FedFed: Feature Distillation against Data Heterogeneity in Federated Learning

Zhiqin Yang et al, NeurIPS 2023[1]

Presented by:

Souvik Sarkar
Department of Computer Science and Engineering
IIT Hyderabad

Guided by
Prof. C Krishna Mohan

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Content

Introduction of Federated Learning

Federated Learning is a decentralized machine learning approach where models are trained on multiple devices or servers without sharing data.

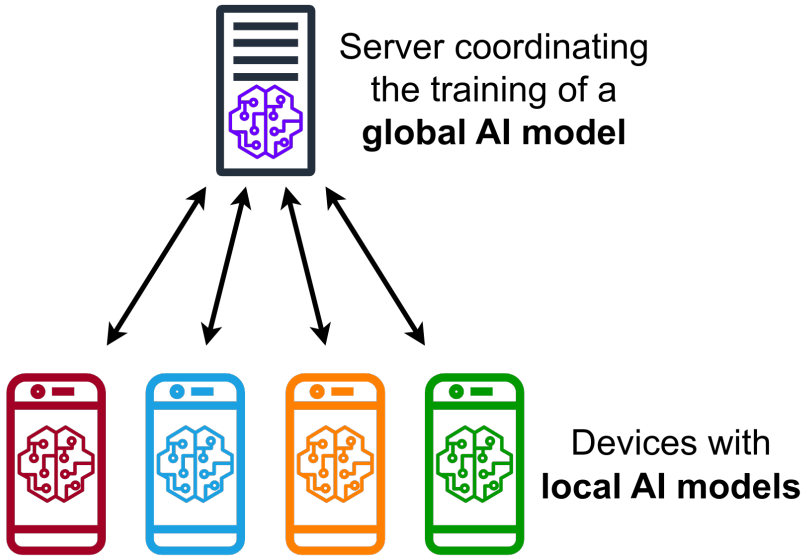


Figure 1: FL architecture

Introduction of FL

Global Objective

Minimize $L(\phi)$ over all clients' data distributions:

$$\min_{\phi} L(\phi) = \sum_{k=1}^{K} \lambda_k L_k(\phi_k)$$

Local Objective for Client k

$$L_k(\phi_k) = \mathbb{E}_{(x,y)\sim P(X_k,Y_k)} \left[\ell(\phi_k; x, y)\right]$$

Data remains local on clients; models are trained on private data, then aggregated.

Motivation - Importance of FL

- **Data Privacy Preservation**
  - Sensitive data (e.g., healthcare, financial) stays on local devices, reducing privacy risks.
- **Reducing Centralized Data Storage Costs**
  - Removes the need to centralize large datasets, reducing infrastructure and storage costs.
- **Scalability**
  - FL allows for distributed training across a large number of devices, improving scalability.
- **Security and Robustness**
  - FL can mitigate risks of a single point of failure compared to centralized models.

Motivation - Challeneges in FL

- **Data Privacy**
  - Data stays local, but updates may leak sensitive information.
- **Communication Overhead**
  - Frequent device-server communication leads to high bandwidth usage.
- **Heterogeneity**
  - **Data Heterogeneity :** Data on devices is often non-identically distributed (Non-IID), causing model bias.
  - **Device Heterogeneity :** Devices have varying computational capabilities, affecting model training speed.
- **Security Threats**
  - Vulnerable to adversarial attacks like model poisoning.

Problem Statement

Challenge:

- Federated Learning (FL) faces **data heterogeneity**, i.e., distribution shifting among clients.

Dilemma:

- **Sharing client information** helps mitigate heterogeneity, but it risks compromising privacy while aiming to improve model performance.

Key Question:

- Is it possible to share only **partial features** to address data heterogeneity while preserving privacy?

Proposed Solution

Proposed Solution: Federated Feature Distillation (FedFed)

- **Partition data** into:
  - **Performance-sensitive features:** Greatly contribute to model performance (shared globally).
  - **Performance-robust features:** Limited contribution to model performance (kept locally).
- Clients train models on both local and shared data to balance privacy and performance.

Challenges

- **Goal**: Efficiently share minimal information between clients while retaining **privacy**.
- **Challenges**:
  - How to divide data into **performance-sensitive** and **performance-robust** features.
  - Preserve local **private data** without hindering global model performance.

