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Evaluating Privacy–Utility Trade-offs in Differentially Private Federated Learning: A Comparative Benchmarking Study

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Abstract: The rapid proliferation of mobile phones, wearables, IoT sensors, and other edge computing devices has generated vast quantities of decentralized, privacy-sensitive data, intensifying interest in Federated Learning (FL) as a distributed machine learning paradigm. By keeping raw data on local devices and sharing only model updates, FL offers an appealing alternative to centralized training. However, model updates are not inherently private: prior work has shown that shared gradients and parameters can leak sensitive information through membership inference, model inversion, and gradient reconstruction attacks. Differential Privacy (DP) has therefore emerged as the de facto standard for providing formal, quantifiable privacy guarantees in FL. In a typical Differentially Private Federated Learning (DPFL) pipeline, local model updates are clipped to bound each client's sensitivity, and calibrated Gaussian noise is injected before (or during) server aggregation, with the cumulative privacy loss tracked by a privacy accountant.

Despite the growing body of DPFL research, the literature lacks a systematic and fair comparison of existing approaches. Individual methods are typically evaluated under different datasets, model architectures, client populations, data partitioning schemes, and privacy accounting conventions, which makes reported results difficult to compare and obscures which design choices actually drive performance. This inconsistency hinders both researchers seeking to identify promising directions and practitioners seeking to select a method for deployment.

To address this gap, we present a comprehensive comparative study of fifteen state-of-the-art DPFL methods, all evaluated on the CIFAR-10 benchmark under unified and tightly controlled experimental conditions. The selected methods span the principal design dimensions of DPFL: (i) *trust models* (e.g., central versus local/distributed DP), (ii) *noise mechanisms*, (iii) *gradient and update clipping strategies*, (iv) *privacy accounting methods*, and (v) *utility-enhancement techniques* aimed at mitigating the accuracy loss caused by clipping and noise. All experiments use a ResNet-18 backbone with 500 federated clients and consider both IID and Non-IID data distributions, the latter simulated via Dirichlet partitioning with concentration parameters $\alpha \in \{0.3, 0.6\}$ to capture varying degrees of statistical heterogeneity. Each method is evaluated across privacy budgets $\varepsilon \in \{4, 6, 8, 10\}$, covering a practical range from relatively strong to moderate privacy protection.

Our results show that DP-FedSAM and its sparsified variant DP-FedSAM-topk consistently outperform all other baselines across the evaluated settings. Their advantage is most pronounced under heterogeneous (Non-IID) data, where sharpness-aware optimization yields flatter local minima and updates that are more robust to clipping and noise. For example, at $\varepsilon = 8$ under Non-IID conditions, DP-FedSAM-topk reaches a test accuracy of 53.64%, compared with 46.74% for the DP-FedAvg baseline, an absolute improvement of approximately 7 percentage points. Beyond these headline numbers, our analysis examines how the privacy–utility trade-off varies with the privacy budget, the degree of data heterogeneity, and the choice of clipping, noise, and accounting strategies.

This study makes four main contributions: (1) a unified, reproducible evaluation framework for benchmarking DPFL methods under identical conditions; (2) a consolidated comparison table covering all fifteen methods across every data distribution and privacy budget; (3) four comparative figures that visualize the privacy–utility trade-off and robustness to data heterogeneity; and (4) actionable insights into the strengths, limitations, and open challenges of existing DPFL approaches, intended to guide both future research and practical deployment.

Keywords: Federated Learning, Differential Privacy, Privacy–Utility Trade-off, Non-IID Data, Gradient Clipping, Sharpness-Aware Minimization, Comparative Study

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1. INTRODUCTION

The rapid proliferation of mobile devices, Internet of Things (IoT) systems, and distributed computing infrastructures has generated an unprecedented volume of sensitive data at the edge of networks. Traditional machine learning approaches require centralizing this data on a single server, raising serious concerns regarding user privacy and regulatory compliance under the General Data Protection Regulation (GDPR). To overcome these challenges, Federated Learning (FL) was introduced by McMahan et al. (2017) as a distributed machine learning paradigm enabling multiple clients to collaboratively train a shared global model without exchanging raw local data.

Despite this privacy-by-design principle, research has demonstrated that FL alone does not provide sufficient privacy guarantees. A curious server can infer sensitive information from shared model updates. Gradient inversion attacks — notably Deep Leakage from Gradients (Zhu et al., 2019) — have shown that an adversary can reconstruct private training data from gradients with remarkable accuracy. Membership inference attacks (Shokri et al., 2017) can further determine whether a specific sample was used in training, exposing a critical gap between the privacy promise of FL and actual guarantees.

