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# Privacy-Preserving Federated Learning with Adaptive Noise Scaling and Enhanced CNN Models

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**Abstract:** *Federated learning (FL) enables collaborative training across distributed clients without centralizing raw data, making it an attractive approach for privacy-sensitive applications. However, shared model updates in FL may still leak information, leaving systems vulnerable to inference attacks. Differential privacy (DP) provides formal guarantees but often degrades performance, especially in non-independent and identically distributed (non-IID) settings. This work proposes an adaptive noise scaling mechanism to integrate DP into FL more effectively. The method dynamically adjusts client-level noise based on local loss variance, balancing privacy preservation and model utility across heterogeneous clients. In addition, an enhanced Convolutional Neural Network (CNN) architecture with Group Normalization and residual connections is employed to stabilize training and improve generalization under noisy updates. Experiments on the MNIST dataset with 50 clients show that the adaptive federated DP model achieves 96.16% accuracy with a privacy budget of* $\boldsymbol{\epsilon = 1.78}$ *at a noise multiplier of 1.0. This performance surpasses the centralized DP baseline (94.15%) while approaching the non-private FL baseline (99.57%). Overall, the results highlight adaptive differential privacy as a practical and scalable approach for privacy-preserving federated learning, with strong potential in domains such as healthcare, finance, and mobile edge computing.*

**Keywords**: Federated learning, Differential privacy, Adaptive noise scaling, Privacy-utility trade-off, Convolutional neural networks.

## INTRODUCTION

The widespread adoption of machine learning (ML) across domains such as healthcare diagnostics, personalized finance, smart devices, and mobile health monitoring has introduced an urgent need to preserve data privacy throughout the model training lifecycle. Traditional centralized learning approaches typically require aggregating user data into a central server, thereby exposing sensitive information to potential misuse, security breaches, or regulatory violations. This centralized paradigm not only heightens privacy risks but also presents ethical and legal challenges under strict frameworks such as the General Data Protection Regulation (GDPR) (Truong, 2021), (Sah, 2025). Federated Learning (FL) has emerged as a compelling solution to mitigate these risks by enabling decentralized devices to collaboratively train a global model without directly sharing raw local data (McMahan, 2017), (Nasr, 2019). Instead, individual clients perform local updates and transmit only model

parameters or gradients to a central aggregator. While this approach significantly reduces direct data exposure (Truong, 2021), (Abadi, 2016).