Methodology - FedFed Overview

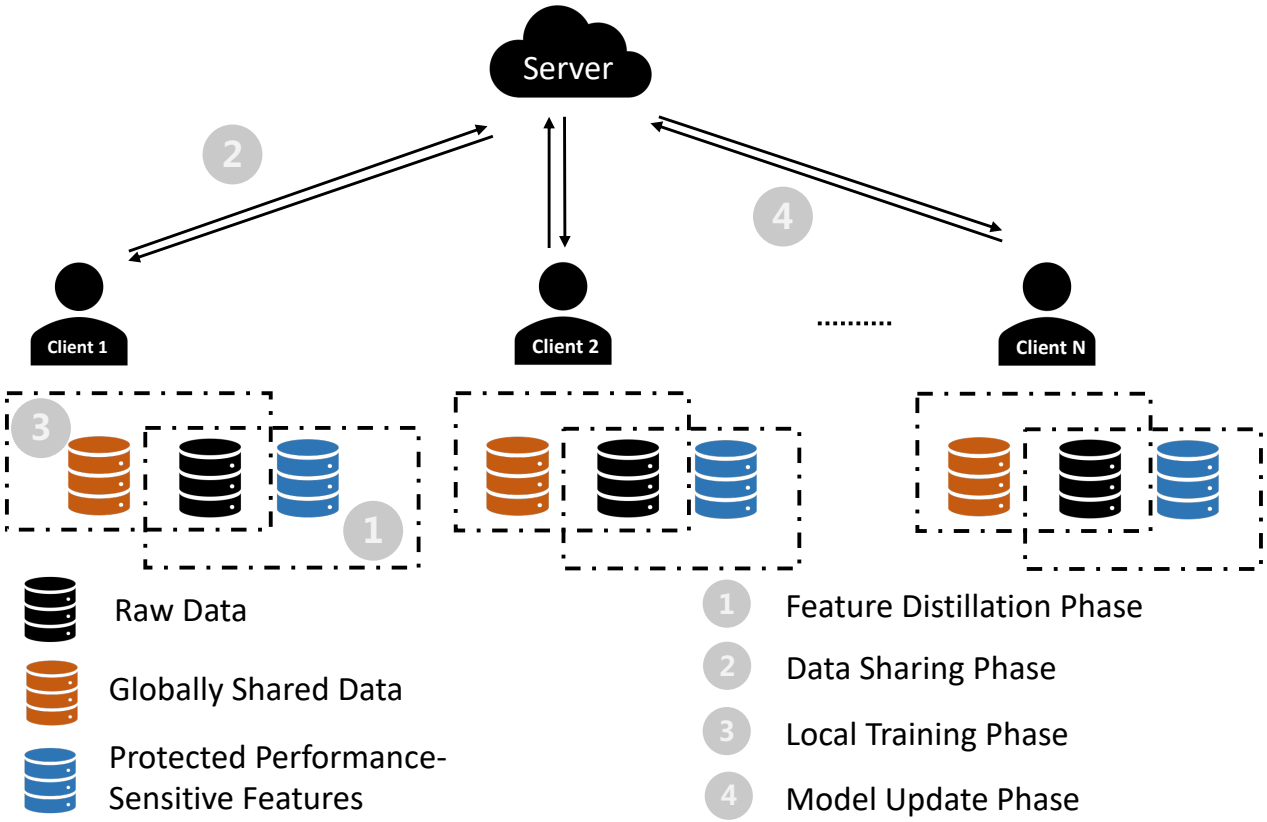
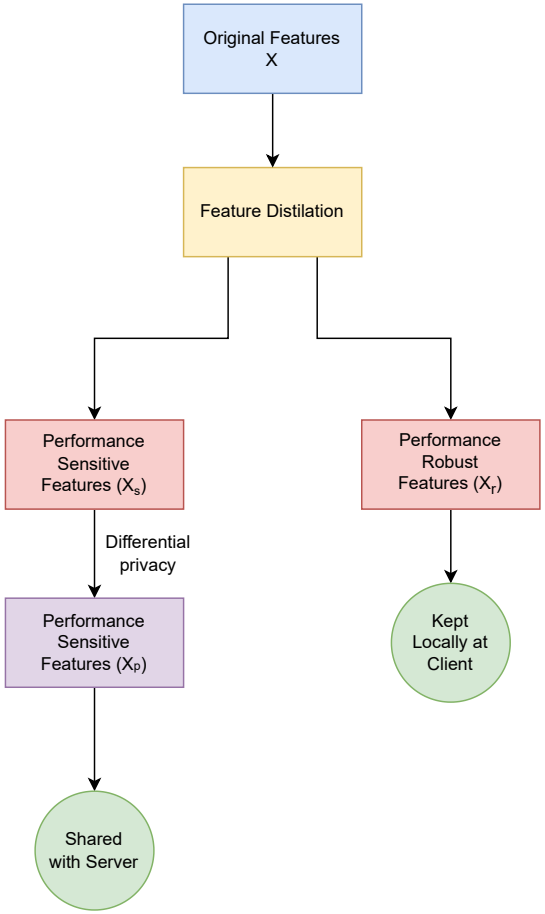


Figure 2: FedFed overview

Methodology - FedFed Overview



Methodology - Partitions

Definition : (Valid Partition)

A partition strategy is a method to partition a variable X into two parts in the same measure space such that $X = X_1 + X_2$. This strategy is valid if it satisfies:

(i) $H(X_1, X_2 \mid X) = 0$

(ii) $H(X \mid X_1, X_2) = 0$

(iii) $I(X_1; X_2) = 0$

where $H(\cdot)$ denotes the information entropy and $I(\cdot)$ denotes the mutual information.

Methodology - Partitions

Definition : (Performance-sensitive and Performance-robust Features)

Let $X = X_s + X_r$ be a valid partition strategy. We define:

- X_s as **performance-sensitive features** such that $I(X; Y \mid X_s) = 0$, where Y is the label of X.
- X_r as **performance-robust features**.

Methodology - Information Bottleneck

To divide the Features in two Partitions Authors takes inspiration from the **Information Bottleneck (IB)** Method [2].

- **Goal**: Compress input X while retaining information relevant to the output Y.

Objective :

$$L_{IB} = I(X;Y|Z), \quad \text{s.t.} \quad I(X;Z) \leq I_{IB}$$

- **Z**: Latent embedding that captures essential information.
- **IB's Goal**: Minimize mutual information between X and Y, while compressing X.

Methodology - Feature Distillation in FedFed

- **Goal**: Partition data features into:
  - **Performance-sensitive**: Essential for model performance.
  - **Performance-robust**: Retain private data information but not crucial for performance.

Objective :

$$\min_{Z} I(X;Y|Z), \text{ s.t. } I(X;X-Z|Z) \geq I_{FF}$$

- $X - Z$: Performance-robust features.
- Z: Performance-sensitive features for prediction.

Methodology - IB vs FedFed

- **FedFed**:
  - Aims to make the dismissed features (performance-robust features) **similar** to the original private data.
- **Information Bottleneck (IB)**:
  - Aims to make the preserved features (performance-sensitive features) as **dissimilar** as possible from the original data.
- **Information Dismissal:**
  - FedFed dismisses information directly in the **data space**.
  - IB works in the **representation space** (latent space).