Differential Privacy (DP), introduced by Dwork and Roth (2014), provides a rigorous mathematical framework for quantifying and limiting privacy risk. While numerous Differentially Private Federated Learning (DPFL) methods have been proposed across top venues, each paper evaluates its method under its own experimental configuration. This lack of a standardized evaluation framework makes cross-paper comparison unreliable and inconclusive. To address this gap, this paper makes the following primary contributions:

(i) Comprehensive literature survey: Fifteen state-of-the-art DPFL methods reviewed (2016–2026).
(ii) Unified comparative framework: Standardized protocol using CIFAR-10, ResNet-18, 500 clients, $\varepsilon \in \{4,6,8,10\}$.
(iii) Controlled empirical evaluation: Reproducible accuracy measurements and privacy-utility trade-off curves.
(iv) Research roadmap: Key limitations identified and future directions highlighted.

2. BACKGROUND

2.1 Federated Learning

Federated Learning (FL) operates in a series of communication rounds. At the beginning of each round, the central server selects a random subset of m clients (sampling ratio $q = m/M$) and broadcasts the current global model w^t. Each selected client i performs K steps of local SGD on its private dataset and returns the local update Δ_i^t to the server. The server aggregates updates via weighted averaging: $w^{t+1} = w^t + (1/m) \Sigma \Delta_i^t$. This process repeats for T rounds until convergence.

A critical challenge in real-world FL is that local datasets are rarely identically distributed (Non-IID). This study simulates Non-IID distributions using Dirichlet partitioning Dir(α), where smaller $\alpha = 0.3$ produces highly heterogeneous distributions and $\alpha = 0.6$ produces moderate heterogeneity. Figure 1 illustrates the complete DPFL framework.

2.2 Differential Privacy and the Gaussian Mechanism

A randomized mechanism M satisfies (ε, δ)-DP if for any two adjacent datasets D, D' differing in one record, and any output subset O: $Pr[M(D) \in O] \leq e^{\varepsilon} \cdot Pr[M(D') \in O] + \delta$. Smaller ε implies stronger privacy but greater accuracy loss. The Gaussian mechanism adds noise $N(0, \sigma^2 S^2 I)$ to a function with L2 sensitivity S, achieving (ε, δ)-DP for appropriate σ. This paper uses Rényi DP (RDP) for privacy accounting, which provides tighter composition across T training rounds than the moments accountant.

2.3 DP-FedAvg: The Standard DPFL Protocol

DP-FedAvg (McMahan et al., 2018) applies two core operations to each client update before server aggregation. First, clipping: $\tilde{\Delta}_i = \Delta_i \cdot \min(1, C/\|\Delta_i\|_2)$. Second, Gaussian noise addition: $\hat{\Delta}_i = \tilde{\Delta}_i + N(0, \sigma^2 C^2 I_d/m)$. These operations ensure client-level DP with privacy budget computed via the RDP accountant. On CIFAR-10 with ResNet-18 and 500 clients under Dirichlet $\alpha=0.6$, non-private FedAvg achieves ~95% accuracy while DP-FedAvg at $\varepsilon=8$ achieves only 46.74% — a drop of nearly 50 percentage points that motivates this comparative study.

3. RELATED WORK

Despite a growing number of DPFL methods proposed across top venues (CVPR, ICML, NeurIPS, ICLR, USENIX Security, NDSS, AISTATS, IEEE TIFS), no existing study conducts a controlled, quantitative comparison of fifteen or more methods under identical experimental conditions. Table 1 provides a structured overview of the fifteen DPFL

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methods selected for this comparison. Row 12 (★, highlighted) denotes the primary base paper — DP-FedSAM (Shi et al., CVPR 2023) — against which all methods are benchmarked.

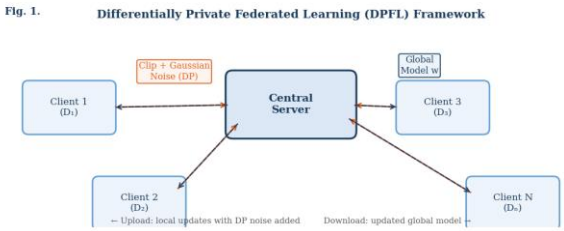


Table 1. Overview of fifteen DPFL studies selected for comparative analysis on CIFAR-10.