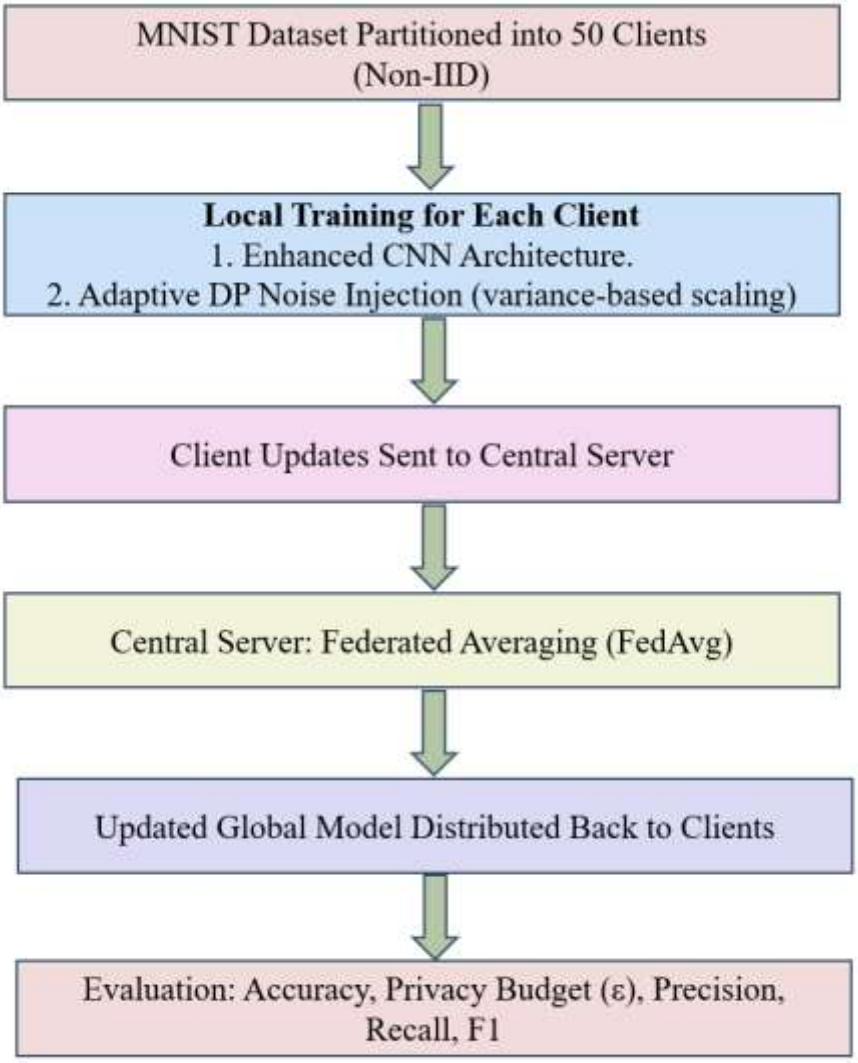


**Figure 1. Overview of our proposed framework.**

Differential Privacy (DP) (Nasr, 2019), (Deng, 2020) provides a rigorous mathematical framework to address privacy concerns by introducing calibrated noise into the training process, ensuring the statistical insignificance of any single data point's contribution. However, integrating DP into FL presents several practical challenges. Notably, the trade-off between model utility and privacy becomes more pronounced in decentralized, non-independent and identically distributed (non-IID) data scenarios, conditions prevalent in real-world applications such as edge computing, telemedicine, and distributed sensing (Hangyu, 2024). Uniformly adding noise often results in uneven performance degradation across clients, particularly when their data distributions vary significantly.

To address this challenge, we propose an adaptive differential privacy mechanism for federated learning, dynamically adjusting the noise injected into each client's training process based on their individual data characteristics. Specifically, we extend the Opacus DP framework by introducing a variance-based noise scaling strategy: clients with stable loss trajectories are allocated higher noise budgets, while clients with volatile training behaviours receive reduced noise to ensure model convergence. This adaptive strategy aims to balance privacy protection effectively with training efficacy, particularly within heterogeneous federated environments.

The key contributions of this paper are twofold:

- We introduce a novel variance-based adaptive noise mechanism tailored explicitly for federated learning under differential privacy.
- We design and implement an advanced CNN architecture featuring Group Normalization and residual connections to enhance model robustness in privacy-constrained scenarios.

We validate our proposed method through experiments on the MNIST dataset, a benchmark for handwritten digit classification, under a non-IID federated setting with 50 clients across 10 communication rounds.

## RELATED WORKS

In this section, we reviewed existing works on federated learning and differential privacy from different perspectives.

### A. Privacy Preservation in Federated Learning

Despite FL's decentralization, recent studies have shown that exchanged model updates can leak sensitive information about local datasets, such as membership and attribute inference attacks (Truong, 2021), (Abadi, 2016). Differential Privacy (DP) provides a formal framework for quantifying and controlling privacy leakage by introducing carefully calibrated noise during training (Deng, 2020). The integration of DP into FL presents significant challenges due to the delicate trade-off between privacy guarantees and model utility (Sah, 2025), (Nasr, 2019), (Hangyu, 2024). Recent advances focus on privacy enhanced decentralized FL frameworks designed for dynamic edge networks (Nasr, 2019), (Bian, 2025), as well as cryptographic methods like homomorphic encryption to secure aggregation without sacrificing accuracy (Sheller, 2020).

