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Original Article

Evaluation Framework for Centralized and Decentralized Aggregation Algorithm in Federated Systems

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Abstract

In recent years, the landscape of federated learning has witnessed significant advancements, particularly in decentralized methodologies. This research paper presents a comprehensive comparison of Centralized Hierarchical Federated Learning (HFL) with Decentralized Aggregated Federated Learning (AFL) and Decentralized Continual Federated Learning (CFL) architectures. While HFL, in its centralized approach, faces challenges such as communication bottlenecks and privacy concerns due to centralized data aggregation, AFL and CFL provide promising alternatives by distributing computation and aggregation processes across devices. Through evaluation of Fashion MNIST and MNIST datasets, this study demonstrates the advantages of decentralized methodologies, showcasing how AFL and CFL outperform HFL in precision, recall, F1 score, and balanced accuracy. The analysis highlights the importance of decentralized aggregation mechanisms in AFL and CFL, which effectively enables collaborative model training across distributed devices. This comparative study contributes valuable insights into the evolving landscape of federated learning, guiding researchers and practitioners towards decentralized methodologies for enhanced performance in collaborative model training scenarios. The performance gap observed in HFL is primarily attributed to communication latency and model divergence at the central node, whereas AFL and CFL distribute the computational load, reducing synchronization delays.

Categories: Optimization Algorithms, Parallel and Distributed Algorithms, Distributed Systems

Keywords: hierarchical federated learning, aggregated federated learning, continual federated learning, decentralized aggregation, distributing computing

Introduction

Federated learning (FL) represents a revolutionary approach to machine learning, transforming traditional centralized methodologies by enabling collaborative model training across multiple distributed devices [1]. Initially conceptualized to address privacy concerns inherent in centralized data aggregation, FL has evolved into various forms, including Centralized Hierarchical Federated Learning (HFL), Decentralized Aggregated Federated Learning (AFL), and Decentralized Continual Federated Learning (CFL) [2]. These adaptations accommodate diverse applications and scalability requirements, leveraging the copious amount of data produced at the edge while prioritizing data privacy and security [3].

The evolution of FL has prompted advancements in aggregation algorithms, distinguishing it from traditional centralized approaches [4]. Unlike centralized aggregation, where data is gathered and analyzed in one place, FL employs distributed optimization algorithms to aggregate model updates while preserving data privacy at the local level [5]. Recent trends in Decentralized Federated Learning (DFL) emphasize scalable and efficient aggregation algorithms, such as gossip-based protocols and secure multi-party computation, ensuring robustness and scalability in large-scale distributed

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environments [6]. This paper aims to explore the fundamental principles, methodologies, and applications of FL, shedding light on its significance and potential implications for various industries. By examining the nuances of HFL, AFL, and CFL, we aim to offer an in-depth comprehension of FL's role in shaping the future of machine learning.

Problem statement and contributions

The research provides a comprehensive comparison among three prominent paradigms within FL: HFL, AFL, and CFL. In this investigation, emphasis is placed on evaluating their efficacy and efficiency within the context of client-server architectures [7,8]. The study leverages two widely recognized datasets, MNIST [9] and Fashion-MNIST [10], as benchmarks for performance assessment.

A distinctive aspect of this study lies in its detailed comparative analysis of HFL and DFL paradigms using real-world datasets. A thorough evaluation, based on various performance metrics, is presented, offering an understanding of the advantages and disadvantages of the FL methodologies [11]. By delivering a detailed knowledge of the effectiveness and productivity of FL paradigms, this research aims to make a substantial impact on the current discussions in the domain of FL.

Furthermore, this study considers the security implications of shifting from a single point of failure in HFL (the central server) to a distributed trust model in AFL and CFL. By removing the central aggregator, decentralized methodologies inherently mitigate the risk of a single-point server breach, although they introduce new requirements for peer-to-peer authentication.

Terms and terminologies

The following terms and terminologies are discussed in reference to the performance of our work:

Accuracy

In Centralized FL and DFL strategies, accuracy represents the ratio of correctly identified cases to the overall number of Fashion MNIST and MNIST images that were categorized. The formula for accuracy is depicted in (1). This pivotal metric highlights the effectiveness of collaborative model training methodologies.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}}$$

Precision

In Centralized FL and DFL strategies, precision evaluates the quality of positive pre dictions among all positive predictions made for Fashion MNIST and MNIST images classified. The formula for precision is provided in (2).

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall

In Centralized FL and DFL strategies, recall measures the model's capacity to accurately detect true positives from the total number of actual positives in the classification of Fashion MNIST and MNIST images. The formula for recall is given in (3).

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1 Score

In Centralized and DFL strategies, the F1 score calculates the weighted average of precision and recall for the classified images in the Fashion MNIST and MNIST datasets and is calculated using (4). It balances both metrics and provides a single value to evaluate a model's overall performance.

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

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Aggregation (Using FedAvg Algorithm)

In Centralized FL, aggregation refers to the process of combining local model updates from participating clients (devices) into a global model held by a central server. In DFL, aggregation is decentralized, where clients directly communicate and collaboratively aggregate their model updates without relying on a central server. The formula for aggregation using the FedAvg algorithm is depicted in (5):

$$\theta_g = \sum_{c=1}^{N} \frac{n_c}{N} \theta_c$$

where θ_g is the global model parameter, θ_c is the local client model parameter, n_c is the specific client, and N is the total number of clients.

Build Time

In Centralized FL, the build time denotes the duration required to train a global model on the central server using aggregated updates from individual clients. In DFL, the build time is distributed across clients, as each client trains its local model independently. The overall build time depends on the parallelization and coordination among clients.

$$\text{Build Time} = \text{End Time (model training)} - \text{Start Time (model training)}$$

Classification Time

In Centralized FL, the classification time refers to the inference (prediction) time when using the global model managed by the central server. In DFL, the classification time refers to the inference time when using local models on individual clients.

$$\text{Classification Time} = \text{End Time (model evaluation)} - \text{Start Time (model evaluation)}$$

Related work

Recent years have witnessed considerable progress in the domain of DFL. The present study adds to a body of literature reviews by offering an exhaustive summary of the latest advancements, informed by an array of scholarly articles.

A. Challenges of FL: FL is a highly relevant field of research but is challenged by communication issues and heterogeneities. One of the main hurdles is ensuring efficient communication across the peers in the federated network [12]. The distribution of data across multiple devices often results in non-independent and identically distributed (non-i.i.d.) and unbalanced datasets [13]. Managing heterogeneous systems within the same network is another significant challenge. Privacy concerns also come into play, necessitating the development of privacy preserving methods [14].

B. Applications and Advantages of DFL: In their enlightening study, Martínez Beltrán et al. [15] explain the basic principles of DFL, including its frameworks, evolving trends, and inherent challenges. Their work effectively demonstrates how DFL operates across a network of devices, preserving data privacy while enabling collaborative model training.

C. Survey and Exploration of Diverse Scenarios in DFL: In a comprehensive survey by Yuan et al. [16], invaluable insights into the landscape and trajectories of DFL are provided. Their analysis covers communication overhead, model aggregation techniques, and privacy preservation mechanisms. Concurrently, research by Nair et al. [17] delves into the practical implications of DFL in multi-robot scenarios.

D. Research Directions in DFL: Nguyen et al.'s [13] innovative approach to DFL, tailored for training on medical data that is widely dispersed, of inferior quality, and confidential, exemplifies pioneering solutions to pressing challenges.

Materials And Methods

In this section, we delve into the architecture and algorithms underpinning both centralized and decentralized FL methodologies.

Hierarchical federated learning

Figure *1* and Figure *2* explain the functioning of HFL, a collaborative approach to distributed model training while ensuring the protection of data privacy and security. It begins by initializing the global model parameters, followed by iterative training rounds [18]. At the global server, gradients are aggregated with updates from other groups [19]. The aggregated parameters are then disseminated back to the groups for further refinement [20].