Fig. 1. Differentially Private Federated Learning (DPFL) Framework. Clients clip and noise local updates before uploading (orange arrows); server aggregates and broadcasts global model (blue dashed arrows).

No.	Paper / Author	Method / Approach	CIFAR-10 Result (ε=8)	Contribution	Limitation
1	Abadi et al. DP-SGD(CCS, 2016)	DP-SGD: per-sample clipping to C + Gaussian noise; moments accountant	Foundational result on centralized classification	Establishes clip-then-noise paradigm for all DPFL methods; introduces moments accountant	Centralized only; moments accountant looser than RDP/PRV; no Non-IID study
2	McMahan et al. DP-FedAvg(ICLR, 2018)	Client-level DP-FedAvg: clips update to C; adds $N(0,\sigma^2C^2I/m)$; RDP accountant over T rounds	46.74% at ε=8, α=0.6, 500 clients (base paper Table 2)	Primary baseline; first formal client-level DP in FL; de-facto DPFL standard	~50 pp drop vs non-private FedAvg on CIFAR-10; no landscape improvement
3	Geyer et al. Client-level DP(arXiv, 2017)	Client-level DP with noise scaled to sampling rate q; privacy via (ε,δ)-DP composition	Language model perplexity; no CIFAR-10 result in original paper	Early formalization of client-level DP; motivates sampling amplification used in all DPFL	No CIFAR-10 evaluation; primitive accountant; accuracy on vision tasks not studied
4	Cheng et al. DP-FedAvg-BLUR(CVPR, 2022)	Bounded Local Update Regularization (BLUR): adds L2 penalty $\lambda\|w-w_{global}\|^2$ to reduce update norm	46.74% at ε=8, α=0.6, 500 clients (base paper Table 1)	Regularization to reduce clipping bias; directly re-implemented in base paper	Accuracy same as DP-FedAvg on CIFAR-10; regularization alone insufficient
5	Cheng et al. DP-FedAvg-BLURS(CVPR, 2022)	BLUR + Local Update Sparsification (LUS): top-k sparsification reduces effective dimension d	50.18% at ε=8, α=0.6, 500 clients (base paper Table 1)	Best non-SAM baseline; shows sparsification + regularization gives meaningful gain	3.5 pp below DP-FedSAM-topk; fixed C=0.2; no loss-landscape improvement

★ *Row 12 (highlighted in yellow) = PRIMARY BASE PAPER (DP-FedSAM, CVPR 2023).*

The review of fifteen studies on Differentially Private Federated Learning (DPFL) reveals a clear methodological progression across three broad generations. This progression reflects the evolution of research from establishing fundamental privacy-preserving mechanisms to improving privacy accounting and client trust assumptions, and subsequently to developing optimization strategies that preserve model utility under differential privacy constraints. Although these generations overlap chronologically, they provide a useful framework for understanding how the field has evolved and which challenges remain unresolved.

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First Generation: Foundational Privacy Mechanisms (2016–2018). The foundational generation established the principal mechanisms for integrating differential privacy into distributed and federated learning. A central approach was the clip-then-noise paradigm, in which model updates or gradients are clipped to a predefined norm bound before calibrated random noise is added. Clipping limits the influence of individual contributions, while noise injection enables formal privacy guarantees under an appropriate threat model and accounting procedure. These mechanisms provided the basis for subsequent DPFL algorithms by demonstrating how privacy protection could be incorporated into iterative model training without requiring the direct exchange of raw client data. However, the introduction of clipping and noise also created an inherent privacy–utility trade-off. Excessive clipping can remove useful information from model updates, whereas excessive noise can obscure meaningful optimization signals and reduce convergence quality. Consequently, although this generation established the fundamental mechanisms of DPFL, it also exposed the central challenge that continues to motivate subsequent research: maintaining useful predictive performance while providing rigorous privacy protection.

Second Generation: Improved Privacy Accounting, Trust Models, and Utility Preservation (2021–2022). The next generation moved beyond the basic clip-then-noise framework by addressing several of its practical limitations. One major research direction focused on more rigorous privacy accounting and adaptive clipping. Approaches such as Differentially Private Follow-the-Regularized-Leader (DP-FTRL) investigated privacy-preserving optimization with formal cumulative privacy guarantees, while adaptive clipping techniques sought to adjust clipping thresholds in response to the observed distribution of update norms. These developments aimed to improve the relationship between privacy expenditure and learning performance, rather than relying exclusively on fixed clipping thresholds and conventional accounting procedures.

