Appendix
SFedHIFI: Fire Rate-Based Heterogeneous Information Fusion for Spiking Federated Learning

Anonymous submission

1 Datasets Details

We conducted experiments using three popular datasets, Fashion-MNIST (Xiao, Rasul, and Vollgraf 2017), CIFAR-10, and CIFAR-100 (Krizhevsky, Hinton et al. 2009).

- **Fashion-MNIST** comprises 60,000 28×28 grayscale images across 10 apparel categories. As a modern replacement for the classic MNIST handwritten digit dataset (LeCun et al. 1998), it maintains identical image dimensions while presenting more challenging classification tasks. We selected this dataset to: (1) validate SFedHIFI's baseline performance on lightweight yet non-trivial tasks, and (2) ensure comparability with classical FL studies.
- **CIFAR-10** contains 50,000 training and 10,000 test images (32×32 RGB) spanning 10 generic object classes. As a computer vision benchmark, its higher input dimensionality (RGB channels) and real-world noise make it ideal for evaluating SFedHIFI's cross-modal learning capability and knowledge fusion performance under imbalanced data distributions.
- **CIFAR-100** extends the challenge with 100 classes at the same resolution as CIFAR-10, containing only 500 training samples per class. The presence of more classes in the dataset leads to finer-grained categorization and greater sample sparsity, both of which impose rigorous challenges on the stability of SFL. Therefore, we use it to validate SFedHIFI's capabilities of leveraging cross-client knowledge to maintain performance under extreme Non-IID conditions (clients typically possess significantly fewer than 100 categories).

2 Data Partitioning Details

Like previous works (Li, He, and Song 2021; Xiang et al. 2024), we partition the datasets across clients under both IID and Non-IID data settings.

- *IID*: The data distribution is independent and identical across all clients, meaning each client receives an equal number of samples from each class.
- *Non-IID*: We adopt a Dirichlet distribution $Dir(\alpha)$ to simulate non-identical data distributions among clients. The concentration parameter $\alpha = [0.5, 0.3]$ in our experiments, which controls the degree of data heterogeneity across clients: smaller α values produce more pronounced heterogeneity among clients.

3 Baseline Approaches

For a comprehensive comparison, we compare our SFedHIFI with three well-established FL baselines, including: FedAVG (McMahan et al. 2017), FedProx (Li et al. 2020), and FedNova (Wang et al. 2020). FedAVG (McMahan et al. 2017), the classical FL algorithm that demonstrates basic performance; FedProx (Li et al. 2020) for data heterogeneity, the hyperparameter μ_{prox} is set to 0.1 in our experiments; FedNova (Wang et al. 2020) addressing local update discrepancies, our experiments use the 'uniform' option.

4 Implementation Details

Table 1: The training hyperparameter on different Datasets.

Hyperparameters	Fashion-Mnist	CIFAR-10	CIFAR-100
Model	(4*) SNN	Spiking-ResNet18	Spiking-ResNet18
Time window length $\mathcal{T}$		10	
V_{rest}		0.0	
Optimizer		SGD	
Momentum		0.9	
Weight decay		5e-4	
Batchsize		32	
Local Epoch		2	
The firing threshold Vth	0.5	1.0	1.0
Learning Rate(LR)	0.01	0.1	0.1
Round	500	500	800
LR Decay step(0.1)	[250,375]	[250,375]	[300,575]
HIFI Round	225	225	360

The experimental hyperparameters are summarized in Table 1. "(4*) SNN" refers to a simple 4-layer SNN consisting of three convolutional layers and a linear classification head, with kernel sizes of 3×3 and 64, 128, 128 hidden channels, respectively. "HIFI Round" is specific to the proposed SFedHIFI framework and denotes the number of rounds in which the HIFI module is applied during heterogeneous aggregation, aiming to stabilize the SFL process. All baselines are implemented using PyTorch (Paszke et al. 2019) with an NVIDIA 3090 GPU. For fairness, all baselines—including ANN-based FL for energy consumption comparisons—are evaluated under the same heterogeneous environment as SFedHIFI.

References

Krizhevsky, A.; Hinton, G.; et al. 2009. Learning multiple layers of features from tiny images.

LeCun, Y.; Bottou, L.; Bengio, Y.; and Haffner, P. 1998. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11): 2278–2324.

Li, Q.; He, B.; and Song, D. 2021. Model-contrastive federated learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 10713–10722.

Li, T.; Sahu, A. K.; Zaheer, M.; Sanjabi, M.; Talwalkar, A.; and Smith, V. 2020. Federated Optimization in Heterogeneous Networks. In Dhillon, I.; Papailiopoulos, D.; and Sze, V., eds., *Proceedings of Machine Learning and Systems*, volume 2, 429–450.

McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and y Arcas, B. A. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, 1273–1282. PMLR.

Paszke, A.; Gross, S.; Massa, F.; Lerer, A.; Bradbury, J.; Chanan, G.; Killeen, T.; Lin, Z.; Gimelshein, N.; Antiga, L.; Desmaison, A.; Köpf, A.; Yang, E.; DeVito, Z.; Raison, M.; Tejani, A.; Chilamkurthy, S.; Steiner, B.; Fang, L.; Bai, J.; and Chintala, S. 2019. *PyTorch: an imperative style, high-performance deep learning library*. Red Hook, NY, USA: Curran Associates Inc.

Wang, J.; Liu, Q.; Liang, H.; Joshi, G.; and Poor, H. V. 2020. Tackling the objective inconsistency problem in heterogeneous federated optimization. *Advances in neural information processing systems*, 33: 7611–7623.

Xiang, M.; Ioannidis, S.; Yeh, E.; Joe-Wong, C.; and Su, L. 2024. Efficient federated learning against heterogeneous and non-stationary client unavailability. *Advances in Neural Information Processing Systems*, 37: 104281–104328.

Xiao, H.; Rasul, K.; and Vollgraf, R. 2017. Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms. *arXiv preprint arXiv:1708.07747*.