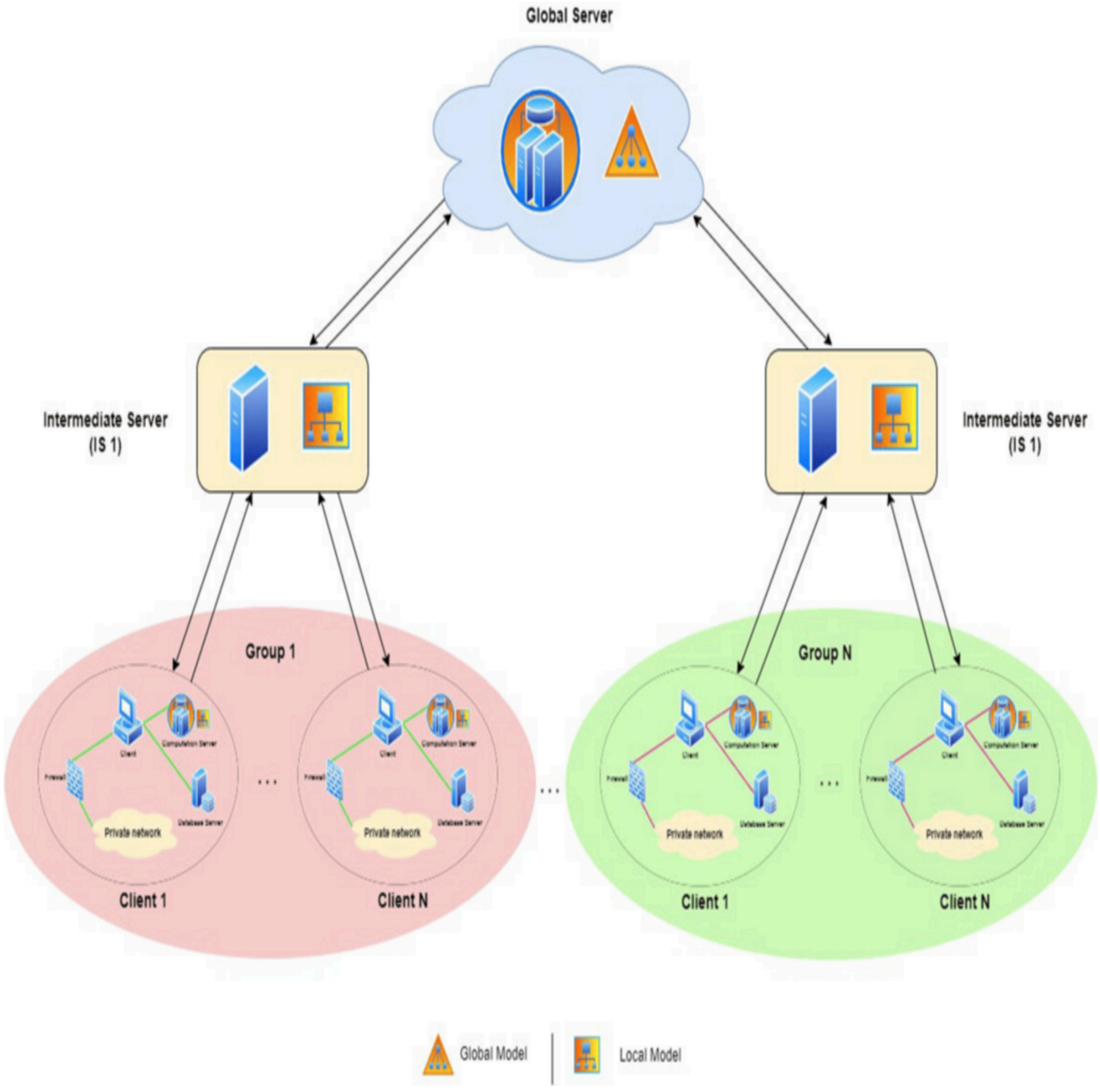


FIGURE 1: Architecture overview of hierarchical federated learning.

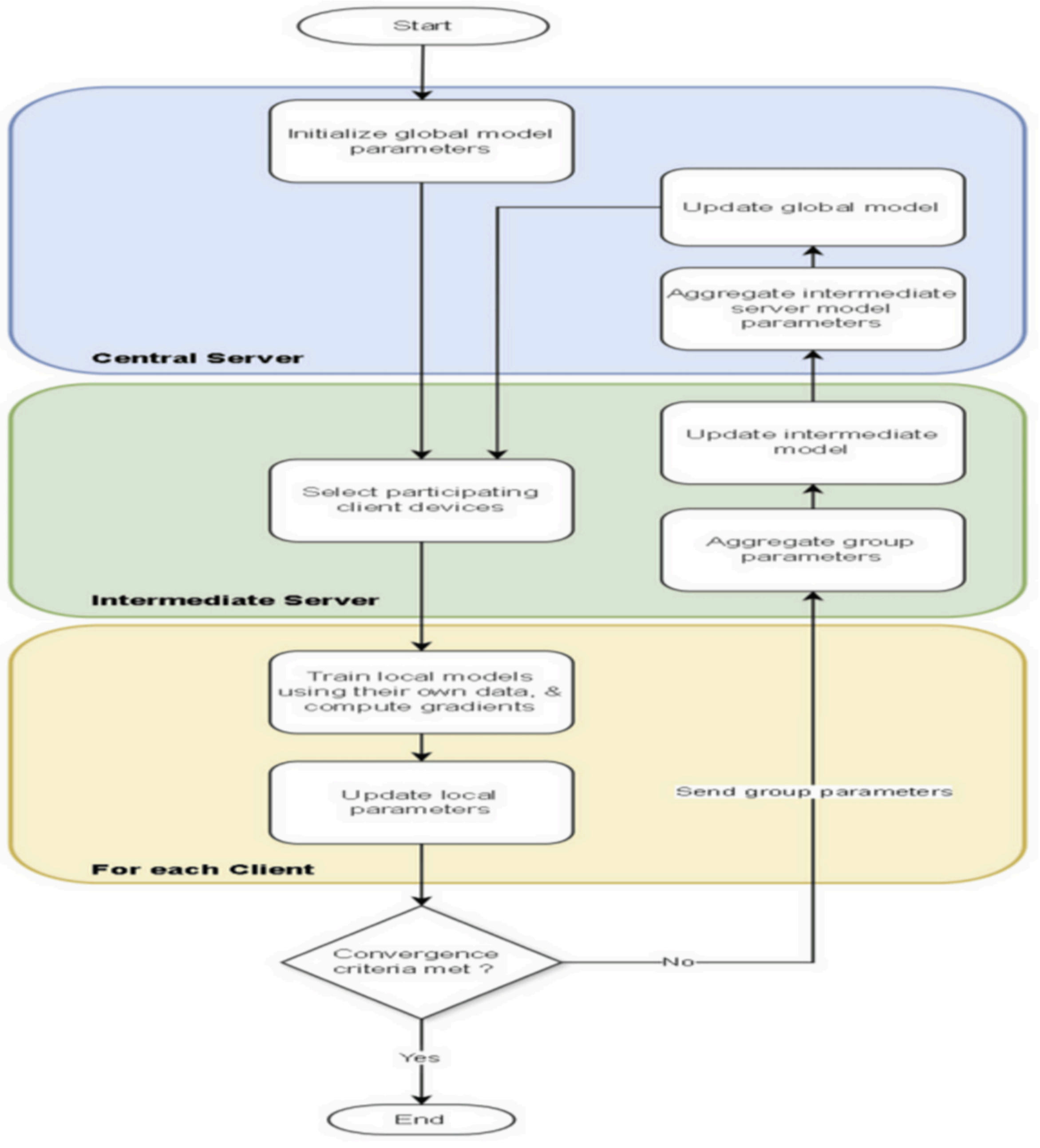


FIGURE 2: Flowchart of hierarchical federated learning.

Decentralized aggregated federated learning

Figure *3* and Figure *4* depict the operational framework of decentralized AFL, which is a cooperative approach to machine learning in which various participants work to gather and train a global model over multiple rounds [21]. AFL operates by selecting a subset of clients in each round, which then individually trains the model locally for several epochs. Following local training, the models are aggregated using a designated aggregation function [22].