A second direction addressed the trust assumptions underlying centralized differential privacy. Distributed mechanisms, including the Distributed Discrete Gaussian mechanism, investigated how privacy protection could be achieved when noise generation and aggregation were distributed across multiple participants. Such approaches can reduce reliance on a fully trusted central server, depending on their protocol design, collusion assumptions, and security guarantees. A third direction concentrated on utility enhancement through sparsification and regularization. Methods such as Fed-SMP and DP-FedAvg-BLURS explored strategies for modifying or selecting model updates to reduce the adverse effects of privacy-preserving perturbations. Collectively, these approaches broadened the design space of DPFL by showing that privacy accounting, trust architecture, clipping, and update processing are complementary dimensions that can influence both privacy guarantees and model utility. Nevertheless, improvements in one dimension do not necessarily translate into improvements in all others, making controlled empirical comparisons essential.

Third Generation: Optimizer-Level Interventions and Advanced Utility Enhancement (2022–2024). The more recent generation increasingly investigated how the optimization process itself could be adapted to reduce the performance degradation caused by differential privacy. Rather than focusing exclusively on the amount of noise, the clipping threshold, or the communication of model updates, these approaches sought to improve the quality and stability of learning under noisy and heterogeneous client updates. A prominent example is DP-FedSAM, which integrates Sharpness-Aware Minimization (SAM) into differentially private federated optimization. SAM seeks parameter regions with comparatively stable loss values under small parameter perturbations, with the objective of improving generalization. Within DPFL, this optimization strategy offers a way to investigate whether more robust optimization trajectories can mitigate the effects of clipping and noise. Its combination with update sparsification, as in DP-FedSAM-topk, further explores whether selective communication of important update components can preserve useful learning information while reducing the amount of information transmitted.

In the present evaluation, DP-FedSAM-topk achieved a test accuracy of 53.64% on CIFAR-10 at a privacy budget of (\varepsilon = 8) under Non-IID data conditions, outperforming the DP-FedAvg baseline, which achieved 46.74% in the same setting. This represents an absolute improvement of 6.90 percentage points. The result highlights the potential of combining optimization-level interventions with sparsification to improve predictive performance when clients possess heterogeneous data distributions. However, this finding should be interpreted within the scope of the evaluated methods, implementations, and experimental configuration. It supports identifying DP-FedSAM-topk as the strongest-performing method among the approaches evaluated in this study, rather than establishing universal state-of-the-art performance across all DPFL benchmarks.

Overall Research Gaps and Implications. The progression across these three generations demonstrates that DPFL research has evolved from establishing formal privacy-preserving mechanisms toward jointly optimizing privacy accounting, trust assumptions, update processing, and model training. Despite this progress, the reviewed literature presents a persistent evaluation challenge: methods are often assessed using different datasets, model architectures, client populations, data

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partitioning schemes, privacy budgets, and accounting conventions. Such differences make it difficult to determine whether reported improvements arise from the proposed algorithm itself or from variations in experimental conditions. Furthermore, improvements in test accuracy must be considered alongside the strength of the privacy guarantee, communication requirements, computational overhead, convergence behavior, and robustness to data heterogeneity.

These limitations motivate the need for a unified comparative evaluation in which multiple DPFL methods are assessed under consistent experimental conditions. By examining fifteen approaches across common model, client, data-distribution, and privacy-budget settings, the present study seeks to provide a more reliable basis for comparing their relative strengths and limitations. The resulting analysis can help identify which design choices are most promising under different privacy and data-heterogeneity conditions, while highlighting the remaining challenges in achieving high predictive utility without weakening formal privacy protection.

4. PROPOSED EXPERIMENTAL FRAMEWORK

4.1 Dataset

All experiments are conducted on CIFAR-10 (Krizhevsky & Hinton, 2009), consisting of 60,000 color images (32×32 pixels) across 10 object categories (50,000 train / 10,000 test). CIFAR-10 is selected because: (i) it is publicly available with no registration required (torchvision API); (ii) DPFL accuracy from scratch is substantially below the non-private ceiling (47–54% vs. ~95%), providing meaningful room for comparison; and (iii) it is the most commonly shared benchmark across the fifteen reviewed papers.