Methodology - FedFed

In this context, the goal is to make the feature distillation process computationally feasible , The new objective function is derived for **client k** :

Objective :

$$\min_{\theta} -\mathbb{E}_{(x,y)\sim P(X_k,Y_k)} \log p(y|x - q(x;\theta)), \quad \text{s.t.} \quad ||x - q(x;\theta)||_2^2 \leq \rho$$

- $\boldsymbol{q(x;\theta)}$: is a generative model produces performance-robust features.
- $\boldsymbol{z(x;\theta) \equiv x - q(x;\theta)}$: represents performance-sensitive features.
- $\boldsymbol{\rho}$: is a hyperparameter that keep performance-sensitive features size bounded.

Methodology - FedFed

Objective : [3] [4]

$$\min_{\theta, w_k} -\mathbb{E}_{(x,y)\sim P(X_k,Y_k)} \ell(f(x - q(x;\theta); w_k), y), \text{ s.t. } \|z(x;\theta)\|_2^2 \leq \rho$$

- $\boldsymbol{f(\cdot; w_k)}$: is Local classifier trained on performance sensitive features to predict. labels.
- $\boldsymbol{\ell(\cdot)}$: is cross entropy loss between predicted label and the actual label.

Methodology - Differential Privacy

Motivation:

- Performance-sensitive features may contain private data.
- Differential Privacy (DP) is introduced to protect these features from privacy attacks, adversarial threats.

Noise Addition:

- Gaussian noise is added :

$$x_r + n, \quad n \sim \mathcal{N}(0, \sigma_r^2 I), \quad x_s + n, \quad n \sim \mathcal{N}(0, \sigma_s^2 I)$$

Training with DP:

- Clients train local models with private and shared data:

$$\min E(x, y) \sim P(X_k, Y_k)\ell(f(x; \varphi_k), y) +$$
$$E(x_p, y) \sim P(h(X_k), Y_k)\ell(f(x_p; \varphi_k), y)$$

- Shared features x_p protect privacy while enabling global model training.

Methodology

Algorithm 1 Feature Distillation

Server input: communication round T_d, DP noise level σ_s^2

Client k**'s input:** local epochs of feature distillation E_d, k-th local dataset $\mathcal{D}^k$ and rescale to $[0, 1]$

Initialization: server distributes the initial model $\mathbf{w}^0, \theta^0$ to all clients

Server Executes:

for each round $t = 1, 2, \cdots, T_d$ **do**

server samples a subset of clients $C_t \subseteq \{1, ..., K\}$,

server **communicates** $\mathbf{w}^t, \theta^t$ to selected clients

for each client $k \in C_t$ **in parallel do**

$\mathbf{w}_k^{t+1}, \theta_k^{t+1} \leftarrow$ Local_FeatDis $(\mathbf{w}^t, \theta^t, \sigma_s^2)$

end for

$\mathbf{w}^{t+1}, \theta^{t+1} \leftarrow$ AGG $(\mathbf{w}_k^t, \theta_k^t, k \in C_t)$

end for

$\mathcal{D}^s = \{\mathcal{D}_k^s\}_{k=1}^K \leftarrow$Collecting $\mathbf{x}_p$ generated by k-th client use Eq (9), where $\mathbf{x}_p = \mathbf{x}_s + \mathbf{n}$

Local_FeatDis($\mathbf{w}^t, \theta^t, \sigma_s^2$):

for each local epoch e with $e = 1, \cdots, E_d$ **do**

$\mathbf{w}_k^{t+1}, \theta_k^{t+1} \leftarrow$ SGD update use Eq (9).

end for

Return $\mathbf{w}_k^{t+1}, \theta_k^{t+1}$ to server

Methodology - FedFed Pipeline

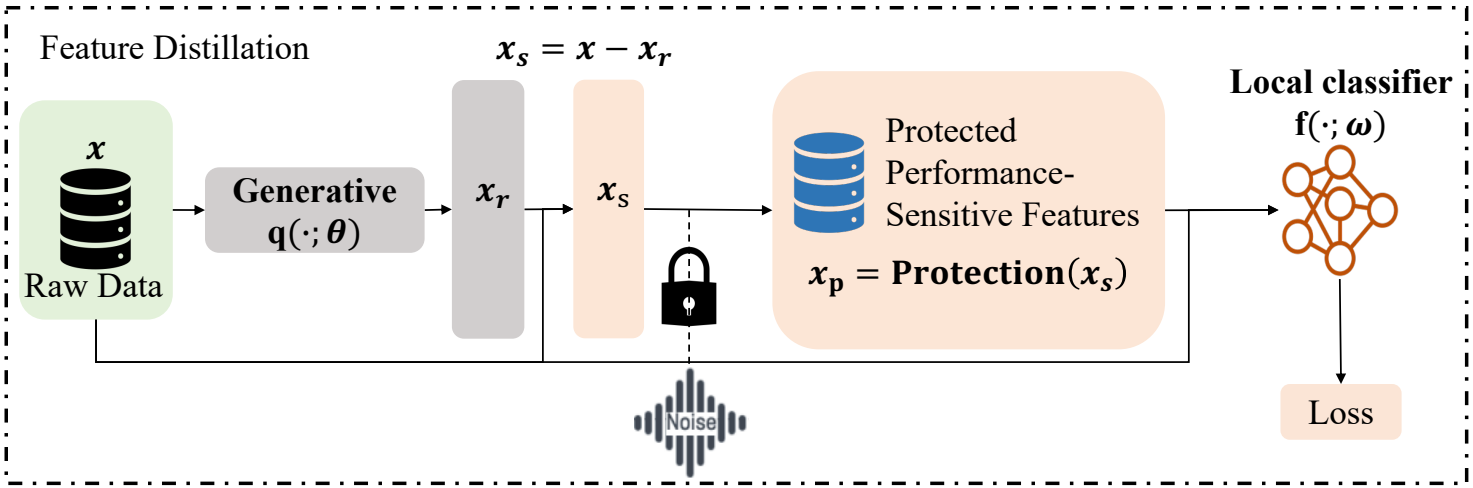


Figure 4: FedFed pipeline

Experimental setup

Models Used:

- ResNet-18: Utilized for feature distillation and classifier.
- β-VAE: Encoder-decoder structure for generating performance-robust features.