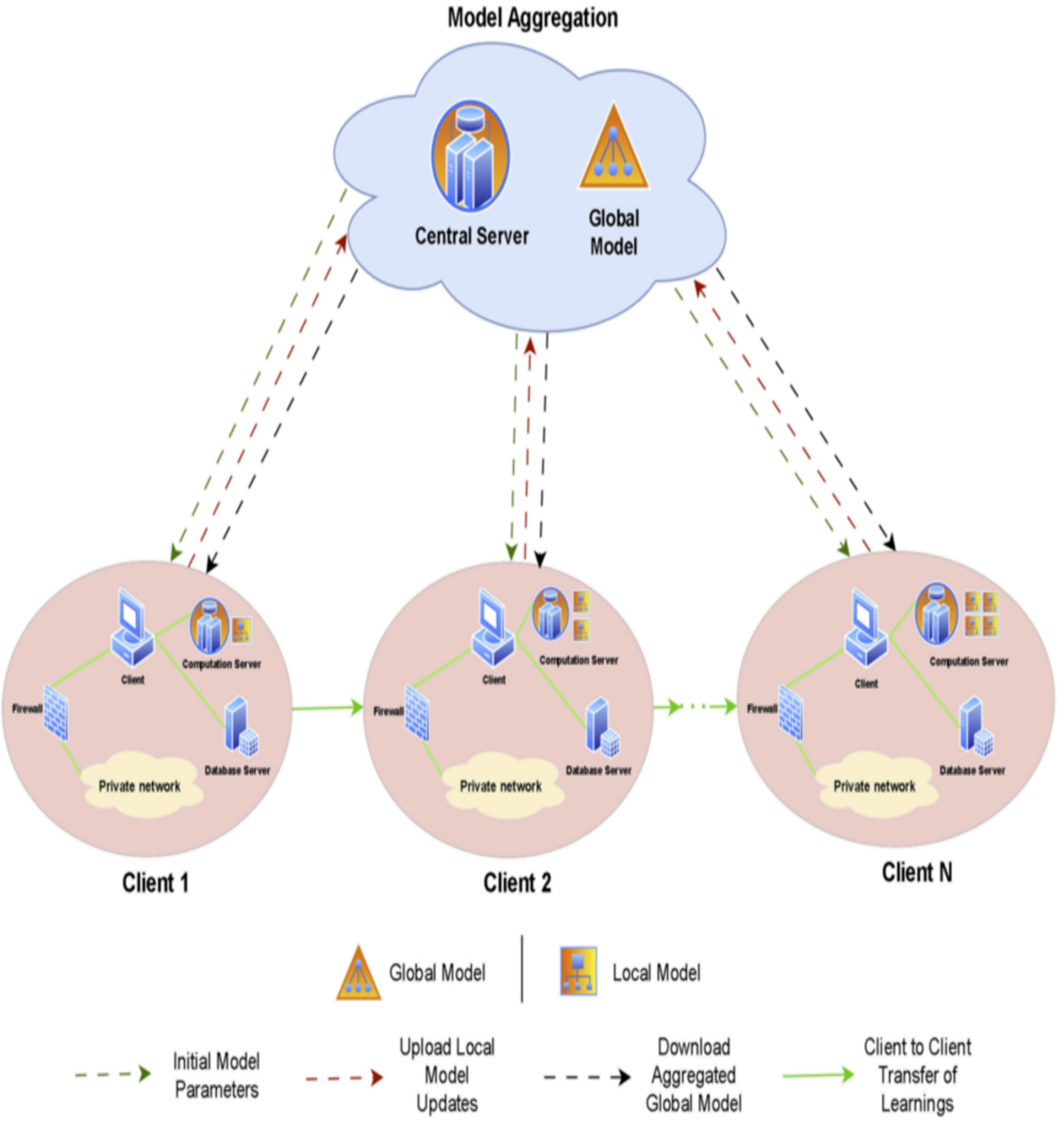


FIGURE 3: Architecture overview of decentralized aggregated federated learning.

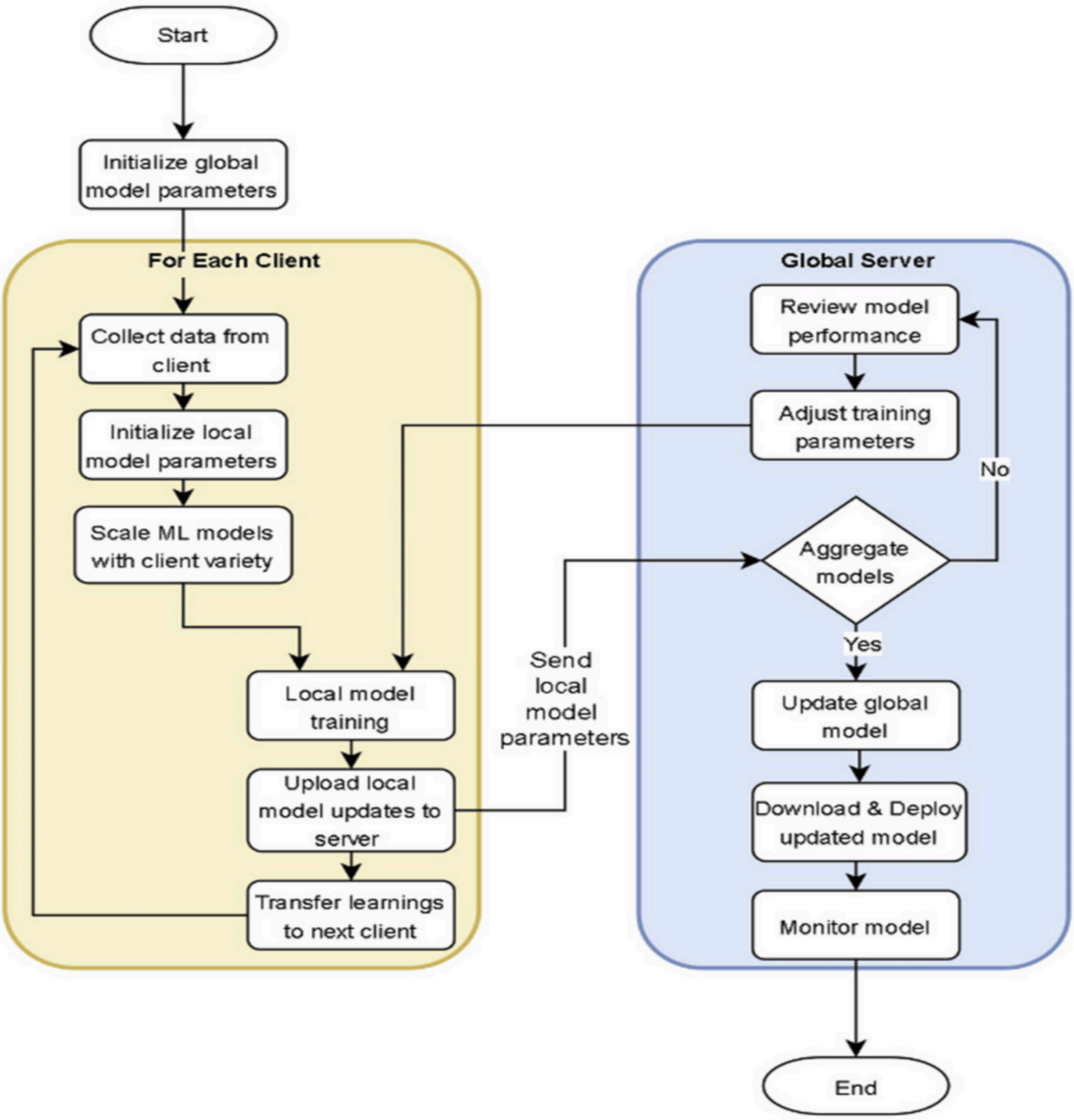


FIGURE 4: Flowchart of aggregated federated learning.

Decentralized continual federated learning

Figure *5* and Figure *6* illustrate the operational workflow of decentralized CFL, offering insights into its iterative training mechanism and collaborative model refinement across multiple client nodes. CFL is an iterative machine learning paradigm wherein numerous clients collaboratively refine a global model across multiple rounds [23]. Crucially, CFL entails the continuous updating of local models, with these updates seamlessly integrated to adapt the parameters of the global model [24].

