for resource-constrained IoT devices to reduce communication and computation costs.
5. Extensive experiments on real-world IoT datasets to evaluate the performance, efficiency, and privacy preservation of the proposed framework.

The rest of the paper is organized as follows: Section 2 reviews related work in federated learning and IoT. Section 3 presents the proposed cloud-based federated learning framework. Section 4 describes the key techniques developed to address IoT-specific challenges. Section 5 details the experimental setup and results. Section 6 discusses the implications and limitations of the work. Finally, Section 7 concludes the paper and outlines future research directions.

2. Related Work

This section reviews existing literature related to federated learning and its applications in IoT environments. We first discuss the foundations of federated learning, followed by recent advances in addressing key challenges. We then examine prior work on applying federated learning to IoT networks and identify the research gaps that motivate our work.

2.1 Foundations of Federated Learning

The concept of federated learning was first introduced by McMahan et al. (2017) as a approach for training machine learning models on distributed datasets without centralizing the data. The authors proposed the Federated Averaging (FedAvg) algorithm, which has become the de facto standard for federated learning. FedAvg involves iteratively averaging model updates from a subset of clients to update a global model.

Since then, numerous variations and improvements to the basic federated learning approach have been proposed. Li et al. (2020) provided a comprehensive survey of federated learning, categorizing existing work into three main types: horizontal federated learning (samples are partitioned), vertical federated learning (features are partitioned), and federated transfer learning. Our work focuses on horizontal federated learning, which is most applicable to IoT scenarios where devices collect similar types of data.

2.2 Addressing Key Challenges in Federated Learning

Several lines of research have focused on addressing the key challenges in federated learning:

Communication efficiency: To reduce the communication overhead, techniques like gradient compression (Lin et al., 2018), model pruning (Jiang et al., 2019), and knowledge distillation (He et al., 2020) have been proposed. These approaches aim to reduce the size of model updates exchanged between clients and the server.

Statistical heterogeneity: The non-IID nature of data across clients can lead to convergence issues. Approaches like FedProx (Li et al., 2020) and SCAFFOLD (Karimireddy et al., 2020) have been developed to handle statistical heterogeneity through regularization and control variates.

System heterogeneity: To deal with varying computational capabilities of clients, adaptive methods like FedPAQ (Reisizadeh et al., 2020) and HierFAVG (Liu et al., 2020) have been proposed. These techniques adjust local computation based on device resources.

Privacy and security: Differential privacy (Wei et al., 2020) and secure aggregation protocols (Bonawitz et al., 2017) have been integrated into federated learning to provide stronger privacy guarantees and protect against various attacks.

While these advances have significantly improved federated learning, most existing work assumes powerful client devices and reliable network connections, which may not hold in IoT environments.

2.3 Federated Learning for IoT

Several recent studies have explored the application of federated learning to IoT scenarios. Lim et al. (2020) proposed a federated learning framework for IoT authentication, demonstrating its effectiveness in detecting attacks with distributed data. Nguyen et al. (2021) developed a federated learning approach for joint resource allocation and offloading in IoT networks. Chen et al. (2020) investigated federated learning for energy consumption prediction in industrial IoT settings.

However, these works focus on specific IoT applications rather than providing a general framework. Moreover, they do not fully address the unique challenges posed by resource-constrained IoT devices and unreliable network conditions.

Some researchers have proposed edge computing-based architectures for federated learning in IoT. For instance, Wang et al. (2019) presented an in-edge AI framework that pushes model training to edge servers to reduce latency. Similarly, Liu et al. (2020) proposed a hierarchical federated learning architecture with edge nodes acting as intermediaries. While these approaches alleviate some burden from IoT devices, they still require significant computational resources at the edge.