Federated Learning Algorithms:

- FedAvg, FedProx, SCAFFOLD, FedNova

Datasets:

- CIFAR-10, CIFAR-100
- Fashion-MNIST (FMNIST)
- SVHN

Experimental Setup

Data Partitioning:

- Dirichlet : Non-IID distribution ($\alpha = 0.1, 0.05$).

Hyperparameters:

- α (Dirichlet Parameter): 0.1, 0.05.
- K (Number of Clients): 10, 100.
- E_d (Local Epochs for Feature Distillation): 1, 5.
- T_d (Communication Rounds): Varied based on experiments.
- ρ (DP Strength Parameter): Adjusted for privacy vs accuracy tradeoff.
- σ_s^2 (DP Noise Level): For privacy protection.

Results

	centralized training ACC = 75.56% w/(w/o) **FedFed**							
	ACC↑	Gain↑	Round ↓	Speedup↑	ACC↑	Gain↑	Round ↓	Speedup↑
	$\alpha = 0.1, E = 1, K = 10$ (Target ACC =67%)				$\alpha = 0.05, E = 1, K = 10$ (Target ACC =61%)			
FedAvg	**69.64**(67.84)	1.8↑	**283**(495)	×**1.7** (×1.0)	**68.49**(62.01)	6.48↑	**137**(503)	×**3.7**(×1.0)
FedProx	**70.02**(65.34)	4.68 ↑	**233**(None)	×**2.1**(None)	**69.03**(61.29)	7.74↑	**141**(485)	×**3.6**(1.0)
SCAFFOLD	**70.14**(67.23)	2.91↑	**198**(769)	×**2.5**(× 0.6)	**69.32**(58.78)	10.54↑	**81**(None)	×**6.2**(None)
FedNova	**70.48**(67.98)	2.5↑	**147**(432)	×**3.4**(×1.1)	**68.92**(60.53)	8.39↑	**87**(None)	×**5.8**(None)
	$\alpha = 0.1, E = 5, K = 10$ (Target ACC =69%)				$\alpha = 0.1, E = 1, K = 100$ (Target ACC =48%)			
FedAvg	**70.96**(69.34)	1.62↑	**79**(276)	×**3.5**(×1.0)	**60.58**(48.21)	12.37↑	**448**(967)	×**2.2**(×1.0)
FedProx	**69.66**(62.32)	7.34↑	**285**(None)	×**1.0**(None)	**67.69**(48.78)	18.91↑	**200**(932)	×**4.8**(×1.0)
SCAFFOLD	**70.76**(70.23)	0.53↑	**108**(174)	×**2.6**(×1.6)	**66.67**(51.03)	15.64↑	**181**(832)	×**5.3**(×1.2)
FedNova	**69.98**(69.78)	0.2↑	**89**(290)	×**3.1**(×1.0)	**67.62**(48.03)	19.59↑	**198**(976)	×**4.9**(×1.0)