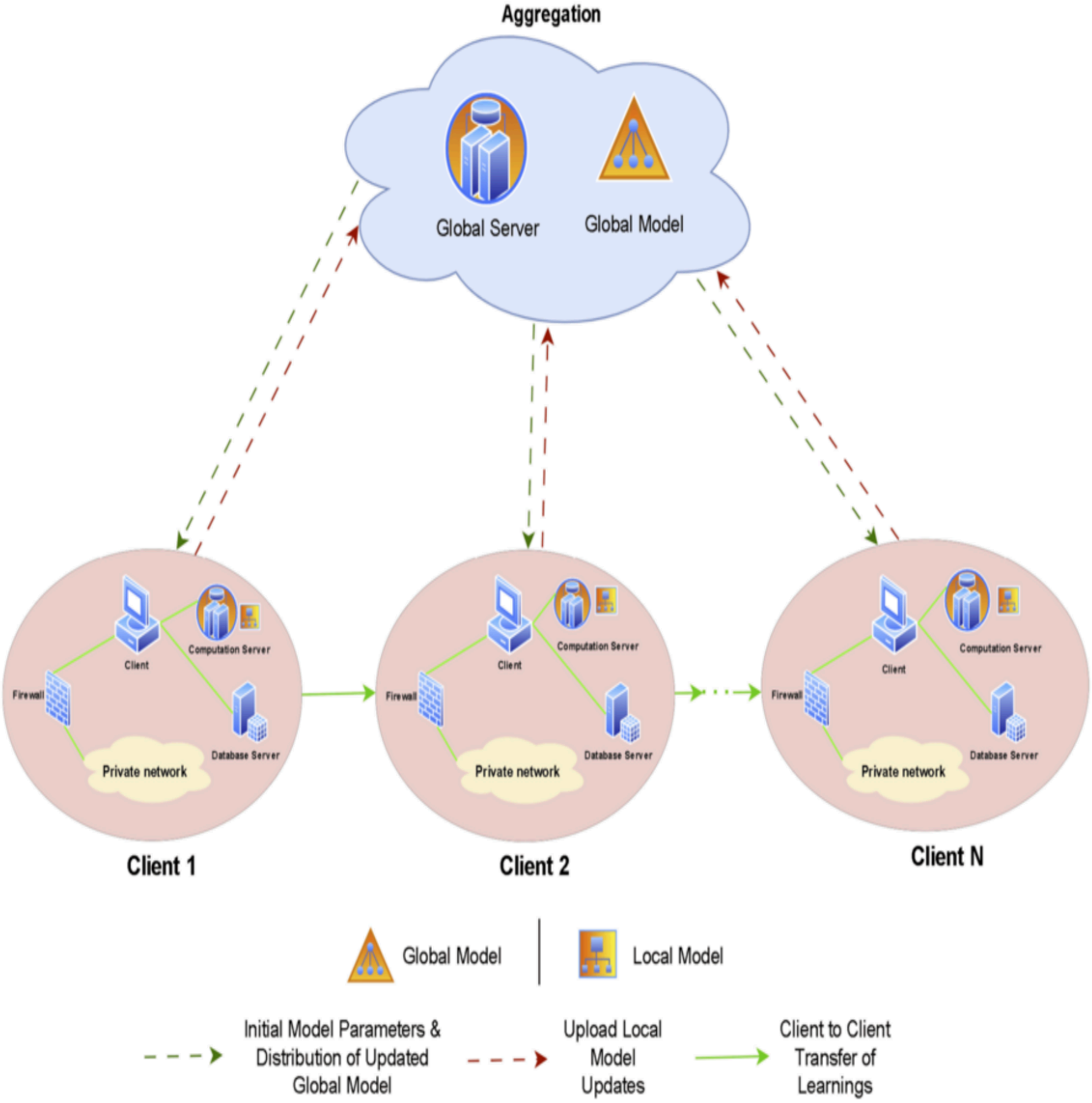


FIGURE 5: Architecture overview of decentralized continual federated learning.

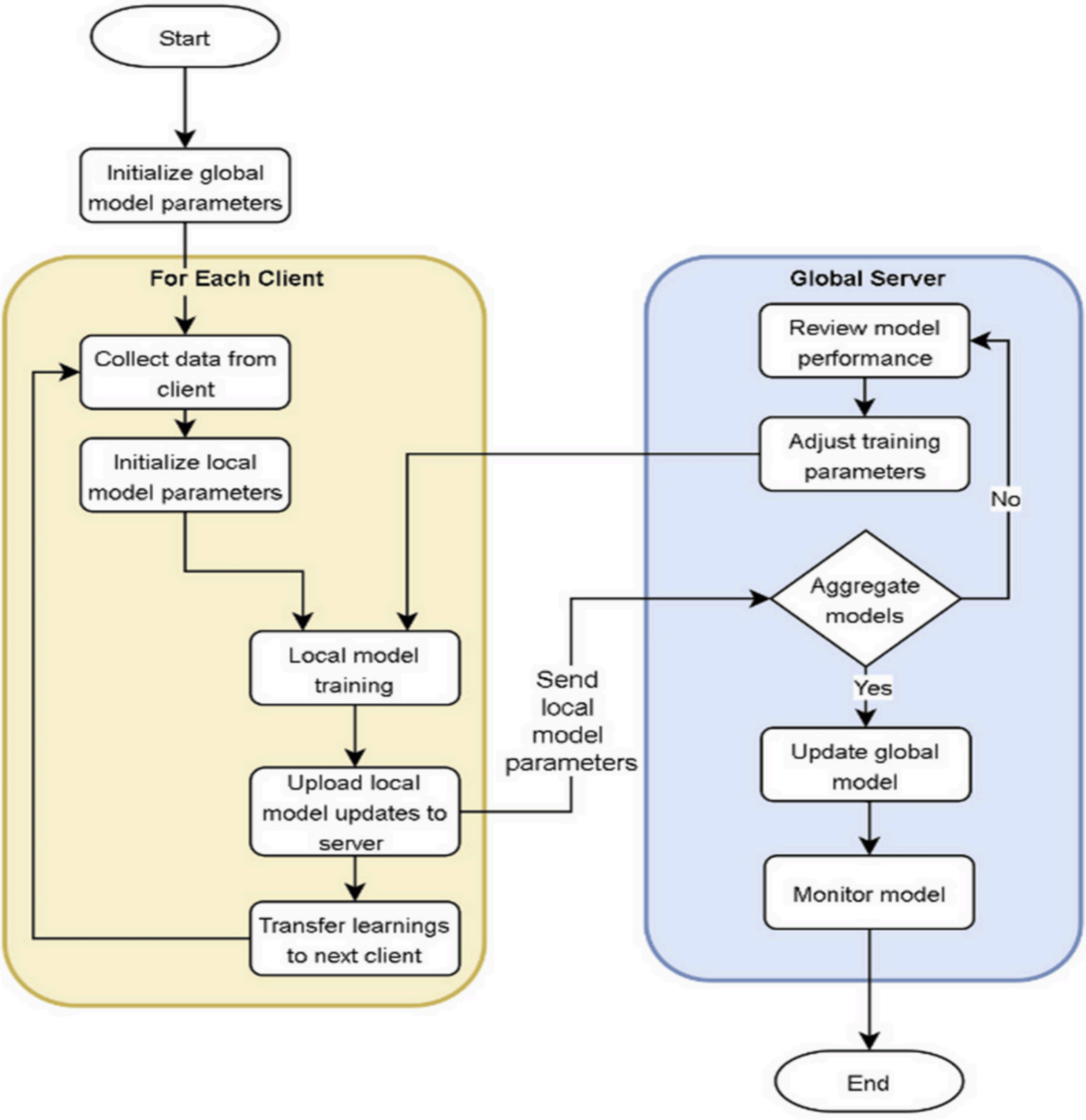


FIGURE 6: Flowchart of continual federated learning.

CNN architecture

In the experiment, an identical Convolutional Neural Network (CNN) is utilized due to its established efficacy in handling image data. As illustrated in Figure *7*, the chosen CNN architecture includes three convolutional layers with 16, 12, and 10 filters, each with a filter size of 3 × 3. Two max-pooling layers are incorporated to downsample the feature maps. The ReLU activation function is employed in hidden layers.

To ensure a controlled comparative environment, all three paradigms (HFL, AFL, and CFL) utilized identical hyperparameters, including a learning rate of 0.01, a batch size of 32, and were trained for an equal number of total communication rounds.

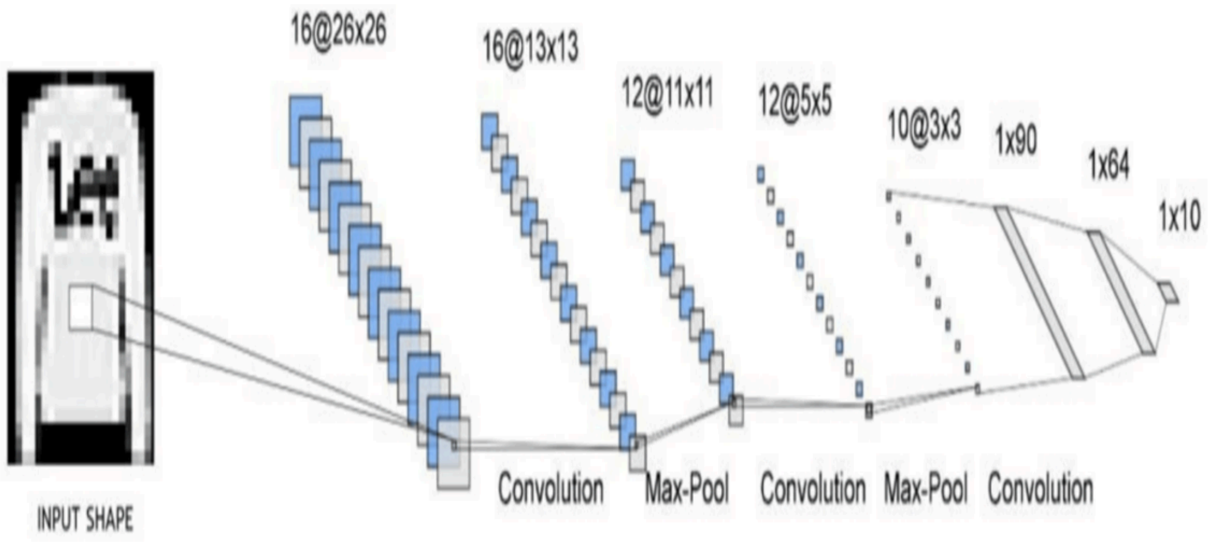


FIGURE 7: Proposed CNN architecture layers.