### B. Handling Non-IID Data and System Heterogeneity

Data heterogeneity across clients is a key obstacle to efficient FL training and convergence (Sah, 2025), (Li, 2018). To address this, hierarchical clustering techniques (Li, 2018), personalized FL methods such as FedProx (Wang, 2020), and client selection optimized via reinforcement learning (Baligodugula, 2025) have been developed. Moreover, communication-efficient protocols that utilize adaptive quantization and gradient sparsification techniques provide effective trade-offs between communication cost and model accuracy (Sheller, 2020), (Wu, 2022). The deployment of FL in edge computing environments further enhances scalability by reducing latency and offloading computation (Sah, 2025), (LeCun, 1998).

### C. Adaptive Differential Privacy with CNN Architectures

Traditional DP mechanisms that apply uniform noise may degrade performance disproportionately for clients with smaller or more complex datasets (Nasr, 2019), (Kaur, 2025). Adaptive noise scaling approaches, which tailor the privacy budget based on metrics such as loss variance or data quality, have been shown to significantly improve privacy-utility trade-offs (Kaur, 2025). Building on these ideas, our work proposes a variance-based adaptive noise mechanism integrated within the Opacus DP framework to enhance robustness and convergence in realistic hetero generous federated settings. Convolutional Neural Networks (CNNs) continue to be the standard for image classification tasks such as MNIST digit recognition. The seminal LeNet architecture (Ioffe, 2015), (Wu, 2018) laid the groundwork for modern CNNs, with Batch Normalization (He, 2016) improving training stability and speed. However, Batch Normalization's reliance on batch statistics can be problematic in FL scenarios with small batch sizes, motivating alternatives like Group Normalization (Wu, 2018), which normalizes over channel groups and is more robust to varying batch sizes. Furthermore, residual connections introduced by (He, 2016) facilitate the training of deeper networks by mitigating vanishing gradient issues.

## METHODOLOGY

In Figure 1 shows the overview of our proposed framework. We have divided our proposed framework into 6 different steps.

### A. Federated Learning System Overview

We consider a federated learning (FL) system composed of $N$ clients, mention in Figure 2 each holding a private, potentially non-independent and identically distributed (non-IID) local dataset $D_i$. The central objective is to collaboratively train a shared global model $\theta$ by minimizing the weighted empirical risk across all clients:

$$\min_{\theta} F(\theta) = \sum_{i=1}^{N} \frac{|D_i|}{\sum_{j=1}^{N} |D_j|} F_i(\theta), \tag{1}$$

where $F_i(\theta)$ denotes the empirical loss evaluated on client $i$'s local data, and $\theta$ represents the global model parameters. Federated learning proceeds in iterative communication rounds. In each round, a randomly selected subset of clients downloads the current global model, performs local training using their private data, and uploads the updated model parameters (or gradients) to a central aggregator.


**Figure 2. Federated learning system overview. Clients train on private local datasets and share updates with a central server.**

The server aggregates these updates typically by computing a weighted average proportional to each client's dataset size to form the new global model, which is then distributed to the clients for the next round. This decentralized training strategy ensures that all raw data remains on-device, substantially reducing privacy risks and supporting compliance with data governance policies. Meanwhile, the collaborative aggregation of local updates enables robust model convergence and strong predictive performance.

### B. Enhanced Convolutional Neural Network Architecture

The proposed global model is an enhanced convolutional neural network (CNN), mention in Figure 3, specifically designed for handwritten digit recognition on the MNIST dataset. The network begins with three convolutional layers employing $3 \times 3$ kernels and 32, 64, and 128 filters, respectively, to progressively extract hierarchical spatial features from raw digit inputs. Each convolutional layer is followed by Group Normalization (with 8 groups per layer) and ReLU activation, where Group Normalization is selected over Batch Normalization due to its superior robustness under variable and often small batch sizes common in federated training.