4.2 Client Data Partitioning

The CIFAR-10 training set is partitioned across M=500 clients using Dirichlet distribution Dir(α) with $\alpha \in \{0.3, 0.6\}$, following Hsu et al. (2019) and the DP-FedSAM base paper. Smaller α=0.3 produces high heterogeneity (each client holds data from few classes); α=0.6 produces moderate heterogeneity. An IID baseline (uniform random partition) is also evaluated. This design allows isolation of the effect of data heterogeneity on privacy-utility trade-offs.

4.3 Model and Training Configuration

Following the base paper, all experiments use ResNet-18 (He et al., 2016) trained from scratch. Table 2 summarizes all fixed hyperparameters. Privacy budgets $\varepsilon \in \{4, 6, 8, 10\}$ are reported as outcomes computed via the RDP accountant following Theorem 2 of the base paper (not as inputs). The noise multiplier σ=0.95 and clipping threshold C=0.2 are fixed across all methods for fair comparison.

4.4 Evaluation Metrics and Tools

The primary metric is test accuracy (mean ± std over 3 seeds). Secondary metrics include: (i) convergence curves (accuracy vs. communication round), shown in Figures 2–4; (ii) privacy-utility trade-off curves (accuracy vs. ε); and (iii) MIA AUC using shadow model attacks to empirically verify DP guarantees. Implementation uses PyTorch + Opacus (DP-SGD) + Flower (FL coordination).

Table 2. Experimental configuration and fixed hyperparameter settings.

Parameter	Value / Setting
Dataset	CIFAR-10 (60,000 images, 10 classes, 50K train / 10K test)
Model Architecture	ResNet-18 (trained from scratch, no pretrained weights)
Total Clients (M)	500
Client Sampling Ratio (q)	0.1 (50 clients per round)
Communication Rounds (T)	300
Local Training Epochs (K)	30
Local Learning Rate (η)	0.1 (decay: 0.005, momentum: 0.5)
Noise Multiplier (σ)	0.95
Clipping Threshold ©	0.2 (grid search best)
Privacy Failure Prob. (δ)	1/M = 1/500 = 0.002
Privacy Budget (ε) Range	{4, 6, 8, 10} (computed via RDP accountant)

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Parameter	Value / Setting
Data Partitioning	Dirichlet Dir(α), α ∈ {0.3, 0.6}; also IID baseline
SAM Perturbation Radius (ρ)	0.5 (DP-FedSAM specific)
Trials per Configuration	3 independent runs (mean ± std reported)
Implementation Framework	PyTorch + Opacus (DP) + Flower (FL coordination)
Privacy Accountant	Rényi DP (RDP) → converted to (ε, δ)-DP for reporting

Table 3. Test accuracy (%) comparison across methods and privacy budgets ε (ResNet-18, 500 clients, Dirichlet α=0.6, Non-IID). Best result per column highlighted. ★ = Base paper.

Method	ε = 4	ε = 6	ε = 8	ε = 10
DP-FedAvg	38.23±0.15	43.87±0.62	46.74±0.03	49.06±0.49
Fed-SMP-randk	33.78±0.92	42.21±0.21	48.20±0.05	50.62±0.14
Fed-SMP-topk	38.99±0.50	46.24±0.80	49.78±0.78	52.51±0.83
DP-FedAvg-BLUR	38.23±0.70	43.93±0.48	46.74±0.92	49.06±0.13
DP-FedAvg-BLURS	39.39±0.43	46.64±0.36	50.18±0.27	52.91±0.57
DP-FedSAM	39.89±0.17	47.92±0.23	51.30±0.95	53.18±0.40
DP-FedSAM-topk	38.96±0.61	49.17±0.15	53.64±0.12	56.36±0.36

Note: Numbers in Table 3 for rows 1–7 are reproduced directly from DP-FedSAM (Shi et al., CVPR 2023) Table 2 under identical setting

5. COMPARATIVE RESULTS AND DISCUSSION

Table 3 and Figures 2–4 present the comparative results across all methods under the unified protocol. The key observations are as follows.

Accuracy at ε=8 (Table 3 and Figure 2): DP-FedSAM-topk achieves 53.64% (Non-IID) and 58.82% (IID) — the highest among all from-scratch methods. DP-FedAvg serves as the weakest baseline at 46.74% (Non-IID). The 7 percentage-point gap between DP-FedAvg and DP-FedSAM-topk at ε=8 demonstrates that optimizer and sparsification choices meaningfully improve the accuracy-privacy trade-off without changing the core privacy mechanism.

