Visual Computing(CS6450)

Project Report

FedFed: Feature Distillation against Data Heterogeneity in Federated Learning

Zhiqin Yang et al, NeurIPS 2023 [1]

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November 24, 2024

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1 Introduction

Federated Learning (FL) is a decentralized machine learning approach where models are trained on multiple devices or servers without sharing data. This ensures data privacy and reduces the risk of data leakage. The FL approach is particularly useful for domains involving sensitive data, such as healthcare and finance.

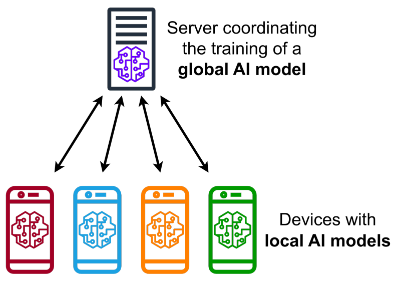

Server coordinating the training of a **global AI model**
Devices with **local AI models**

Figure 1: FL architecture

1.1 Global and Local Objectives

The objective of FL can be divided into global and local perspectives:

- **Global Objective:** Minimize the loss function $L(\phi)$ over all clients' data distributions:

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

- **Local Objective for Client** k:

$$L_k(\phi_k) = E_{(x,y)\sim P(X_k,Y_k)} \left[\ell(\phi_k; x, y)\right] \tag{2}$$

In FL, data remains local on the clients, and models are trained on this private data before being aggregated at the central server.

2 Motivation

2.1 Importance of Federated Learning

The importance of FL can be summarized as follows:

- **Data Privacy Preservation:** Sensitive data (e.g., healthcare, financial) remains 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 many devices, improving scalability.
- **Security and Robustness:** FL can mitigate risks of a single point of failure compared to centralized models.

2.2 Challenges in Federated Learning

Federated learning also poses several challenges:

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

3 Problem Statement

Federated Learning faces significant challenges due to data heterogeneity, specifically distribution shifting among clients. Sharing client information can mitigate this issue, but doing so risks compromising privacy. Therefore, the key question is whether it is possible to share only partial features to address data heterogeneity while preserving privacy.

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?

4 Proposed Solution

4.1 Federated Feature Distillation (FedFed)

FedFed proposes to partition the data into two categories:

- **Performance-sensitive features:** These features contribute significantly to model performance and are shared globally.
- **Performance-robust features:** These features have limited contribution to model performance and are kept locally.

Clients train models on both local and shared data, striking a balance between privacy and performance.

5 Challenges

5.1 Partitioning Data

The goal of FedFed is to efficiently share minimal information between clients while retaining privacy. This presents challenges, including how to partition data into performance-sensitive and performance-robust features, and preserving local private data without hindering global model performance.

6 Methodology

6.1 FedFed Overview

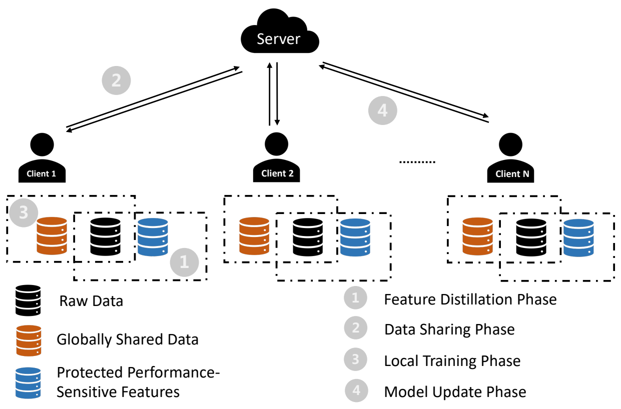


Figure 2: FedFed Overview

6.2 Valid Partition Strategy

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

6.3 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**.