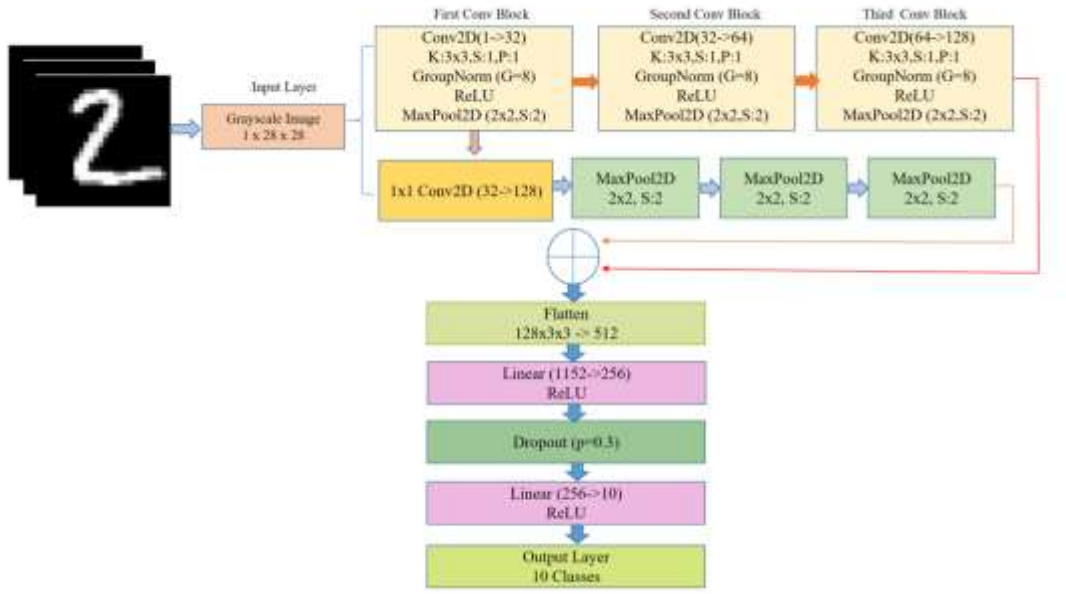


**Figure 3. Our proposed enhanced CNN architecture.**

To further enhance feature representation and reduce computational overhead, $2 \times 2$ max-pooling operations are applied after each convolutional block, effectively condensing feature maps while preserving salient information. A key architectural innovation is the integration of a residual skip connection: the output from the first convolution is projected via a $1 \times 1$ convolution and three successive pooling operations before being added to the third convolutional layer's output. Inspired by ResNet, this design strengthens gradient flow, reduces the risk of vanishing gradients, and improves the model's ability to generalize across heterogeneous client updates. After f lattening, two fully connected layers are employed: the first with 256 units, ReLU activation, and dropout (rate 0.3) for regularization, followed by a final dense layer producing logits for the 10 digit classes. Collectively, this architecture balances accuracy, computational efficiency, and resilience to noisy client updates.

### C. Federated Data Partitioning

To simulate realistic heterogeneity, the MNIST training set is distributed across $N = 50$ clients using a label–skew approach with controlled random admixture. Each client $i$ is assigned two primary digit labels from $\{0,\ldots,9\}$ cyclically, ensuring two dominant classes per client. All training sam ples matching a client's primary labels are included in its local dataset. Remaining samples (labels outside the primary set) undergo an independent Bernoulli trial with probability $p = 0.7$; successful trials assign those samples to the client. Formally, a training example $(x, y)$ is included in client i if $y \in S_i$ or $Ber(p) = 1$. This generates client datasets dominated by two digits but containing some other digits. Partitions are overlapping (samples can appear on multiple clients) and unbalanced (dataset sizes vary), creating a challenging non-IID learning scenario. The primary-label skew induces heterogeneity that slows consensus. This setup allows rigorous evaluation of the adaptive differential privacy (DP) mechanism under realistic non-IID conditions, highlighting its impact on the privacy–utility trade-off during federated learning.