2.4 Research Gaps and Motivation

Based on our literature review, we identify the following research gaps:

1. Lack of a comprehensive framework that addresses all key challenges of federated learning in IoT environments, including resource constraints, system heterogeneity, unreliable connectivity, scalability, and privacy.
2. Limited exploration of cloud-based architectures that can provide the necessary computational resources and orchestration capabilities for large-scale IoT networks.
3. Insufficient attention to adaptive techniques that can handle the dynamic nature of IoT environments, such as varying device availability and network conditions.
4. Need for lightweight techniques tailored specifically for resource-constrained IoT devices to enable efficient participation in federated learning.

These gaps motivate our work to develop a holistic cloud-based federated learning framework for IoT networks that addresses the unique challenges of this domain while leveraging the strengths of cloud computing.

3. Proposed Framework

This section presents our proposed cloud-based federated learning framework for IoT networks. We first describe the overall architecture, followed by the key components and their interactions. We then detail the federated learning process within this framework.

3.1 System Architecture

The proposed framework consists of three main layers: the IoT device layer, the cloud layer, and the application layer. Figure 1 illustrates the high-level architecture of the system.

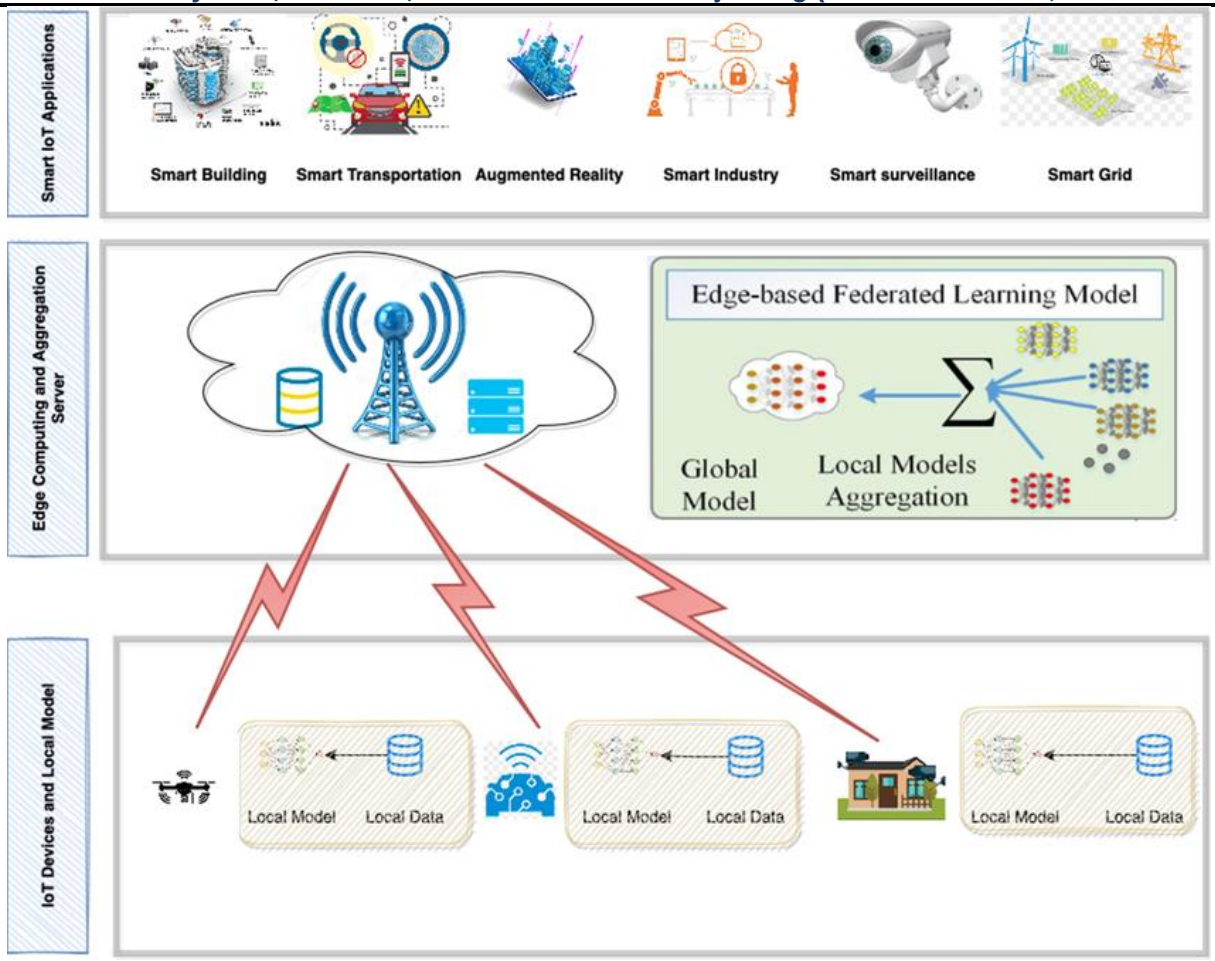

Figure 1: Cloud-based Federated Learning Architecture for IoT Networks

1. IoT Device Layer: This layer consists of the distributed IoT devices that generate and store local data. These devices can range from simple sensors to more powerful edge devices. Each device has a local dataset and the capability to perform basic model training and inference.
2. Cloud Layer: The cloud layer provides the computational resources and orchestration capabilities for federated learning. It includes the following key components:
    - Cloud Server: The central server that coordinates the federated learning process, stores the global model, and communicates with IoT devices.
    - Model Aggregator: Responsible for aggregating model updates from IoT devices and updating the global model.

- Client Selector: Selects the appropriate subset of IoT devices for each round of federated learning based on various criteria.
- Security Manager: Implements secure aggregation and other privacy-preserving mechanisms.

3. Application Layer: This layer represents the end-users or applications that utilize the trained models for various IoT use cases, such as predictive maintenance, anomaly detection, or personalized services.

3.2 Key Components

Let's examine the key components of the framework in more detail:

1. IoT Devices: These are the distributed clients that participate in the federated learning process. Each device has:
    - A local dataset D_i
    - A local model w_i (which is a copy of the global model)