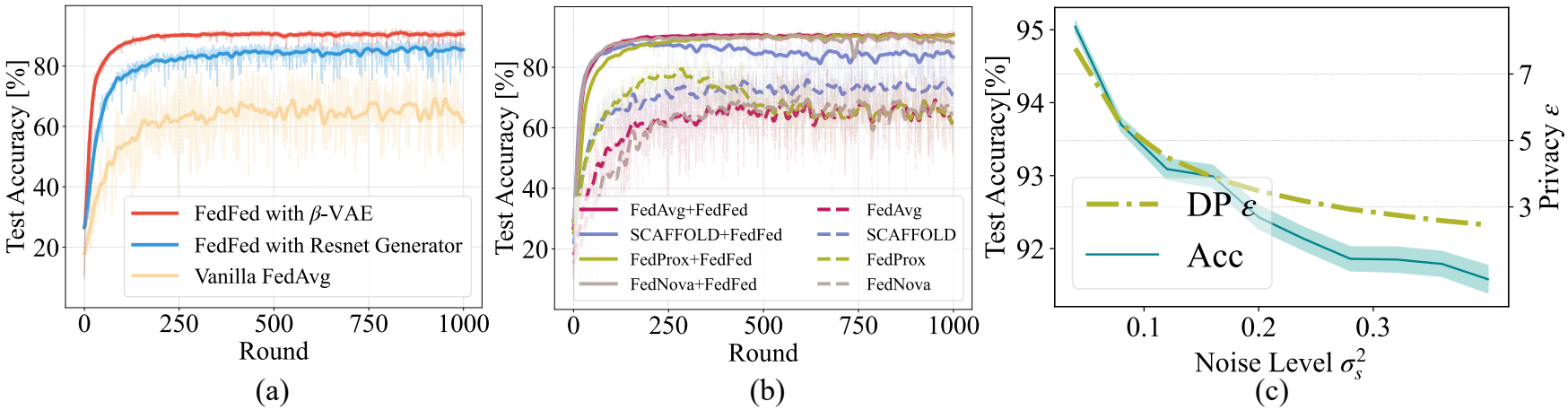
Figure 5: CIFAR-100 results

Results

	centralized training ACC = 96.56% w/(w/o) **FedFed**							
	ACC↑	Gain↑	Round ↓	Speedup↑	ACC↑	Gain↑	Round ↓	Speedup↑
	$\alpha = 0.1, E = 1, K = 10$ (Target ACC =88%)				$\alpha = 0.05, E = 1, K = 10$ (Target ACC =82%)			
FedAvg	**93.21**(88.34)	4.87↑	**105**(264)	×**2.5**(×1.0)	**93.49**(82.76)	10.73↑	**194**(365)	×**1.9**(×1.0)
FedProx	**91.80**(86.23)	5.574↑	**233**(None)	×**1.1**(None)	**93.21**(79.43)	13.78↑	**37**(None)	×**9.9**(None)
SCAFFOLD	**88.41**(80.12)	8.29↑	**357**(None)	×**0.**(None)	**90.27**(75.87)	14.4↑	**64**(None)	×**5.7**(None)
FedNova	**92.98**(89.23)	3.75↑	**113**(276)	×**2.3**(×1.0)	**93.05**(82.32)	10.73↑	**37**(731)	×**9.9**(×0.5)
	$\alpha = 0.1, E = 5, K = 10$ (Target ACC =87%)				$\alpha = 0.1, E = 1, K = 100$ (Target ACC =89%)			
FedAvg	**93.77**(87.24)	6.53↑	**105**(128)	×**1.2**(×1.0)	**91.04**(89.32)	1.72↑	**763**(623)	×0.8(×**1.0**)
FedProx	**91.15**(77.21)	13.94↑	**142**(None)	×**0.9**(None)	**91.41**(88.76)	2.65↑	**733**(645)	×0.8(×**1.0**)
SCAFFOLD	**93.78**(80.98)	12.8↑	**20**(None)	×**6.4**(None)	**92.73**(88.32)	4.41↑	**507**(687)	×**1.2**(×0.9)
FedNova	**93.66**(89.03)	4.63↑	**52**(177)	×**2.5**(×0.7)	**84.05**(81.87)	2.18↑	None(None)	None(None)

Figure 6: SVHN results

Results



(a) Convergence rate of different generative models compared with vanilla FedAvg.
(b) Test accuracy and convergence rate on different federated learning algorithms with or without FedFed under α= 0.1, E = 1, K = 100.
(c) Test accuracy on FMNIST with different noise level σ_s^2.

Our Experimental setup

Model used : ResNet-18 and β-VAE
FL Algorithms used : FedAvg
Data Partitioning:

- Dirichlet : Non-IID distribution ($\alpha = 0.1$).

Hyperparameters:

- α (Dirichlet Parameter): 0.1.
- K (Number of Clients): 10.
- E_d (Local Epochs for Feature Distillation): 1.
- T_d (Communication Rounds): 1000.
- σ_s^2 (DP Noise Level): 0.2 and 0.25.

Our Results : CIFAR-10

Client	Accuracy	Loss
Client 0	53.54	3.48
Client 1	84.11	5.56
Client 2	52.68	2.72
Client 3	59.54	4.57
Client 4	63.75	2.98
Client 5	71.22	2.09
Client 6	48.89	3.11
Client 7	67.34	2.37
Client 8	75.88	8.60
Client 9	65.93	2.61

Table 1: Client Accuracy and Loss Metrics for CIFAR-10 Dataset

Metric	Value
Server Test Accuracy	88.40
Server Total Accuracy	88.52
Server Total Loss	0.38
VAE Server Test Acc	24.75
VAE Server Total Acc	24.70
VAE Server Total Loss	N/A

Table 2: Server Metrics for CIFAR-10 Dataset (Epoch 0)