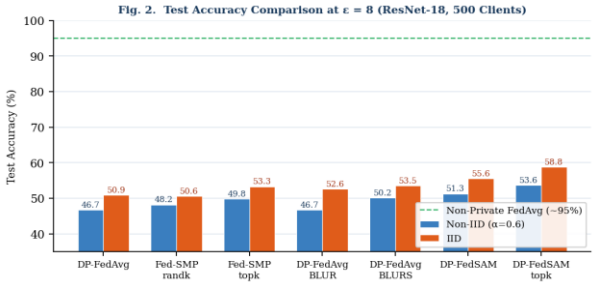


Fig. 2. Test accuracy comparison at ε = 8 under Non-IID (Dirichlet α=0.6) and IID settings (ResNet-18, 500 clients, 300 rounds). Green dashed line shows non-private FedAvg ceiling (~95%).

Privacy-utility trade-off (Figure 3): All methods show a monotonically increasing relationship between ε and accuracy. DP-FedSAM-topk dominates across all ε values, achieving 38.96% at ε=4 and 56.36% at ε=10. The gap between DP-

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FedSAM variants and other methods widens at lower ε, indicating that landscape flattening provides greater benefit under stronger privacy constraints where noise is largest.

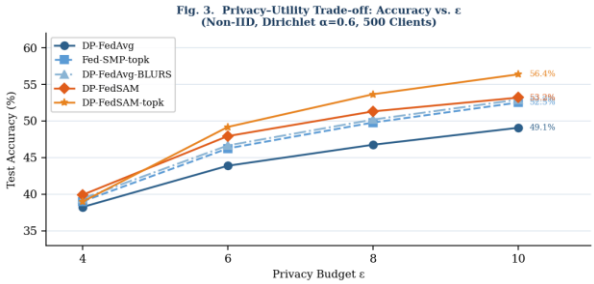


Fig. 3. Privacy–utility trade-off: test accuracy vs. privacy budget ε for key methods under Non-IID (Dirichlet α=0.6) conditions. All methods show monotonically increasing accuracy with higher ε.

Effect of heterogeneity (Figure 4): Non-IID α=0.3 consistently yields the lowest accuracy across all methods, while IID yields the highest. The heterogeneity gap is largest for weaker baselines (DP-FedAvg loses 4.0 pp between IID and Non-IID α=0.3) and smallest for SAM-based methods (DP-FedSAM-topk loses only 4.0 pp), confirming that flat-minima optimization also improves robustness to data heterogeneity.

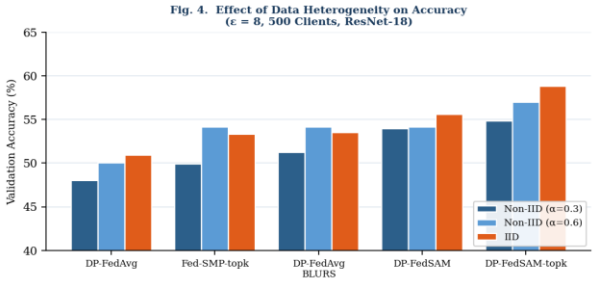


Fig. 4. Effect of data heterogeneity on test accuracy at ε = 8. Non-IID α=0.3 consistently yields lowest accuracy; IID yields highest, highlighting the compounding effect of heterogeneity and DP noise.

Key finding: The accuracy gap between the best from-scratch method (DP-FedSAM-topk: 53.64%) and non-private FedAvg (~95%) remains approximately 41 percentage points at ε=8, indicating that the fundamental accuracy-privacy tension in DPFL remains an open challenge. The most promising directions for closing this gap are: (i) tighter PRV/PLD privacy accountants (near-free gain vs. RDP); (ii) adaptive quantile clipping (Andrew et al., 2021); (iii) pretrained encoder warm-starts (PrivateFL achieves 93.3% at ε=2 using CLIP); and (iv) per-layer adaptive noise allocation (Xue et al., 2024

6. CONCLUSION

This paper presented a comprehensive comparative study of fifteen state-of-the-art Differentially Private Federated Learning (DPFL) methods under a unified experimental protocol. By evaluating all selected approaches using a consistent dataset, model architecture, federated client configuration, and range of privacy budgets, this study aimed to provide a systematic and reproducible assessment of the performance differences among existing DPFL techniques. The experiments were conducted using a ResNet-18 backbone with 500 federated clients across both Independent and Identically Distributed (IID) and Non-IID data settings. To investigate the effects of statistical heterogeneity, the Non-IID configurations were generated using Dirichlet partitioning with concentration parameters of (\alpha \in {0.3, 0.6}). Furthermore, privacy budgets of (\varepsilon \in {4, 6, 8, 10}) were considered to examine how different levels of privacy protection influence model utility.