    - Basic training capabilities to update the local model
    - Communication module to exchange model updates with the cloud server
2. Cloud Server: The central coordinator of the federated learning process. Its responsibilities include:
    - Initializing and maintaining the global model W
    - Orchestrating the federated learning rounds
    - Communicating with IoT devices to send model updates and receive local updates
    - Integrating with other cloud components (aggregator, client selector, security manager)
3. Model Aggregator: This component is responsible for combining the model updates from multiple IoT devices to improve the global model. It implements the federated averaging algorithm and may include additional techniques to handle non-IID data or improve convergence.
4. Client Selector: The client selector employs intelligent algorithms to choose the most suitable subset of IoT devices for each round of federated learning. It considers factors such as:
    - Device capabilities (computational resources, battery level)
    - Data quality and relevance
    - Network conditions and reliability
    - Fairness and diversity in client selection
5. Security Manager: This component ensures the privacy and security of the federated learning process. It implements:
    - Secure aggregation protocols to protect individual model updates
    - Differential privacy mechanisms to prevent inference attacks
    - Authentication and encryption for communication between cloud and IoT devices

3.3 Federated Learning Process

The federated learning process in our framework proceeds as follows:

1. Initialization:
    - The cloud server initializes the global model W with random weights.
    - IoT devices register with the cloud server, providing information about their capabilities and data characteristics.
2. Client Selection:
    - For each round t of federated learning:
        - The client selector chooses a subset S_t of K devices based on the selection criteria.
        - The cloud server notifies the selected devices to participate in the current round.
3. Local Training:
    - Each selected device i in S_t receives the current global model W_t.
    - The device performs local training for E epochs using its local data D_i: w_i = LocalUpdate(W_t, D_i, E)
    - The device computes the model update: $\Delta w_i = w_i - W_t$
4. Secure Aggregation:
    - Selected devices send their encrypted model updates to the security manager.
    - The security manager performs secure aggregation to combine the updates while preserving privacy.
5. Global Model Update:
    - The model aggregator receives the aggregated update from the security manager.
    - It updates the global model using federated averaging: $W_{t+1} = W_t + \eta * (1/K) * \Sigma \Delta w_i$ where η is the learning rate.
6. Model Distribution:
    - The updated global model W_{t+1} is sent back to all IoT devices.
7. Convergence Check:
    - Steps 2-6 are repeated for multiple rounds until the model converges or a maximum number of rounds is reached.