Our Result : CIFAR-10

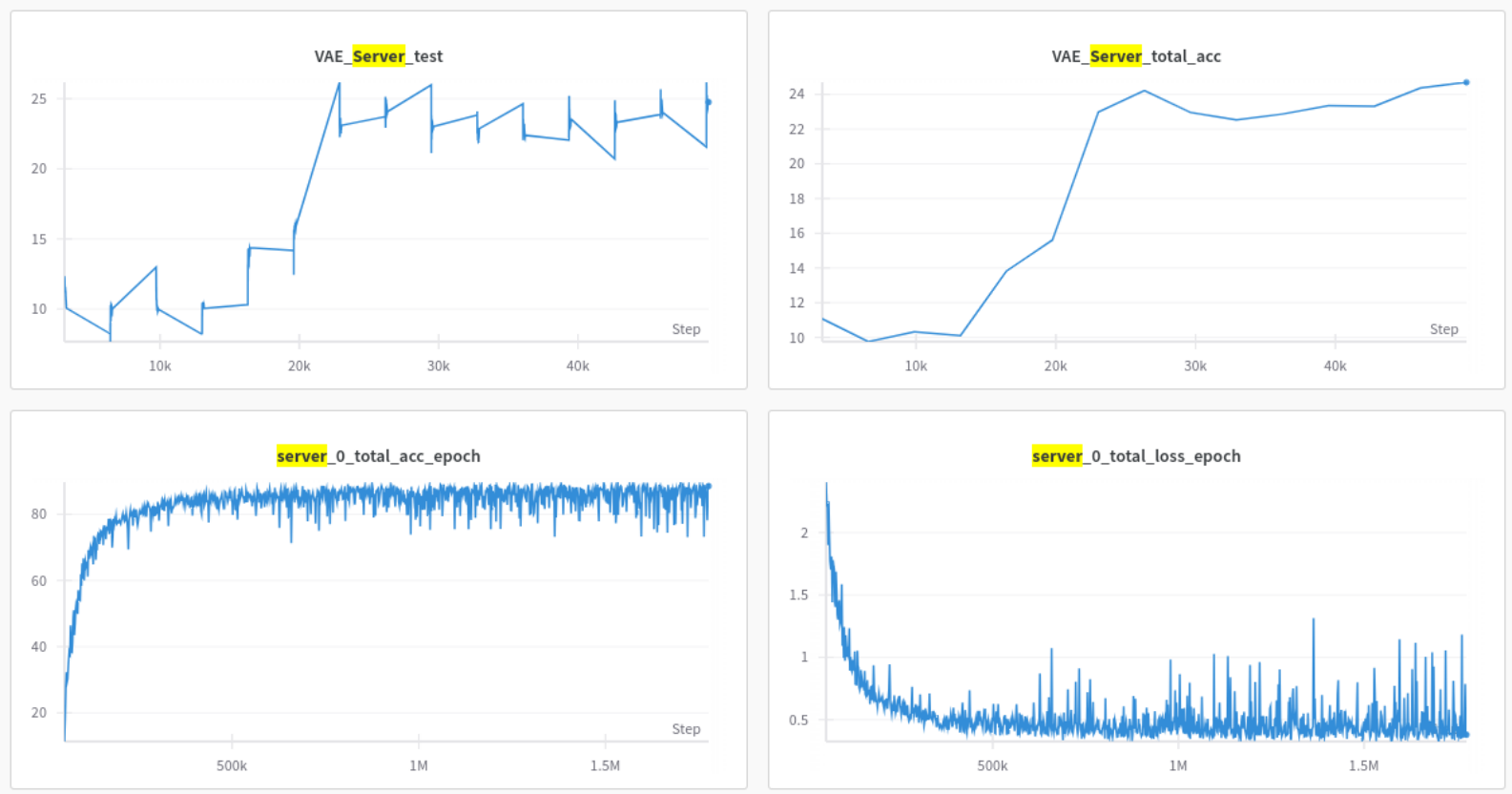


Figure 7: CIFAR-10

Result Comparison :

Metric	Paper's	Our's
Server Test Accuracy	89.17%	88.52%

Table 3: Server Metrics Comparison of CIFAR-10 Dataset

Possible Reason :

- Random initialization of the model parameters can lead to variations in performance.

PathMNIST Dataset Overview

- **Domain**: Biomedical Histopathology (CAMELYON16 dataset)
- **Image Details**:
  - Size: **28x28** (resizable, e.g., to **32x32**)
  - Channels: **Grayscale** (single channel)
- **Classes**: **9 types of tissues** (e.g., tumor, stroma, mucosa)
- **Data Splits**:
  - Training (**89,996**), Validation (**10,004**), Test (**7,180**)
- **Task**: Multi-class tissue classification

Our Results : PathMNIST

Client	Accuracy	Loss
Client 0	62.56	1.65
Client 1	0.00	7.02
Client 2	100.00	1.29
Client 3	91.20	3.24
Client 4	73.10	6.56
Client 5	68.01	1.39
Client 6	58.17	1.84
Client 7	43.96	2.50
Client 8	47.11	2.30
Client 9	80.07	8.68

Table 4: Client Accuracy and Loss Metrics for PathMNIST Dataset

Metric	Value
Server Test Accuracy	28.13
Server Total Accuracy	28.52
Server Total Loss	6.65
VAE Server Test Acc	11.99
VAE Server Total Acc	12.32
VAE Server Total Loss	N/A

Table 5: Server and VAE Metrics for PathMNIST Dataset (Epoch 0)