6.4 Information Bottleneck

To partition the features into performance-sensitive and performance-robust categories, the authors take inspiration from the **Information Bottleneck (IB)** Method [2]. The goal is to compress input X while retaining information relevant to the output Y.

$$L_{IB} = I(X; Y \mid Z), \quad \text{s.t.} \quad I(X; Z) \leq I_{IB} \tag{3}$$

6.5 FedFed vs Information Bottleneck

The key differences between FedFed and IB are:

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

7 Formulation

7.1 Original Objective :

The goal of the traditional information bottleneck method is to:

$$\min_Z I(X; Y \mid Z), \quad \text{subject to} \quad I(X; Z) \leq I_{IB},$$

where Z is the representation, $I(\cdot)$ is the mutual information, and I_{IB} is a constant.

7.2 Revised Objective :

Feature distillation reformulates the problem as:

$$\min_Z I(X; Y \mid Z), \quad \text{subject to} \quad I(X; X - Z \mid Z) \geq I_{FF},$$

where Z represents performance-sensitive features, $X - Z$ represents performance-robust features, and I_{FF} is a constant.

7.3 Performance-Sensitive Features Objective :

The objective for learning performance-sensitive features is defined as:

$$\min_\theta -E_{(x,y)\sim P(X_k,Y_k)} \log p(y \mid z(x;\theta)), \quad \text{subject to} \quad \|z(x;\theta)\|_2^2 \leq \rho,$$

where θ is the parameter of the model, $z(x;\theta)$ represents the performance-sensitive features, and $\rho > 0$ is a constant.

7.4 Improved Objective :

To address the limitations, the improved objective is:

$$\min_{\theta} -E_{(x,y)\sim P(X_k,Y_k)} \log p(y \mid x - q(x;\theta)), \quad \text{subject to} \quad \|x - q(x;\theta)\|_2^2 \le \rho,$$

where $q(x;\theta)$ represents the performance-robust features.

7.5 Feature Distillation Objective :[3]

The realization of feature distillation combines the generative model $q(x;\theta)$ and a local classifier $f(\cdot;w_k)$ as:

$$\min_{\theta,w_k} -E_{(x,y)\sim P(X_k,Y_k)} \ell(f(z(x;\theta);w_k),y), \quad \text{subject to} \quad \|z(x;\theta)\|_2^2 \le \rho,$$

where $z(x;\theta)x - q(x;\theta)$, $f(\cdot;w_k)$ is the local classifier for client k, and $\ell(\cdot)$ is the cross-entropy loss.

8 Differential Privacy

8.1 Motivation

Performance-sensitive features may contain private data. Differential Privacy (DP) is introduced to protect these features from privacy attacks and adversarial threats. Gaussian noise is added to shared features during the training process to enhance privacy.

9 FedFed Algorithm :

Algorithm 1 Feature Distillation

```
Server input: communication round $T_d$, DP noise level $\sigma_s^2$
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
```

Figure 3: FedFed Algorithm

9.1 FedFed Pipeline :

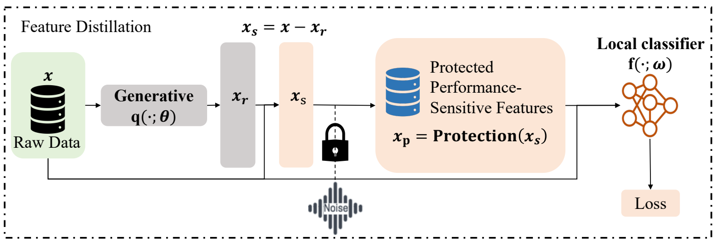

Feature Distillation
$x_s = x - x_r$
x
Raw Data
Generative $q(\cdot;\theta)$
x_r
x_s
Protected Performance-Sensitive Features
x_p = Protection(x_s)
Local classifier $f(\cdot;\omega)$
Noise
Loss

Figure 4: FedFed pipeline

10 Experiments and Results

10.1 Papers's 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

Data Partitioning:

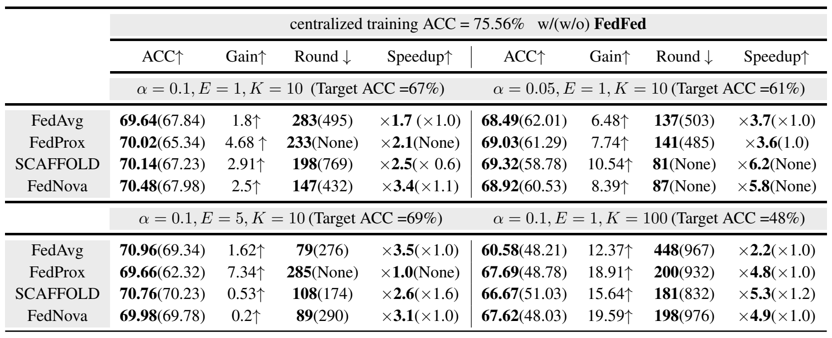
- Dirichlet : Non-IID distribution ($\alpha = 0.1, 0.05$).

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.

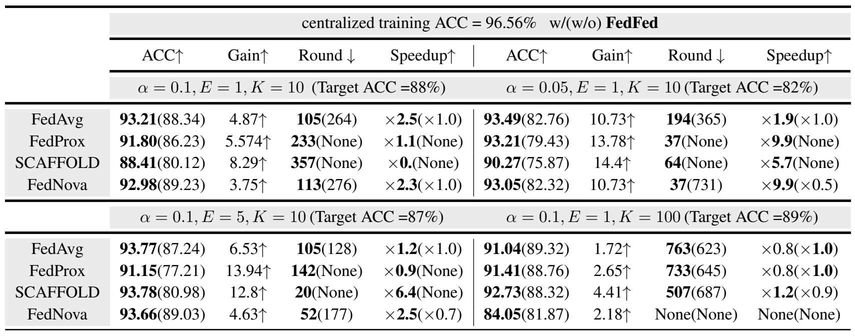
10.2 Paper's Results

The experimental results for CIFAR-10 and SVHN are presented in Figures 5 and 6.



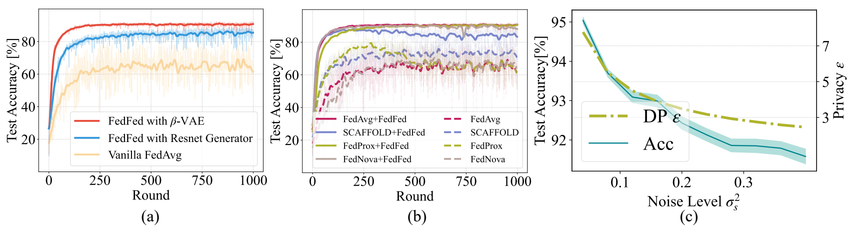
	centralized training ACC = 75.56% w/(w/o) **FedFed**							
	ACC↑	Gain↑	Round ↓	Speedup↑	ACC↑	Gain↑	Round ↓	Speedup↑
	$\alpha = 0.1, E = 1, K = 10$ (Target ACC =67%)				$\alpha = 0.05, E = 1, K = 10$ (Target ACC =61%)			
FedAvg	**69.64**(67.84)	1.8↑	**283**(495)	×**1.7** (×1.0)	**68.49**(62.01)	6.48↑	**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



	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



(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.

10.3 Our's 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.

10.4 Our's Experimental Results :

10.4.1 Results of 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)

Server Metrics :