CNN, Convolutional Neural Network

Results And Discussion

The experimental outcome was achieved using tools such as Python 3.11.4, TensorFlow 2.16.1, Anaconda 2023.03, Jupyter Notebook v7.0.6, and Keras 3.1.1.

Introduction to the dataset

Experiments are conducted on two publicly accessible datasets: MNIST [9] and Fashion MNIST [10]. MNIST comprises handwritten digits (0-9) of size 28 × 28 pixels. Fashion MNIST consists of grayscale images depicting various clothing items from ten different classes.

Design of experiment

A data distribution that follows the i.i.d principle is implemented. The distribution is illustrated in Figure *8*

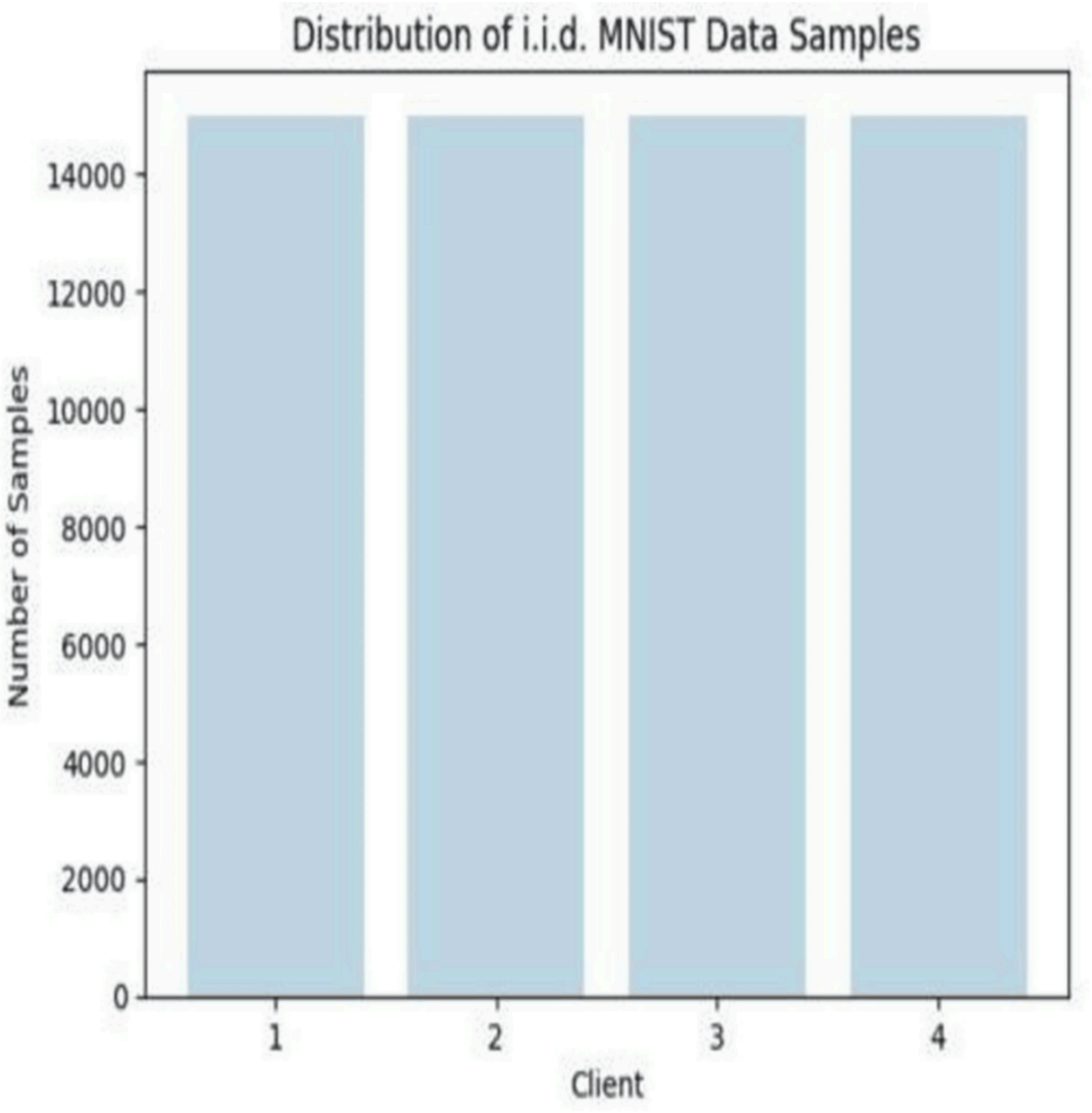


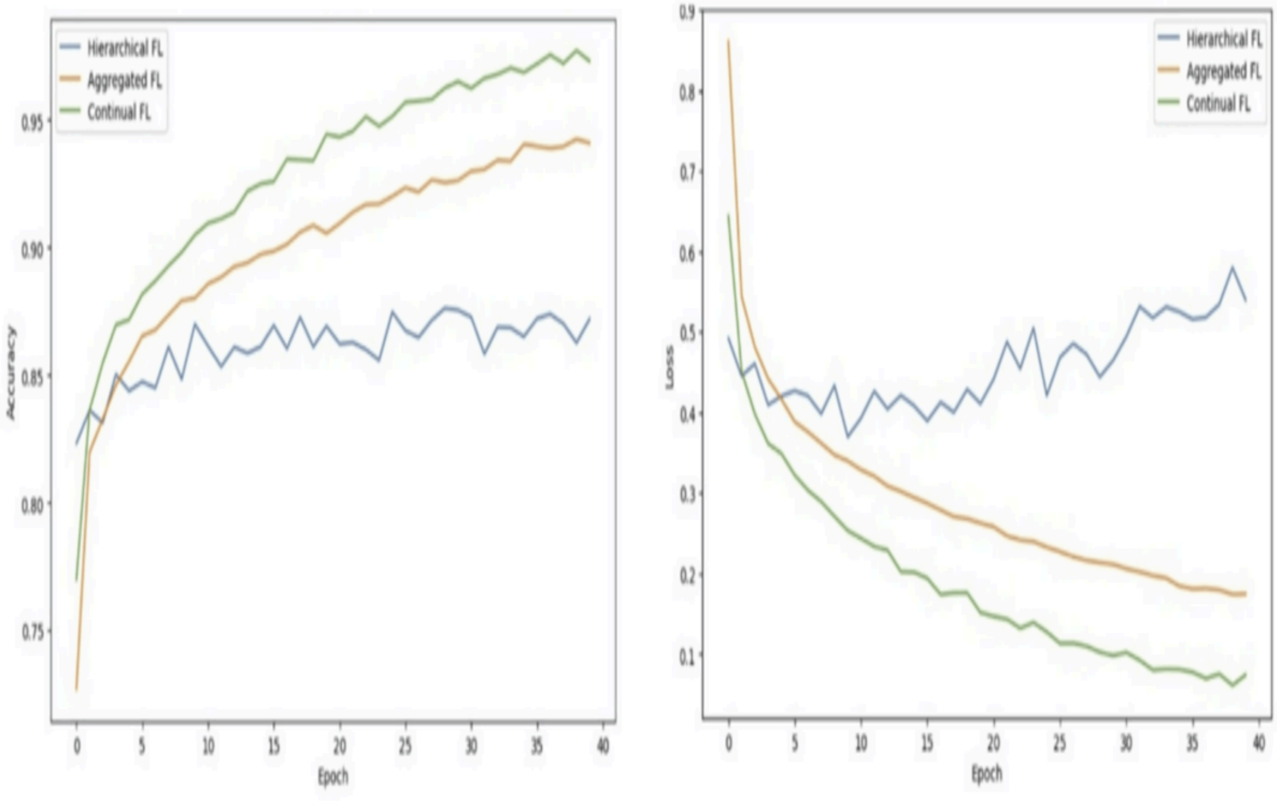
FIGURE 8: Sample of i.i.d. data from one of the clients.

This study compared various FL paradigms. The models were trained using the training data, and their parameters were adjusted based on the evaluation inferred using the validation data. Table *1* presents the comparison of performance measures including Training accuracy, Testing accuracy, Build time, and Classification time.

Environment	Training Acc. (Fashion MNIST)	Testing Acc. (Fashion MNIST)	Build Time (s)	Classification Time (s)	Training Acc. (MNIST)	Testing Acc. (MNIST)	Build Time (s)	Classification Time (s)
Hierarchical FL	0.85	0.41	86.11	0.57	0.93	0.6	88.26	0.55
Aggregated FL	0.93	0.7	55.33	0.47	0.95	0.72	54.02	0.52
Continual FL	0.95	0.88	80.07	0.31	0.96	0.98	79.02	0.29

TABLE 1: Comparing the accuracy and time of the federated learning (FL) environments.