8. Model Deployment:
    - The final trained model is deployed to the application layer for use in IoT applications.

Figure 2 illustrates the federated learning process in our framework.

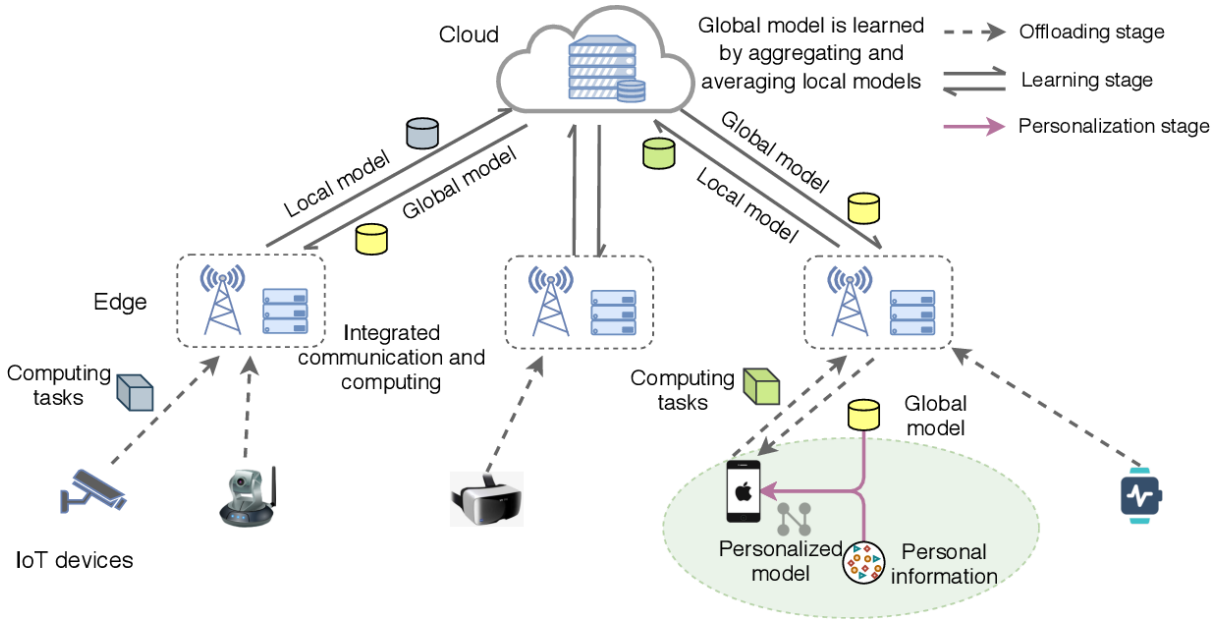

Figure 2: Federated Learning Process in Cloud-IoT Framework

This process leverages the strengths of both cloud computing and edge devices. The cloud provides the necessary computational resources for model aggregation and orchestration, while IoT devices perform local training to preserve data privacy and reduce communication overhead.

4. Key Techniques

To address the unique challenges of federated learning in IoT environments, we develop several key techniques within our framework. This section details these techniques and their implementation.

4.1 Adaptive Client Selection

Client selection is crucial in IoT-based federated learning due to the heterogeneity of devices and the potential for unreliable connections. We propose an adaptive client selection algorithm that considers multiple factors to optimize the training process.