Our Result : PathMNIST

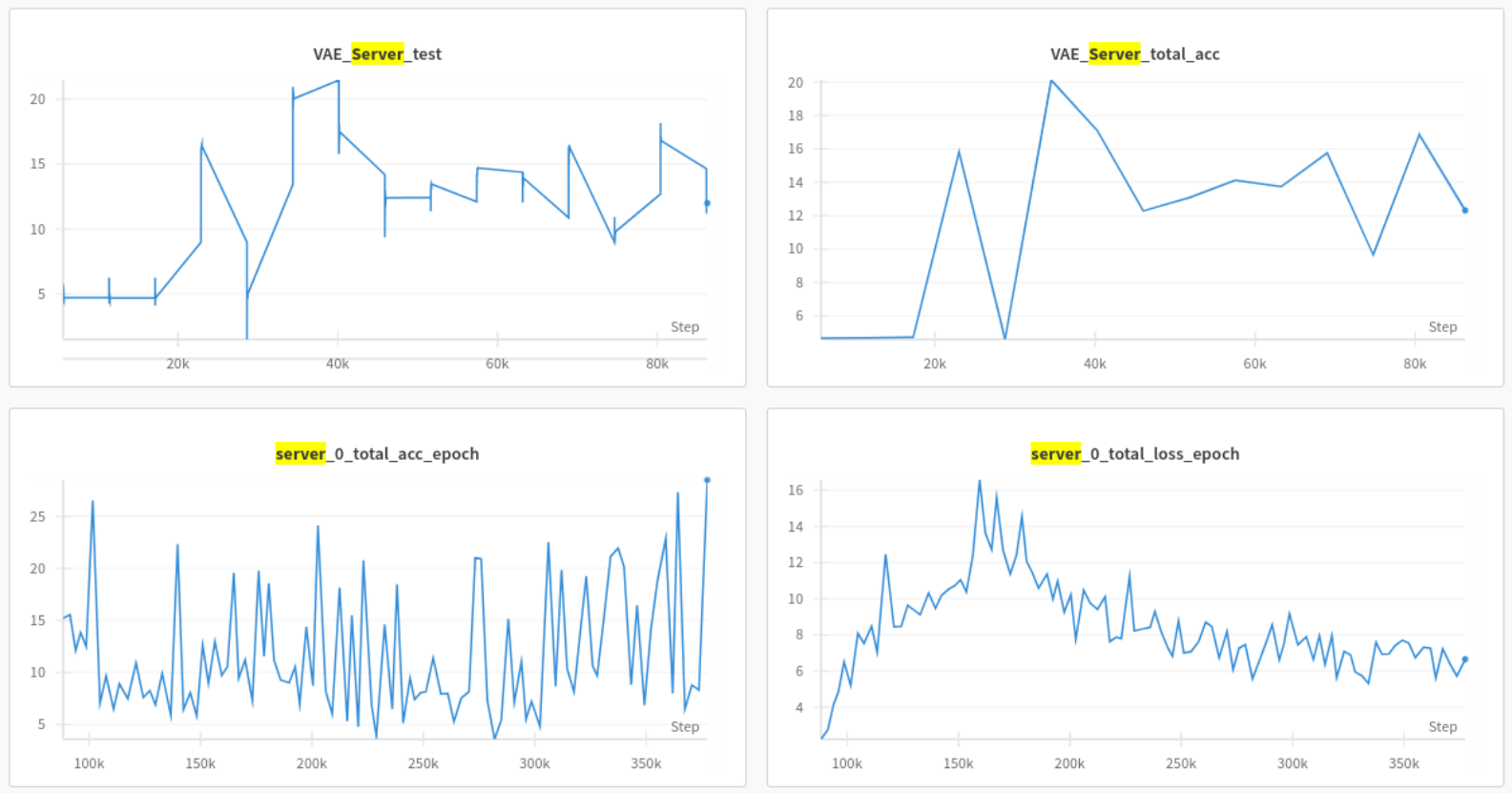


Figure 8: PathMNIST

Comparison

Metric	CIFAR-10	PathMNIST
Client Metrics		
Average Accuracy	66.92%	63.91%
Best Accuracy	84.11%	100.00%
Worst Accuracy	48.89%	0.00%
Average Loss	3.94	3.57
Best Loss	2.09	0.49
Worst Loss	8.60	9.16
Server Metrics		
Server Test Accuracy	77.88%	28.13%
Server Total Accuracy	78.08%	28.52%
Server Total Loss	0.65	6.65
VAE Metrics		
VAE Server Test Accuracy	24.75%	11.99%
VAE Server Total Accuracy	24.70%	12.32%