Based on the observed experimentation results, the DFL approach exhibits superior performance compared to centralized FL methods across both Fashion MNIST and MNIST datasets. The accuracy and loss graph of the testing and training phase during the iterations is shown in Figure 9 (Fashion MNIST) and Figure 10 (MNIST).



(a)

(b)

FIGURE 9: Training accuracy and loss comparison of the federated learning (FL) paradigms (Fashion MNIST): (a) Accuracy comparison and (b) Loss comparison.

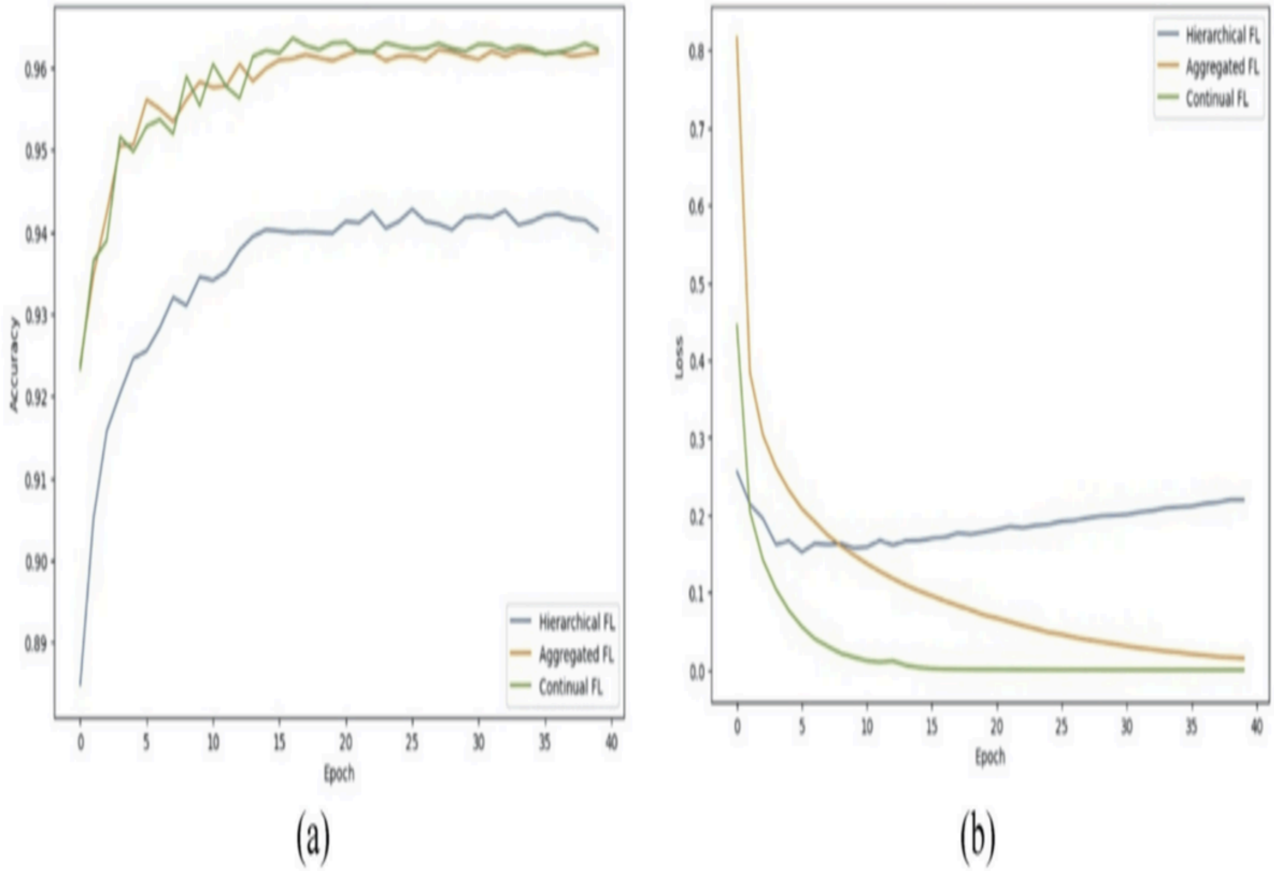
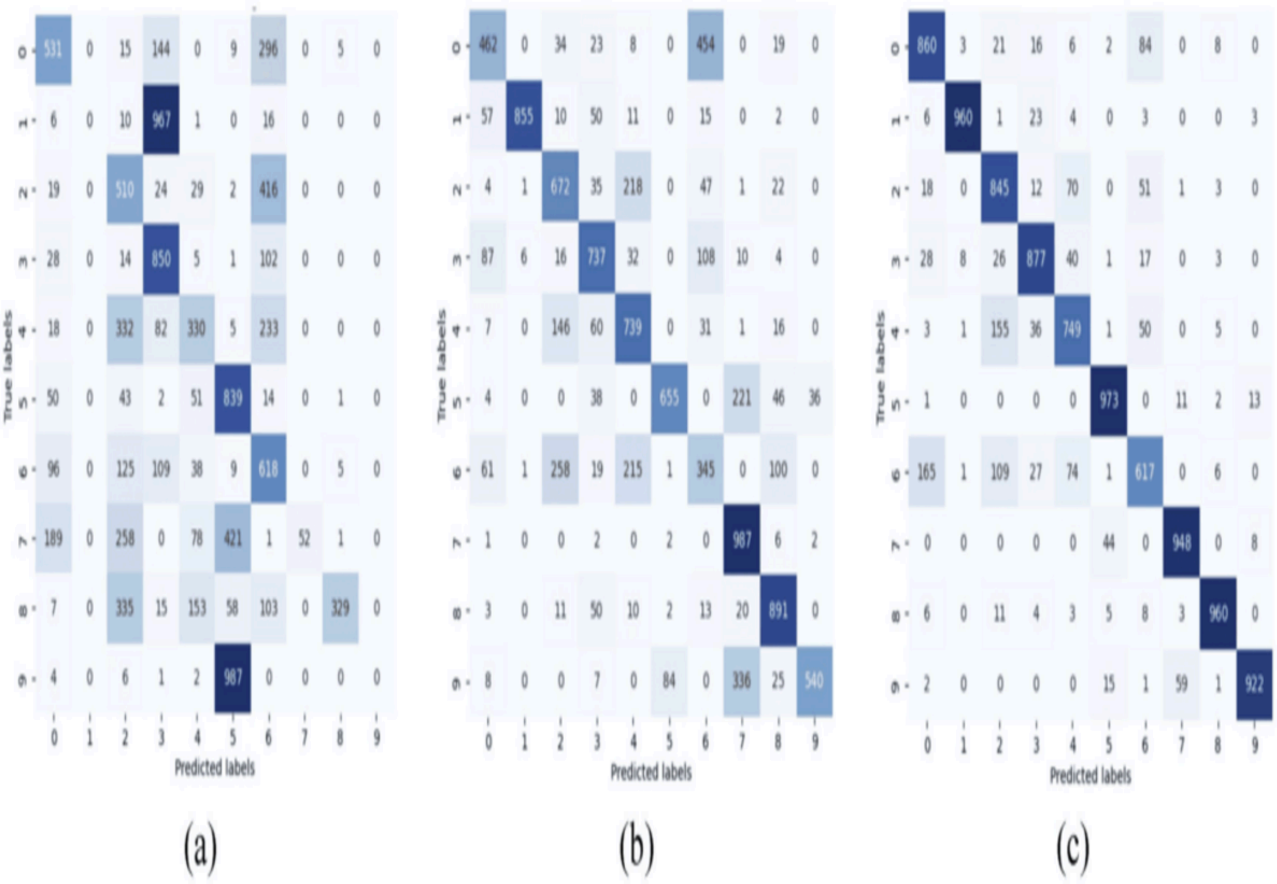


FIGURE 10: Training accuracy and loss comparison of the federated learning (FL) paradigms (MNIST): (a) Accuracy comparison and (b) Loss comparison.

To assess the effectiveness of the proposed approach, the confusion matrix is employed to depict the model's classification performance (Figure 11 for Fashion MNIST and Figure 12 for MNIST).