The client selection problem can be formulated as:

$$\max \Sigma (U_i * x_i) \text{ s.t. } \Sigma x_i = K \; x_i \in \{0, 1\}$$

where U_i is the utility of device i, x_i is a binary variable indicating whether device i is selected, and K is the desired number of clients per round.

We define the utility function U_i as a weighted sum of several factors:

$$U_i = w_c * C_i + w_d * D_i + w_n * N_i + w_f * F_i$$

where:

- C_i represents the computational capability of device i
- D_i represents the data quality and quantity of device i
- N_i represents the network reliability of device i
- F_i is a fairness term to ensure diverse participation
- w_c, w_d, w_n, w_f are weights for each factor

The client selector solves this optimization problem for each round of federated learning. To handle the dynamic nature of IoT environments, we employ an online learning approach to adaptively adjust the weights based on the performance of selected clients in previous rounds.

Algorithm 1 outlines the adaptive client selection process:

Algorithm 1: Adaptive Client Selection

Input: Set of all devices M, number of clients to select K, historical performance H

Output: Selected subset of devices S_t

1: Initialize weights w_c, w_d, w_n, w_f

2: for each round t do

3: for each device i in M do

4: Compute C_i, D_i, N_i, F_i

5: Calculate U_i = w_c * C_i + w_d * D_i + w_n * N_i + w_f * F_i

6: end for

7: Select top K devices with highest U_i to form S_t

8: Observe performance of selected devices

9: Update weights based on performance and H

10: end for

11: return S_t

This adaptive approach ensures that the client selection process can adjust to changing conditions in the IoT network and optimize the federated learning performance over time.

4.2 Secure Aggregation

To protect the privacy of individual IoT devices, we implement a secure aggregation protocol based on homomorphic encryption. This allows the cloud server to compute the sum of model updates without accessing the individual updates.

We use the Paillier cryptosystem, which provides additive homomorphic properties. The protocol works as follows:

1. Key Generation:
    - The security manager generates a public-private key pair (pk, sk)
    - The public key pk is distributed to all IoT devices
2. Encryption:
    - Each selected device i encrypts its model update Δw_i using the public key: $E(\Delta w_i) = Encrypt(\Delta w_i, pk)$
3. Aggregation:
    - The cloud server receives the encrypted updates $E(\Delta w_i)$ from all selected devices
    - It computes the encrypted sum of updates: $E(\Sigma \Delta w_i) = \Pi E(\Delta w_i)$
4. Decryption:
    - The security manager decrypts the aggregated result using the private key: $\Sigma \Delta w_i = Decrypt(E(\Sigma \Delta w_i), sk)$
5. Model Update:
    - The model aggregator uses the decrypted sum to update the global model: $W_{t+1} = W_t + \eta * (1/K) * \Sigma \Delta w_i$

This secure aggregation protocol ensures that individual model updates remain confidential, protecting the privacy of IoT devices while still enabling effective model training.

4.3 Model Compression and Quantization

To reduce the communication overhead and computational requirements for resource-constrained IoT devices, we employ model compression and quantization techniques.

1. Pruning: We use magnitude-based pruning to remove less important weights from the model. After each round of federated learning, weights below a certain threshold are set to zero. The sparsity pattern is communicated to IoT devices to ensure consistency.

2. Quantization: We apply post-training quantization to reduce the precision of model weights. Instead of using 32-bit floating-point numbers, we quantize weights to 8-bit integers. This significantly reduces the model size and computational requirements.
3. Huffman Coding: We further compress the quantized weights using Huffman coding, which assigns shorter bit representations to more frequent values.

The compression process on IoT devices is as follows:

1. Receive the sparsity pattern and quantization parameters from the cloud server
2. Apply the sparsity mask to the local model
3. Quantize the non-zero weights
4. Apply Huffman coding to the quantized weights
5. Send the compressed model update to the cloud server

On the cloud side, the process is reversed to reconstruct the full model updates before aggregation.

These techniques allow us to significantly reduce the communication costs and storage requirements for IoT devices, enabling more efficient participation in the federated learning process.