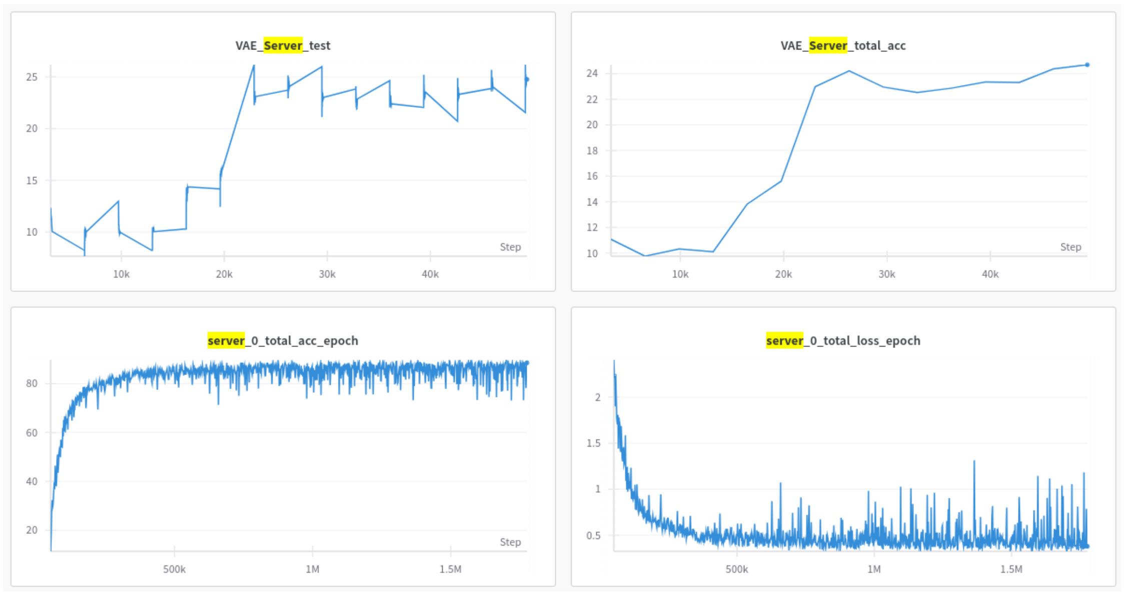


Figure 7: CIFAR-10[4]

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 :

10.4.2 Results of PathMNIST [5] :

Dataset Details :

- Random initialization of the model parameters can lead to variations in performance.
- **Domain**: Biomedical Histopathology
- **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

Results :

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)

Server Metrics :

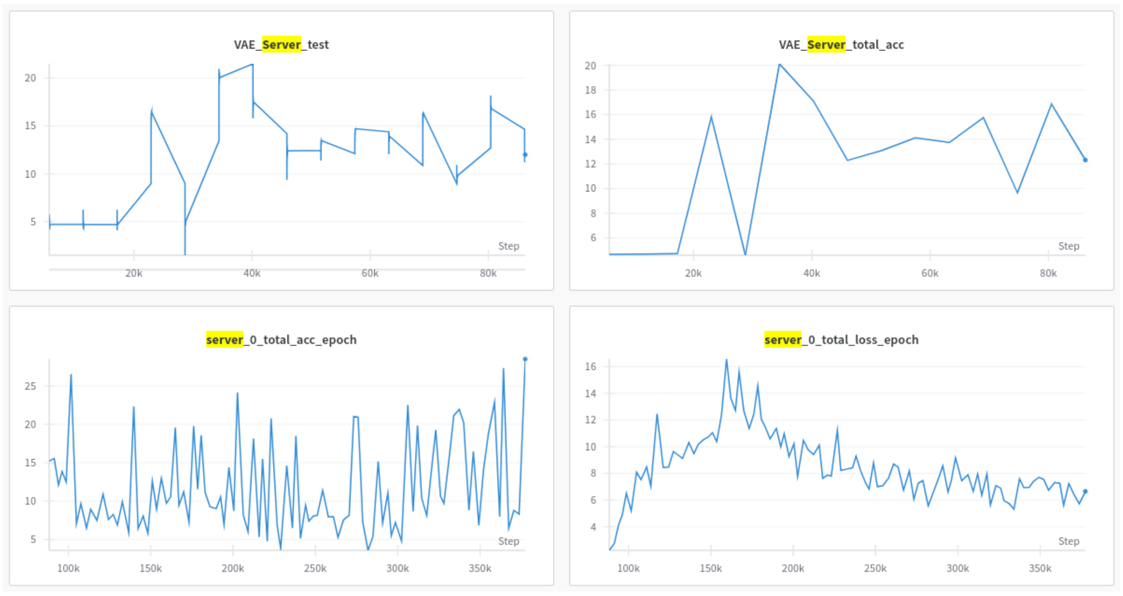


Figure 8: PathMNIST

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%

Table 6: Comparison of CIFAR-10 and PathMNIST Results (100 Communication Rounds)