(a)

	0	1	2	3	4	5	6	7	8	9
0	531	0	15	144	0	9	296	0	5	0
1	6	0	10	967	1	0	16	0	0	0
2	19	0	510	24	29	2	416	0	0	0
3	28	0	14	850	5	1	102	0	0	0
4	18	0	332	82	330	5	233	0	0	0
5	50	0	43	2	51	839	14	0	1	0
6	96	0	125	109	38	9	618	0	5	0
7	189	0	258	0	78	421	1	52	1	0
8	7	0	335	15	153	58	103	0	329	0
9	4	0	6	1	2	987	0	0	0	0

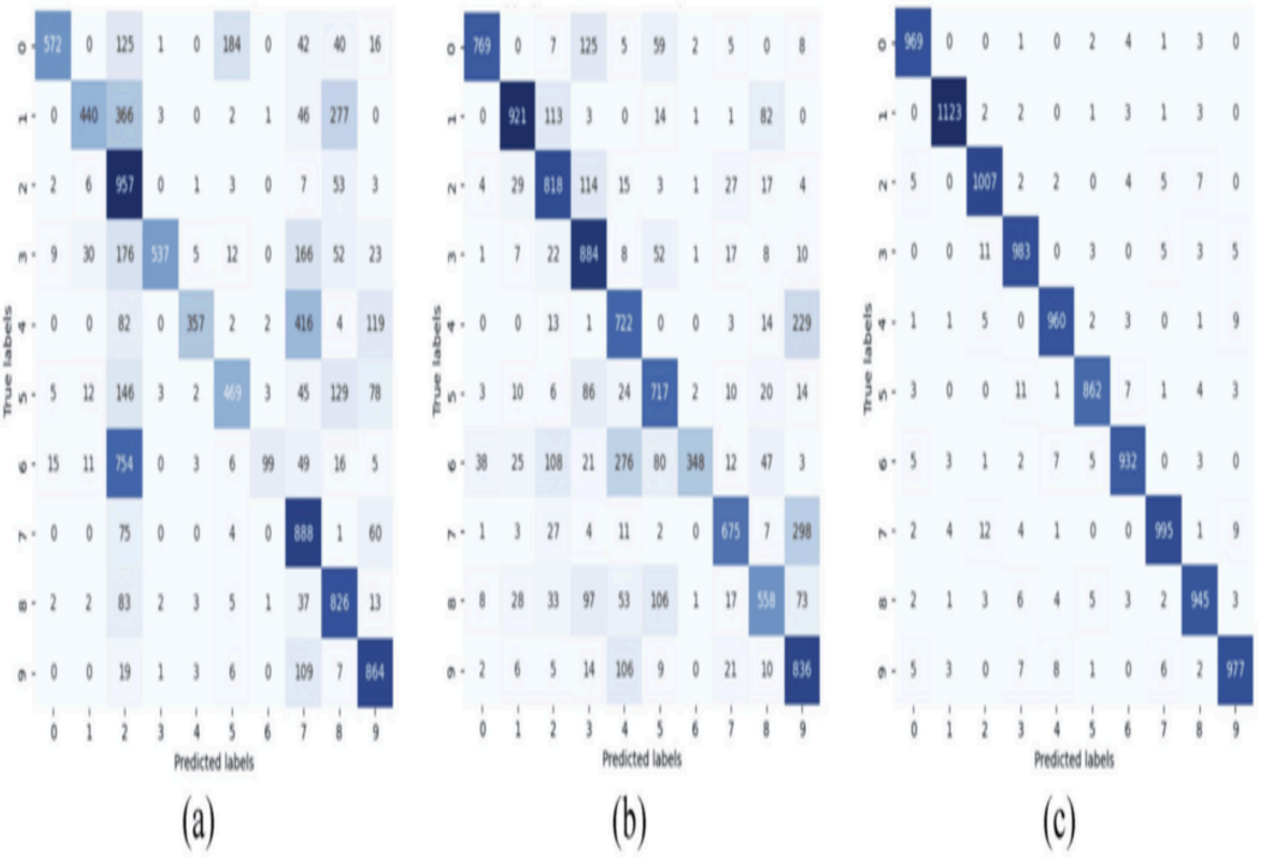
(b)

	0	1	2	3	4	5	6	7	8	9
0	462	0	34	23	8	0	454	0	19	0
1	57	855	10	50	11	0	15	0	2	0
2	4	1	672	35	218	0	47	1	22	0
3	87	6	16	737	32	0	108	10	4	0
4	7	0	146	60	739	0	31	1	16	0
5	4	0	0	38	0	655	0	221	46	36
6	61	1	258	19	215	1	345	0	100	0
7	1	0	0	2	0	2	0	987	6	2
8	3	0	11	50	10	2	13	20	891	0
9	8	0	0	7	0	84	0	336	25	540

(c)

	0	1	2	3	4	5	6	7	8	9
0	860	3	21	16	6	2	84	0	8	0
1	6	960	1	23	4	0	3	0	0	3
2	18	0	845	12	70	0	51	1	3	0
3	28	8	26	877	40	1	17	0	3	0
4	3	1	155	36	749	1	50	0	5	0
5	1	0	0	0	0	973	0	11	2	13
6	165	1	109	27	74	1	617	0	6	0
7	0	0	0	0	0	44	0	948	0	8
8	6	0	11	4	3	5	8	3	960	0
9	2	0	0	0	0	15	1	59	1	922

FIGURE 11: Confusion matrix of the federated learning paradigms (Fashion MNIST): (a) Hierarchical Federated Learning, (b) Aggregated Federated Learning, and (c) Continual Federated Learning.



(a)

	0	1	2	3	4	5	6	7	8	9
0	572	0	125	1	0	184	0	42	40	16
1	0	440	366	3	0	2	1	46	277	0
2	2	6	957	0	1	3	0	7	53	3
3	9	30	176	537	5	12	0	166	52	23
4	0	0	82	0	357	2	2	416	4	119
5	5	12	146	3	2	469	3	45	129	78
6	15	11	754	0	3	6	99	49	16	5
7	0	0	75	0	0	4	0	888	1	60
8	2	2	83	2	3	5	1	37	826	13
9	0	0	19	1	3	6	0	109	7	864

(b)

	0	1	2	3	4	5	6	7	8	9
0	769	0	7	125	5	59	2	5	0	8
1	0	921	113	3	0	14	1	1	82	0
2	4	29	818	114	15	3	1	27	17	4
3	1	7	22	884	8	52	1	17	8	10
4	0	0	13	1	722	0	0	3	14	229
5	3	10	6	86	24	717	2	10	20	14
6	38	25	108	21	276	80	348	12	47	3
7	1	3	27	4	11	2	0	675	7	298
8	8	28	33	97	53	106	1	17	558	73
9	2	6	5	14	106	9	0	21	10	836

(c)

	0	1	2	3	4	5	6	7	8	9
0	969	0	0	1	0	2	4	1	3	0
1	0	1123	2	2	0	1	3	1	3	0
2	5	0	1007	2	2	0	4	5	7	0
3	0	0	11	983	0	3	0	5	3	5
4	1	1	5	0	960	2	3	0	1	9
5	3	0	0	11	1	862	7	1	4	3
6	5	3	1	2	7	5	932	0	3	0
7	2	4	12	4	1	0	0	995	1	9
8	2	1	3	6	4	5	3	2	945	3
9	5	3	0	7	8	1	0	6	2	977

FIGURE 12: Confusion matrix of the federated learning paradigms (MNIST): (a) Hierarchical Federated Learning, (b) Aggregated Federated Learning, and (c) Continual Federated Learning.

Table 2 presents the comparison of performance measures (Precision, Recall, F1 score) obtained from the proposed models.

Environment	Precision (Fashion MNIST)	Recall (Fashion MNIST)	F1 Score (Fashion MNIST)	Accuracy (Fashion MNIST)	Precision (MNIST)	Recall (MNIST)	F1 Score (MNIST)	Accuracy (MNIST)
Hierarchical FL	0.41	0.33	0.4	0.41	0.75	0.6	0.59	0.6
Aggregated FL	0.71	0.68	0.68	0.69	0.76	0.72	0.72	0.72
Continual FL	0.88	0.87	0.86	0.88	0.98	0.98	0.98	0.98

TABLE 2: Comparing the results of different federated learning (FL) environments

Discussion and analysis

This section evaluates the performance of both centralized and DFL strategies. In Table *1*, the lower testing accuracy of HFL (0.41) compared to its training accuracy (0.85) suggests a degree of overfitting at the central server, a common challenge in centralized architectures when dealing with complex datasets like Fashion-MNIST. Our findings demonstrate that DFL approaches, such as AFL and CFL, consistently outperform the centralized approach in terms of accuracy (Figure *13*).