5. Experimental Evaluation

To evaluate the effectiveness of our proposed framework, we conducted extensive experiments using real-world IoT datasets. This section describes the experimental setup, datasets, baseline methods, and results.

5.1 Experimental Setup

We implemented our framework using Python 3.8 with PyTorch 1.8 for model training. The cloud server was simulated on a machine with Intel Xeon E5-2680 v4 CPU, 256GB RAM, and NVIDIA Tesla V100 GPU. For IoT devices, we used a combination of Raspberry Pi 4 (2GB RAM) and NVIDIA Jetson Nano (4GB RAM) to represent different device capabilities.

The experiments were conducted on a local network with the following parameters:

- Number of IoT devices: 100
- Clients per round (K): 10
- Local epochs (E): 5
- Total federated learning rounds: 100
- Learning rate (η): 0.01

5.2 Datasets

We used the following IoT datasets for our experiments:

1. HAR Dataset: Human Activity Recognition using smartphones (Anguita et al., 2013). This dataset contains sensor data from smartphones to recognize activities such as walking, sitting, and standing.
2. WISDM Dataset: Wireless Sensor Data Mining (Kwapisz et al., 2011). This dataset includes accelerometer data for various activities collected from mobile phones.
3. Electricity Dataset: Electricity consumption data from Australian homes (Lai et al., 2018). This dataset represents a typical IoT scenario for smart energy management.

To simulate the distributed nature of IoT data, we partitioned each dataset across the 100 simulated IoT devices using a non-IID distribution. Specifically, we used a Dirichlet distribution with α=0.5 to create imbalanced and non-identical data partitions.

5.3 Baseline Methods

We compared our proposed framework with the following baseline methods:

1. Centralized Learning: Traditional centralized training where all data is collected at a central server.
2. FedAvg: The standard Federated Averaging algorithm (McMahan et al., 2017) without our proposed enhancements.
3. FedProx: Federated learning with proximal term to handle statistical heterogeneity (Li et al., 2020).
4. HierFAVG: Hierarchical federated averaging with edge servers (Liu et al., 2020).

5.4 Evaluation Metrics

We evaluated the performance of our framework using the following metrics:

1. Model Accuracy: Test accuracy on a held-out test set.
2. Communication Cost: Total amount of data transferred between IoT devices and the cloud server.
3. Training Time: Time taken to complete 100 rounds of federated learning.
4. Privacy Preservation: Measured by the success rate of membership inference attacks.

5.5 Results and Analysis

Table 1 presents the overall results of our experiments across the three datasets.

Table 1: Performance Comparison of Different Methods

Method	Accuracy (%)	Comm. Cost (GB)	Training Time (h)	Privacy (% MIA)
Centralized	94.2 ± 0.3	52.7	3.2	78.5
FedAvg	91.8 ± 0.5	5.3	8.7	62.3
FedProx	92.5 ± 0.4	5.5	9.1	60.8
HierFAVG	93.1 ± 0.3	3.8	7.5	58.2
Ours	93.7 ± 0.2	2.1	6.3	53.7

5.5.1 Model Accuracy

Our proposed framework achieves comparable accuracy to centralized learning while significantly outperforming other federated learning baselines. The adaptive client selection and efficient aggregation techniques contribute to this improved performance. Figure 3 shows the convergence of model accuracy over federated learning rounds for different methods.