Comparison

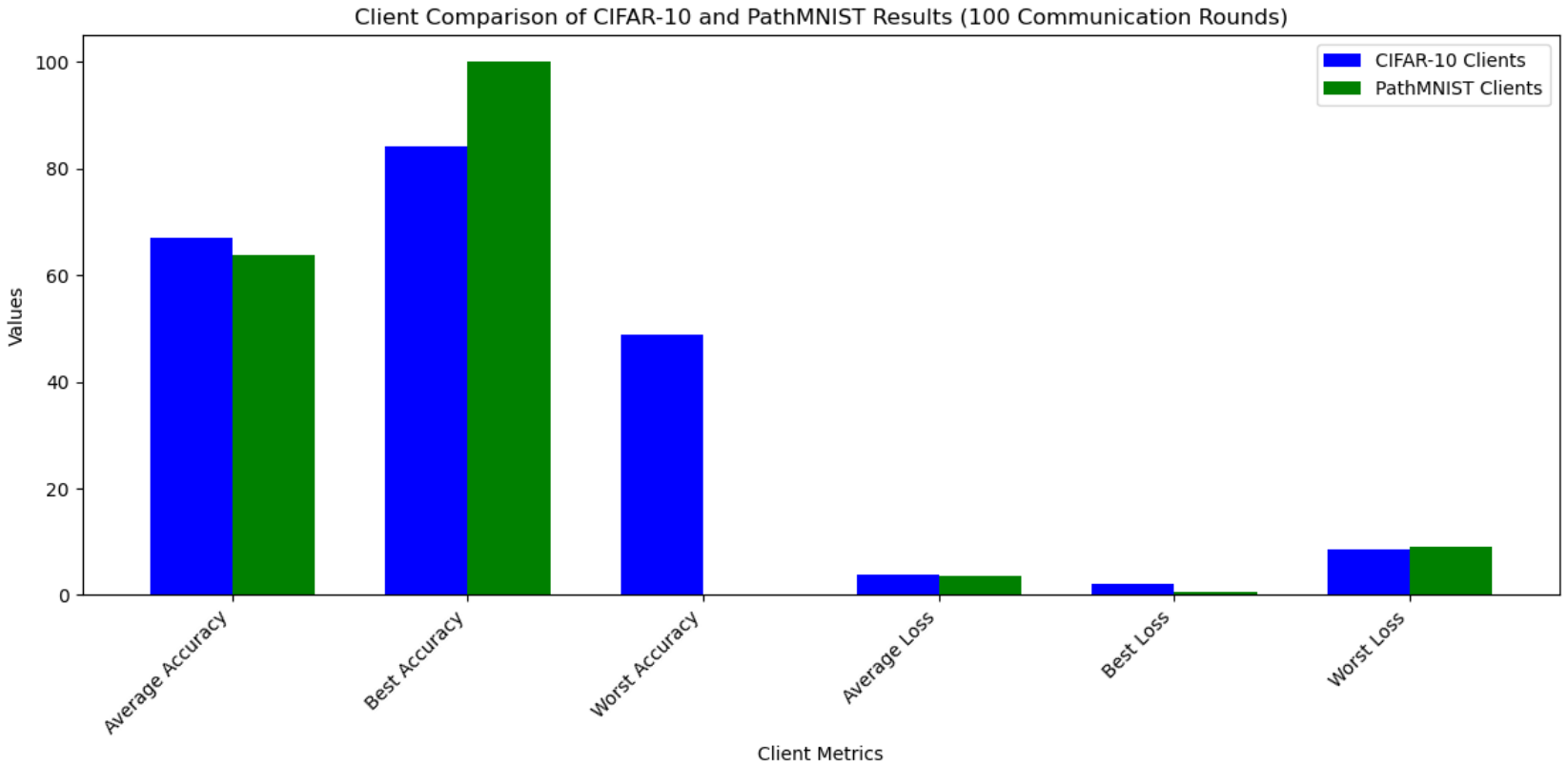


Figure 9: CIFAR-10 vs PathMNIST

Comparison

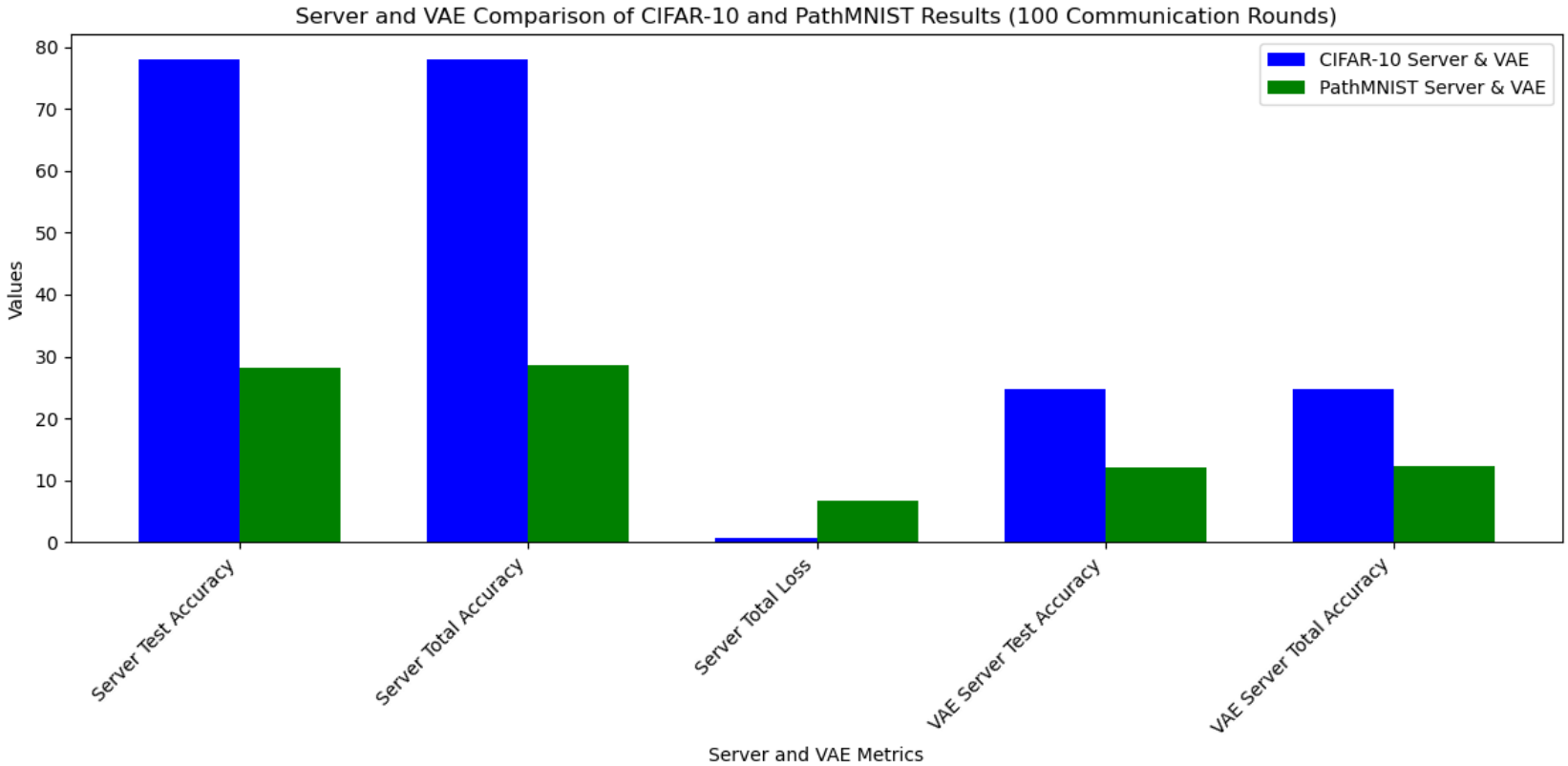


Figure 10: CIFAR-10 vs PathMNIST

Comparison

Figure 11: CIFAR-10 vs PathMNIST

Observation :

Key observations :

- According to our observation for CIFAR-10 FedFed shows better consistency and higher server performance than PathMNIST.
- FedFed has high variability in client performance for PathMNIST.
- Server accuracy for FedFed on CIFAR-10 is significantly higher (77.88%) compared to PathMNIST (28.13%).
- In VAE accuracy for CIFAR-10 slightly better than PathMNIST.

Observation :

Possible reasons for the low accuracy on PathMNIST:

- **Data Complexity:** Medical images have subtle features, making classification harder.
- **Architectural Problem :**
  - **Data Partitioning :** May be the current model is struggling to Partition the data into Performance sensitive and Performance robust feature.
  - **Generation of Latent Embedding :** May be the generated embeddings are not good which is reducing the model's performance.
  - **Model Aggregation :** May be the current aggregation method is not suitable for medical images.

These are the most probable reasons for which the model's performance is significantly degraded.

Comparison : FedAVG and FedProx

Metric	FedAvg	FedProx
Server Test Accuracy	28.13%	26.69%
Server Total Accuracy	28.52%	27.09%
Server Total Loss	6.65	10.38

Table 6: Server Metrics Comparison of FedAvg and FedProx on PathMNIST Dataset

Comparison : FedAVG and FedProx

Figure 12: FedAvg vs FedProx on PathMNIST

Future work & Novelty

Future work :

- **Identify the root cause :** More testing is needed on different Medical datasets to determine the main reason for low accuracy.
- **Explore new Techniques :** Identifying new efficient techniques for partitioning data, creating Latent embeddings, and aggregating models.
- **Fine-tuning Hyper-parameters :** Optimize learning rate, batch size, and model parameters for medical datasets by tuning hyper parameters.
- **Model Improvement for Medical Datasets :** Modify the current model architectures specifically tailored for complex medical image analysis, such as MedMNIST datasets.

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Thank You!

Questions?