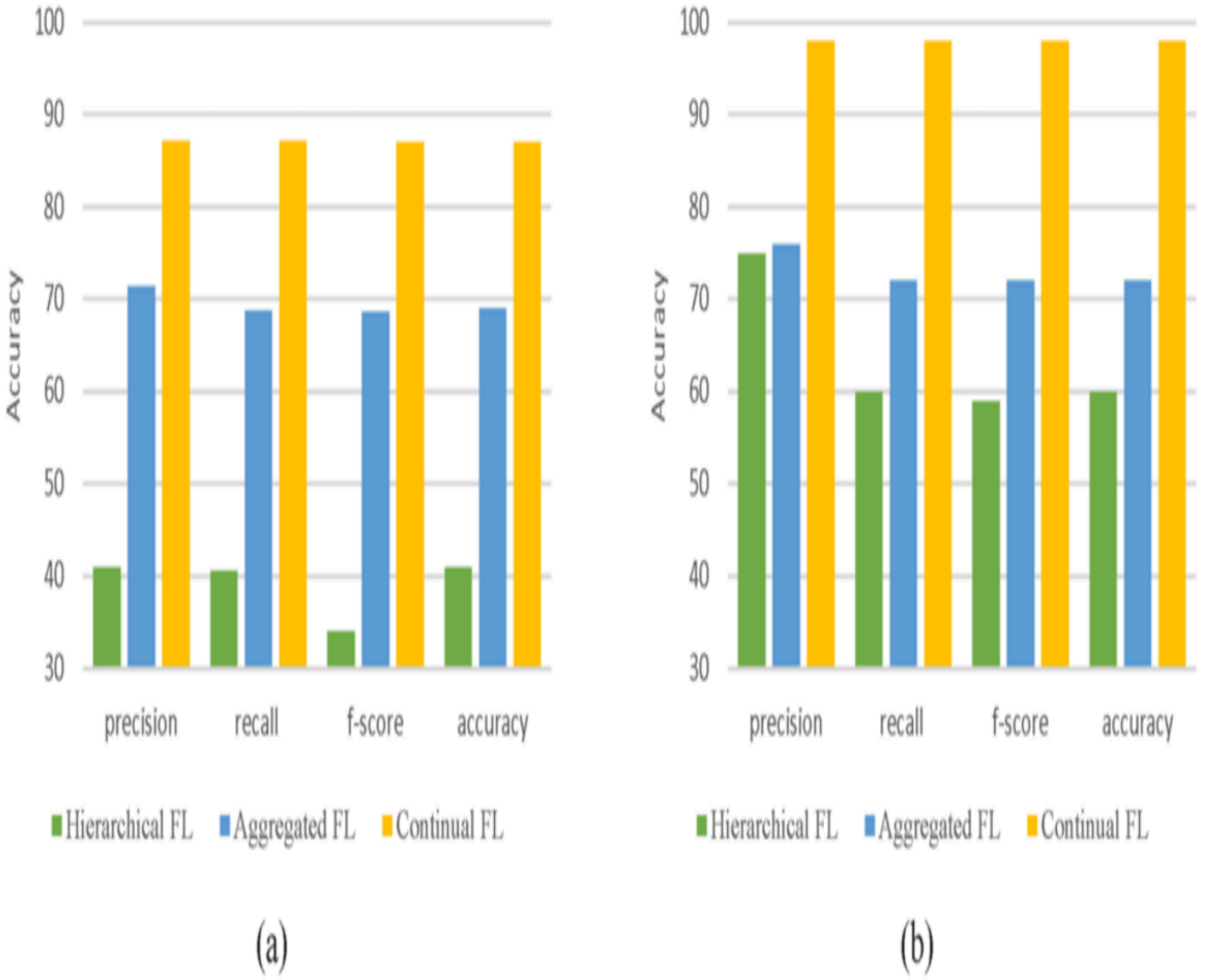
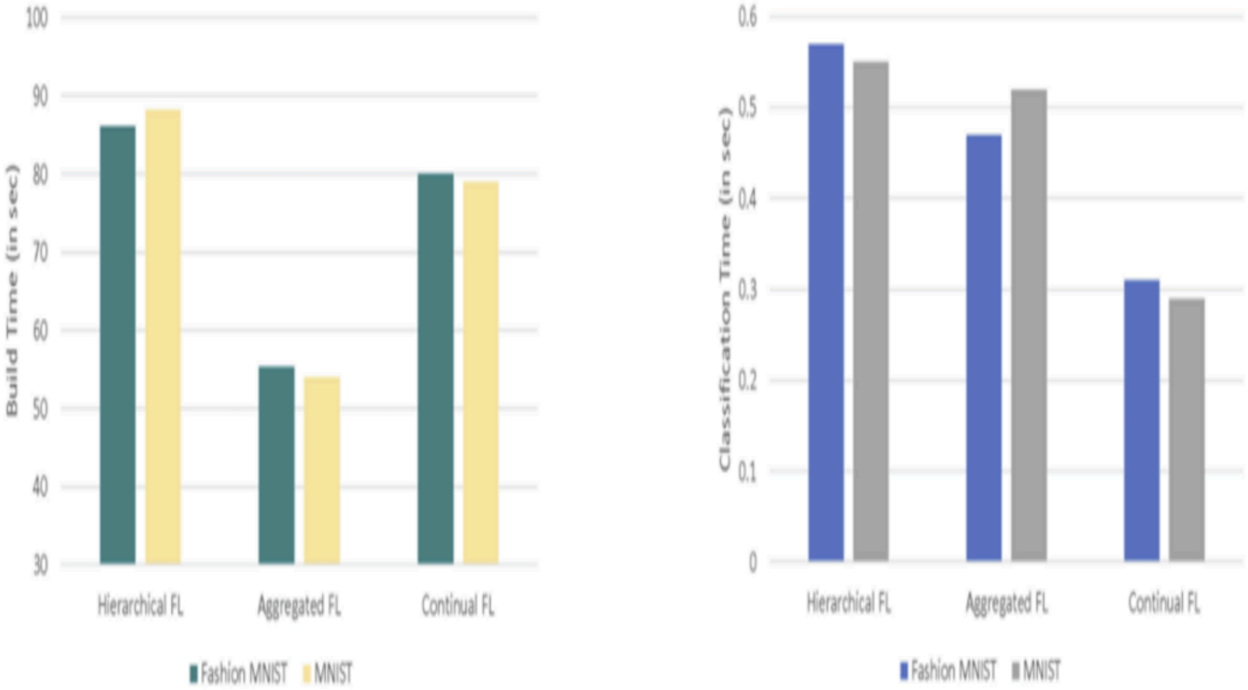


FIGURE 13: Accuracy of federated learning (FL) paradigms on two datasets: (a) Fashion MNIST and (b) MNIST.

In addition, the findings suggest that while AFL demonstrates the shortest build time across both datasets, it comes at the expense of training and testing accuracy compared to CFL. Furthermore, in terms of classification time, CFL showcases a notable advantage over both HFL and AFL (Figure *14*).



(a)

(b)

FIGURE 14: Computational efficiency of federated learning (FL) paradigms: (a) Build Time and (b) Classification Time.

Conclusions

This research examines various FL strategies in private data environments and identifies the decentralized CFL method as exceptionally promising. The experimental results demonstrate that decentralized methodologies, specifically AFL and CFL, consistently outperform the centralized HFL approach in accuracy, precision, and F1 score across both MNIST and Fashion-MNIST datasets. Notably, CFL achieved the highest testing accuracy and a significant reduction in classification time (down to 0.29 s), suggesting that distributing the computational load effectively reduces synchronization delays and model divergence inherent in centralized systems.

The high efficiency and low latency demonstrated by CFL indicate strong viability for real-time applications, such as mobile health diagnostics and autonomous IoT sensors, where data privacy is paramount. Future research should focus on exploring diverse combinations of data distributions and on addressing system heterogeneity to ensure robustness against non-i.i.d data. By transitioning from a single point of failure in HFL to a distributed trust model in AFL and CFL, these decentralized paradigms offer a scalable and resilient framework for the evolving landscape of collaborative model training.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Sumit Chongder

Acquisition, analysis, or interpretation of data: Sumit Chongder

Drafting of the manuscript: Sumit Chongder

Critical review of the manuscript for important intellectual content: Sumit Chongder

Supervision: Sumit Chongder

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Intellectual property info:** The author holds a registered copyright for software code related to this research, issued by the Government of India (Copyright Registration No. SW-19383/2024). The copyrighted software was developed independently as part of academic research. This copyright does not affect the objectivity of the research, and no commercial exploitation, licensing, or financial benefit related to this work has occurred. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The data and program code supporting this study are openly available in the GitHub repository {REPOSITORY: GitHub} at {DOI/URL: https://github.com/Sumitchongder/Evaluation-Framework-for-Centralized-and-Decentralized-Aggregation-Algorithms-in-Federated-Systems}. A preprint version of this manuscript is openly available in the arXiv repository {REPOSITORY: arXiv} at {DOI/URL: https://arxiv.org/abs/2512.10987}, reference {ACCESSION ID: arXiv:2512.10987}.

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The author declares that this research was conducted independently as a self-driven project. No academic supervisor, guide, or institutional mentorship was involved in the conception, execution, analysis, or writing of this work.

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