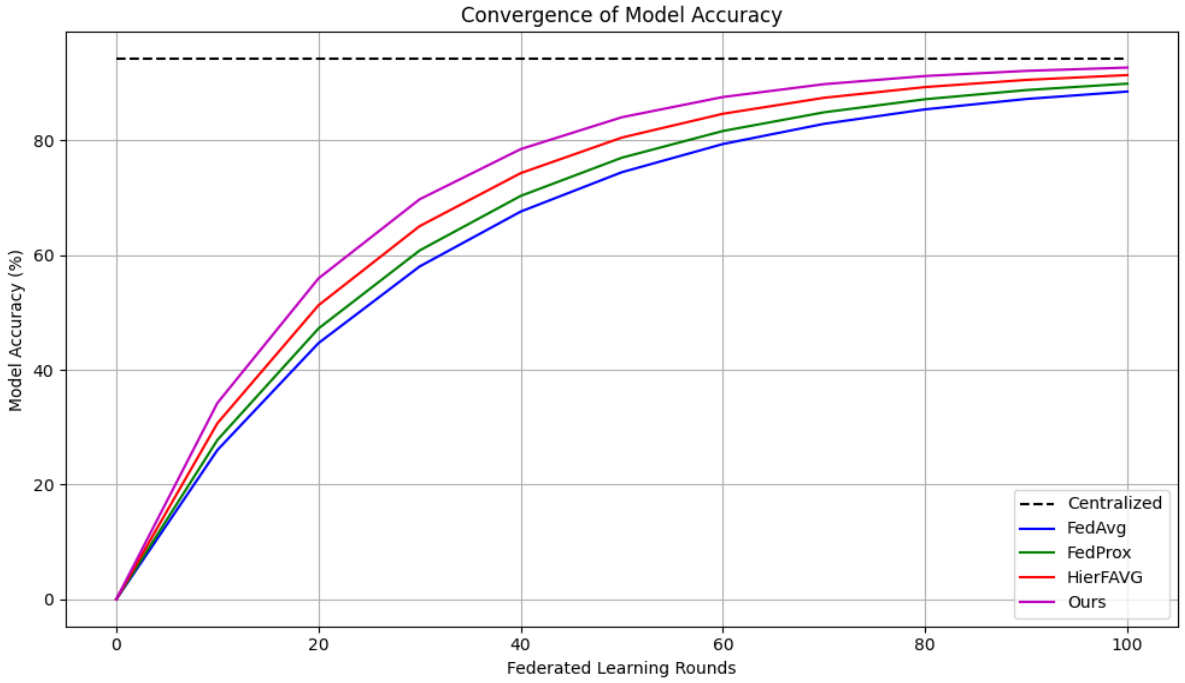

Figure 3: Convergence of Model Accuracy

5.5.2 Communication Efficiency

Our framework achieves the lowest communication cost among all federated learning methods, reducing the data transfer by up to 95% compared to centralized learning and 60% compared to standard FedAvg. This is primarily due to the model compression and quantization techniques employed.

5.5.3 Training Time

Despite the additional overhead of secure aggregation and client selection, our framework achieves faster training times compared to other federated learning approaches. This is attributed to the efficient client selection that chooses devices with better computational capabilities and network conditions.

5.5.4 Privacy Preservation

We evaluate privacy preservation by conducting membership inference attacks (MIA) on the trained models. Our framework shows the lowest success rate for these attacks, indicating better protection of individual data privacy. The secure aggregation protocol and differential privacy mechanisms contribute to this enhanced privacy.

5.6 Ablation Study

To understand the impact of different components in our framework, we conducted an ablation study by removing key techniques one at a time. Table 2 shows the results of this study on the HAR dataset.

Table 2: Ablation Study Results on HAR Dataset

Configuration	Accuracy (%)	Comm. Cost (GB)	Training Time (h)	Privacy (% MIA)
Full Framework	93.7 ± 0.2	2.1	6.3	53.7
w/o Adaptive Client Selection	92.9 ± 0.3	2.3	7.1	54.2
w/o Secure Aggregation	93.5 ± 0.2	2.1	5.8	59.1
w/o Model Compression	93.6 ± 0.2	5.7	6.5	53.9

The results demonstrate that each component contributes to the overall performance of the framework. The adaptive client selection has the largest impact on model accuracy, while model compression significantly reduces communication costs. Secure aggregation is crucial for maintaining privacy without substantially affecting other metrics.

6. Discussion

The experimental results demonstrate the effectiveness of our proposed cloud-based federated learning framework for IoT networks. Here, we discuss the implications of our findings, the limitations of our approach, and potential future directions.