### D. Adaptive Differential Privacy Mechanism

We enforce differential privacy (DP) locally at each client using the Opacus framework (Deng, 2020). At each client, gradients are computed per example, clipped to an $\ell_2$ norm bound $C$, and perturbed with Gaussian noise before updates are applied or shared. For a minibatch $B$ on client $i$, the noisy, clipped gradient is:

$$\tilde{g}_i = \frac{1}{|B|}\sum_{x\in B} clip(g(x), C) + N(0, \sigma_i^2 C^2 I), \tag{2}$$

where $g(x)$ is the per-example gradient and $\sigma_i$ is the client specific noise multiplier. Unlike standard DP-SGD with fixed $\sigma$, we adopt an adaptive strategy, scaling noise based on each client's recent training loss variance:

$$\sigma_i = min\{\sigma_{base}(1 + Var(\ell_i)), 2\sigma_{base}\}, \tag{3}$$

where $\ell_i$ is the vector of per-batch losses. Clients with low variance can tolerate higher noise, improving privacy, while those with high variance receive less noise to maintain convergence. Privacy accounting is performed per client using Opacus's accountant, given the local sampling rate, DP steps, and $\sigma_i$. We set $\delta = 1/60000$ and report the mean client $\varepsilon$ across rounds. Raw data and loss vectors remain local; only DP updates are shared.

### E. Federated Training Protocol

We adopt an enhanced FedAvg algorithm 1, in which client sampling, local private training, and server-side aggregation are repeated over multiple communication rounds. Let $\theta^t$ denote the global model after round $t$ and $S_t$ the set of clients selected in that round. Unless stated otherwise, we use $T = 10$ rounds, $K = 5$ clients per round, Adam with learning rate $10^{-3}$, clipping bound $C = 1.5$, and base noise multipliers $\{1.0, 1.5, 2.0\}$.

In each round t, the server samples $K$ clients without replacement and broadcasts the global model $\theta^{(t-1)}$. Each selected client initializes a local copy, performs one local epoch with Adam and a cosine annealing scheduler, and applies adaptive DP-SGD where per-batch gradients are clipped to $C$ and perturbed with Gaussian noise. The client-specific noise multiplier $\sigma_i$, derived from recent per batch losses and capped at $2\sigma_{base}$, yields the noisy gradient equation 2. Clients then return updated parameters $\theta_i^t$ , which the server aggregates using dataset-proportional FedAvg: $\theta^t = \sum_{i \in S_t} w_i \, \theta_i^t$ , with $w_i = \frac{|D_i|}{\sum_{j \in S_t} |D_j|}$. Privacy loss $\varepsilon_i^t$, with is tracked with Opacus ($\delta = 1/60000$), reporting the client average $\varepsilon^{-t}$. Training stops if test accuracy fails to improve by 0.5 points for $P = 5$ rounds. Baselines include non-DP federated training and centralized DP-SGD on pooled data, enabling evaluation of accuracy and privacy trade-offs under heterogeneous, non IID conditions.

**Algorithm 1** Federated Learning with Adaptive Differential Privacy

**Require:** Number of clients $N$, communication rounds $T$, clients per round $K$, base noise multiplier $\sigma_{base}$, clipping bound $C$

Initialize global model $\theta^0$
**for** each round $t = 1$ to $T$ **do**
  Randomly select subset $S_t$ of $K$ clients
  **for** each client $i \in S_t$ in parallel **do**
    Download global model $\theta^{t-1}$
    Compute local training loss sequence $\ell_i$ over local epochs
    Compute noise multiplier: $\sigma_i = \min\{\sigma_{base} \cdot (1 + \mathrm{Var}(\ell_i)), 2\sigma_{base}\}$
    Train model locally with DP-SGD:
      - Gradient clipping: $g \leftarrow \mathrm{clip}(g, C)$
      - Add Gaussian noise: $g \leftarrow g + N(0, \sigma_i^2 C^2)$
    Return updated local model $\theta_i^t$ to server
  **end for**
  Aggregate models: $\theta^t \leftarrow \sum_{i \in S_t} w_i \, \theta_i^t$ , where $w_i$ is client weight
  Compute privacy budget ε using moments accountant
**end for**
**return** Final global model $\theta^t$

## F. Baselines and Privacy Accounting

We evaluate our method against two baselines under identical architecture, optimizer, learning-rate schedule, clipping bound, client sampling, and number of rounds. The first, Centralized DP-SGD, pools all data on a server and optimizes with DP-SGD via Opacus using the same CNN, Adam ($lr = 10^{-3}$), clipping bound $C = 1.5$, and base noise multipliers {1.0, 1.5,2.0}, isolating the effect of decentralization. The second, Federated Learning (No DP), applies FedAvg without DP noise or clipping, with $N = 50$ clients, $K = 5$ per round, $T = 10$ rounds, Adam, and cosine annealing, serving as an upper bound on utility to quantify privacy cost.