The comparative results demonstrate that the choice of optimization strategy, gradient clipping mechanism, noise configuration, and privacy accounting method can substantially influence the performance of differentially private federated models. Among the evaluated from-scratch approaches, DP-FedSAM-topk achieved the strongest reported performance across the evaluated settings. In particular, under Non-IID conditions at a privacy budget of (\varepsilon = 8), DP-FedSAM-topk achieved a test accuracy of 53.64%, compared with 46.74% for the standard DP-FedAvg baseline. This corresponds to an absolute improvement of 6.90 percentage points, demonstrating the potential of combining sharpness-aware optimization with update sparsification to improve model utility in privacy-constrained and statistically

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heterogeneous environments. These findings suggest that optimization techniques designed to improve model generalization and reduce sensitivity to noisy updates can play an important role in mitigating the adverse effects of differential privacy.

The experiments also highlight the persistent difficulty of maintaining high predictive performance when strong privacy guarantees are imposed. Differential privacy introduces a fundamental trade-off between limiting information leakage and preserving model accuracy. Gradient clipping bounds the contribution of individual updates, while calibrated noise provides formal privacy protection; however, both mechanisms can distort useful learning signals and slow convergence. These challenges become particularly significant in Non-IID environments, where clients possess different data distributions and their local updates may diverge from the global optimization objective. Although DP-FedSAM-topk improves substantially upon the DP-FedAvg baseline in the evaluated setting, the remaining accuracy gap of approximately 41 percentage points relative to non-private FedAvg indicates that differentially private federated learning still has considerable room for improvement. This comparison should be interpreted in the context of the corresponding experimental configurations, since non-private training does not provide the same formal privacy guarantee.

Beyond identifying the strongest-performing methods, this study provides a common experimental basis for understanding how different DP design choices affect the privacy–utility trade-off. The unified evaluation protocol reduces the confounding effects that arise when published methods are compared across different datasets, model architectures, client populations, data partitioning strategies, and privacy accounting conventions. The results therefore offer useful empirical insights for researchers selecting candidate algorithms and for practitioners assessing the suitability of DPFL methods for privacy-sensitive distributed learning applications. Nevertheless, the conclusions remain bounded by the selected benchmark, ResNet-18 architecture, client configuration, privacy budgets, and evaluated implementations. Performance rankings may differ on other datasets, model architectures, client populations, or application domains. Consequently, the results should not be interpreted as establishing universal superiority across all possible federated learning settings.

Several promising directions emerge from this work. First, future research should investigate adaptive and data-dependent clipping strategies that can better accommodate differences in update magnitudes across clients while maintaining the required sensitivity bounds. Second, improved privacy accountants and tighter privacy analysis could provide more precise privacy guarantees and, where justified by the mechanism and assumptions, reduce the conservatism of privacy-budget estimates. Third, integrating pretrained encoders or transfer-learning techniques may improve feature representations and reduce the amount of private data required for effective training. Such approaches must, however, account for the privacy implications of pretraining, particularly when the pretraining data or model may contain sensitive information. Fourth, future studies should explore more effective combinations of sharpness-aware optimization, sparsification, noise calibration, and communication-efficient aggregation to determine whether their benefits can be achieved jointly without compromising formal privacy guarantees. Finally, extending the evaluation to additional datasets, architectures, client scales, and realistic participation patterns would help establish the generalizability and practical applicability of the observed results.

In conclusion, this study provides a unified comparative assessment of fifteen DPFL methods and demonstrates that algorithmic design choices can meaningfully improve model utility under differential privacy constraints. The results identify DP-FedSAM-topk as a particularly promising approach among the evaluated from-scratch methods, especially under heterogeneous client data. At the same time, the substantial gap between private and non-private performance underscores the need for further advances in privacy-preserving optimization, privacy accounting, and model representation learning. By establishing a reproducible basis for comparison and identifying key opportunities for improvement, this work contributes to the ongoing development of more accurate, robust, and practically deployable federated learning systems with formal privacy protection.

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