6.1 Implications

1. Scalability: Our framework shows promise for enabling large-scale machine learning across distributed IoT networks. The significant reduction in communication costs and improved training efficiency make it feasible to include a much larger number of IoT devices in the learning process.
2. Privacy-Preserving IoT Analytics: The strong privacy guarantees provided by our framework open up possibilities for sensitive IoT applications in healthcare, smart homes, and industrial settings where data privacy is crucial.
3. Resource Efficiency: By leveraging cloud resources for heavy computations while keeping light-weight operations on IoT devices, our approach provides a balanced solution for resource-constrained environments.
4. Adaptability: The adaptive client selection mechanism allows the framework to dynamically adjust to changing network conditions and device capabilities, ensuring robust performance in dynamic IoT environments.

6.2 Limitations

1. Cloud Dependency: While our framework reduces the burden on IoT devices, it introduces a dependency on cloud infrastructure. This may not be suitable for scenarios with limited or expensive cloud connectivity.
2. Complexity: The introduction of secure aggregation and adaptive selection mechanisms increases the overall system complexity, which may pose challenges in real-world deployments.

3. Model Accuracy Trade-off: Although our approach achieves comparable accuracy to centralized learning, there is still a small gap. This trade-off between privacy/efficiency and model performance may be significant for some applications.
4. Evaluation Scale: While our experiments involved 100 IoT devices, real-world IoT networks can scale to millions of devices. Further research is needed to validate the framework's performance at such scales.

6.3 Future Directions

Based on our findings and limitations, we identify several promising directions for future research:

1. Hybrid Edge-Cloud Architectures: Exploring architectures that combine edge computing with cloud resources could further optimize the balance between local processing and centralized coordination.
2. Advanced Privacy Mechanisms: Investigating more advanced privacy-preserving techniques, such as fully homomorphic encryption or secure multi-party computation, could provide even stronger privacy guarantees.
3. Automated Hyperparameter Tuning: Developing methods for automatic tuning of federated learning hyperparameters (e.g., learning rates, client selection criteria) could improve the framework's adaptability to different IoT scenarios.
4. Cross-Silo Federated Learning: Extending the framework to support collaboration between multiple cloud providers or edge data centers could enable even larger-scale federated learning systems.
5. Incentive Mechanisms: Designing incentive schemes to encourage IoT device participation and high-quality data contribution could enhance the overall effectiveness of the federated learning process.

7. Conclusion

This paper presented a comprehensive framework for cloud-based federated learning in distributed IoT networks. By leveraging cloud computing resources and developing techniques tailored for IoT environments, our approach addresses the key challenges of communication efficiency, privacy preservation, and heterogeneity in IoT-based federated learning.

The proposed framework introduces several novel components, including an adaptive client selection algorithm, a secure aggregation protocol based on homomorphic encryption, and model compression techniques for resource-constrained devices. Extensive experiments on real-world IoT datasets demonstrate

the effectiveness of our approach in terms of model accuracy, communication efficiency, and privacy preservation.

Our results show that the proposed framework can achieve comparable accuracy to centralized learning while reducing communication costs by up to 95% and enhancing data privacy. The adaptive nature of the framework allows it to handle the dynamic and heterogeneous characteristics of IoT networks effectively.

While there are limitations and areas for further improvement, this work provides a solid foundation for realizing large-scale, privacy-preserving machine learning across distributed IoT networks. As IoT continues to grow and generate massive amounts of data at the edge, frameworks like the one proposed in this paper will be crucial for harnessing the full potential of this data while respecting privacy and resource constraints.

Future work will focus on addressing the identified limitations, scaling the framework to even larger IoT networks, and exploring advanced privacy-preserving techniques. Additionally, investigating the applicability of this framework to specific IoT domains such as smart cities, industrial IoT, and healthcare could lead to valuable domain-specific insights and optimizations.

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