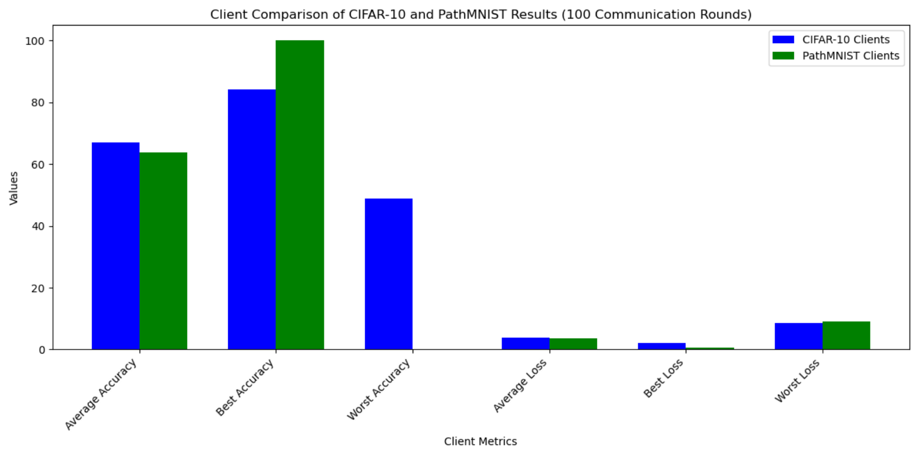


Figure 9: CIFAR-10 vs PathMNIST

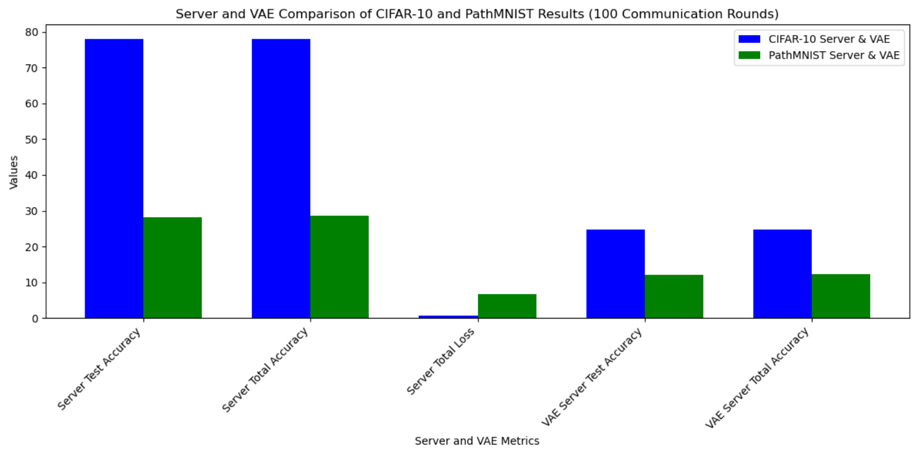


Figure 10: CIFAR-10 vs PathMNIST

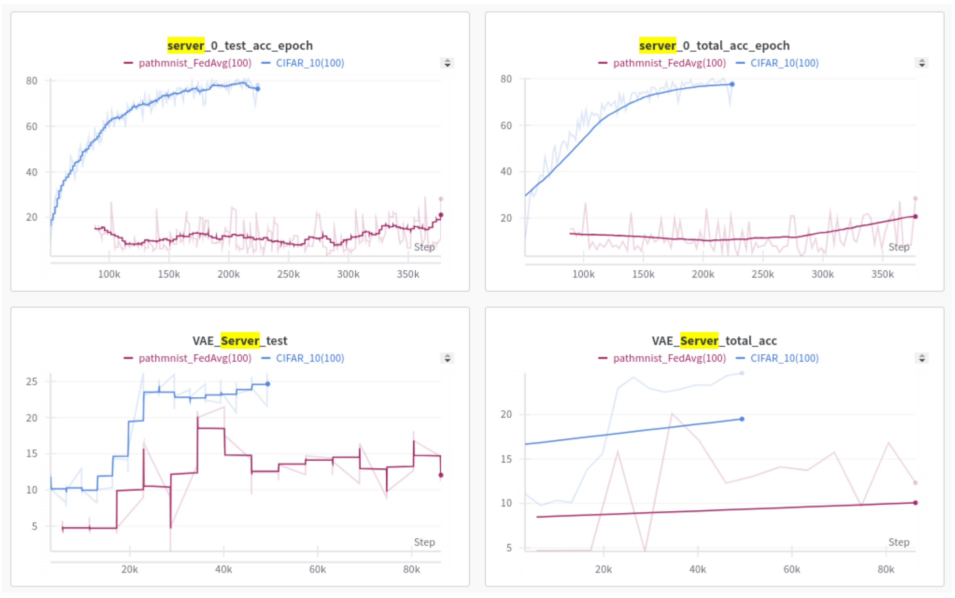


Figure 11: CIFAR-10 vs PathMNIST

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.

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.

More Results :

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 7: Server Metrics Comparison of FedAvg and FedProx on PathMNIST Dataset

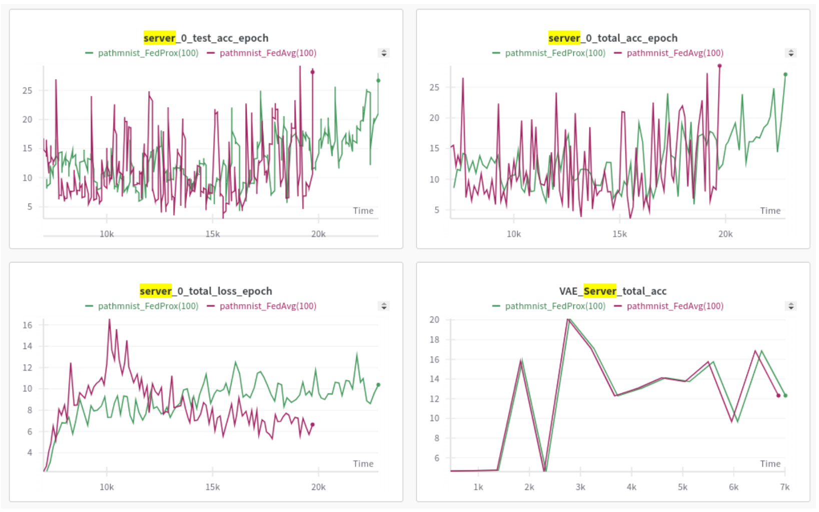


Figure 12: FedAvg vs FedProx on PathMNIST

11 Future Work

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.

12 Conclusion

The FedFed approach aims to address data heterogeneity in Federated Learning by sharing only performance-sensitive features while retaining performance-robust features locally. This method helps in balancing the trade-off between data privacy and model performance. However, challenges remain, particularly in determining optimal partition strategies and enhancing the robustness of latent embedding generation.

References

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[5] J. Yang, R. Shi, D. Wei, *et al.*, "Medmnist v2 - a large-scale lightweight benchmark for 2d and 3d biomedical image classification," *Scientific Data*, vol. 10, no. 1, Jan. 2023, ISSN: 2052-4463. DOI: `10.1038/s41597-022-01721-8`. [Online]. Available: `http://dx.doi.org/10.1038/s41597-022-01721-8`.