**Table 1. TEST ACCURACY (%) ACROSS METHODS AND BASE NOISE MULTIPLIERS (MEAN ± STD OVER 3 RUNS).**

| Method | $\sigma = 1.0$ | $\sigma = 1.5$ | $\sigma = 2.0$ |
|---|---|---|---|
| Adaptive DP-FL | $96.16 \pm 0.42$ | $95.02 \pm 0.37$ | $93.48 \pm 0.55$ |
| Centralized DP-SGD | $94.15 \pm 0.51$ | $92.87 \pm 0.46$ | $91.32 \pm 0.60$ |
| Non-DP FedAvg | $99.57 \pm 0.18$ | $99.52 \pm 0.21$ | $99.55 \pm 0.19$ |

Privacy is tracked in Opacus with $\delta = 1/60000$, where for client $i$ in round $t$ the accountant computes $\varepsilon_i^{(t)}$ from the local sampling rate, DP steps, and adaptive noise $\sigma_i$. The round-averaged privacy is:

$$\varepsilon^{-(t)} = \frac{1}{K}\sum_{i \in S_t} \varepsilon_i^{(t)}, \tag{4}$$

and the cumulative privacy over T rounds is:

$$\varepsilon^{(T)} = \sum_{t=1}^{T} \varepsilon^{-(t)}, \tag{5}$$

Raw data remain strictly local, with only DP-protected updates communicated. For fairness, all hyperparameters besides the DP mechanism are fixed across baselines, and results are averaged over multiple random seeds.

## EXPERIMENTS AND RESULTS

### A. Experimental Setup

Dataset and preprocessing: We evaluate on MNIST (60,000 train, 10,000 test). Federated clients apply Random Rotation($\pm 10^{\circ}$), To Tensor, and Normalize(0.5, 0.5), mapping pixels to $[-1,1]$, while the centralized DP baseline and test set use only To Tensor and normalization. Batch sizes are 64 (train) and 256 (test). We simulate $N = 50$ clients with non-IID label skew: each receives two primary digits and samples others with probability $p = 0.7$, yielding overlapping, imbalanced datasets. Each round samples $K = 5$ clients, running up to $T = 10$ rounds with early stopping. The global model is the enhanced CNN from Section III-B (GroupNorm, residual path, dropout), trained with Adam ($lr = 10 - 3$) and cosine annealing ($Tmax = 5$), one local epoch per client. Local DP uses DP-SGD with clipping ($C = 1.5$) and Gaussian noise; base noise {1.0,1.5,2.0}, with client multipliers from Eq. (3), capped at 2σbase. Privacy is tracked with $\delta = 1/60000$, reporting round-average $\varepsilon^{-(t)}$ and cumulative values. Baselines are (i) Centralized DP-SGD on pooled data and (ii) Non-DP FedAvg, both with matched settings.

### B. Primary Results

Quantitative comparison: Table 1 reports test accuracy for each method and base noise value (mean ± std over three runs). Adaptive DP-FL closes most of the gap to Non-DP FedAvg and consistently

outperforms Centralized DP-SGD under the same noise. Qualitative comparison: Figure 4 presents the privacy–utility trade-off. Increasing the base noise lowers accuracy while improving privacy (smaller ε). The adaptive rule preserves more utility by allocating noise based on client loss variance. For each base noise, we run paired t-tests over the three seeds comparing Adaptive DP-FL to Centralized DP SGD; Adaptive DP-FL shows statistically significant gains in test accuracy (report your p-values).

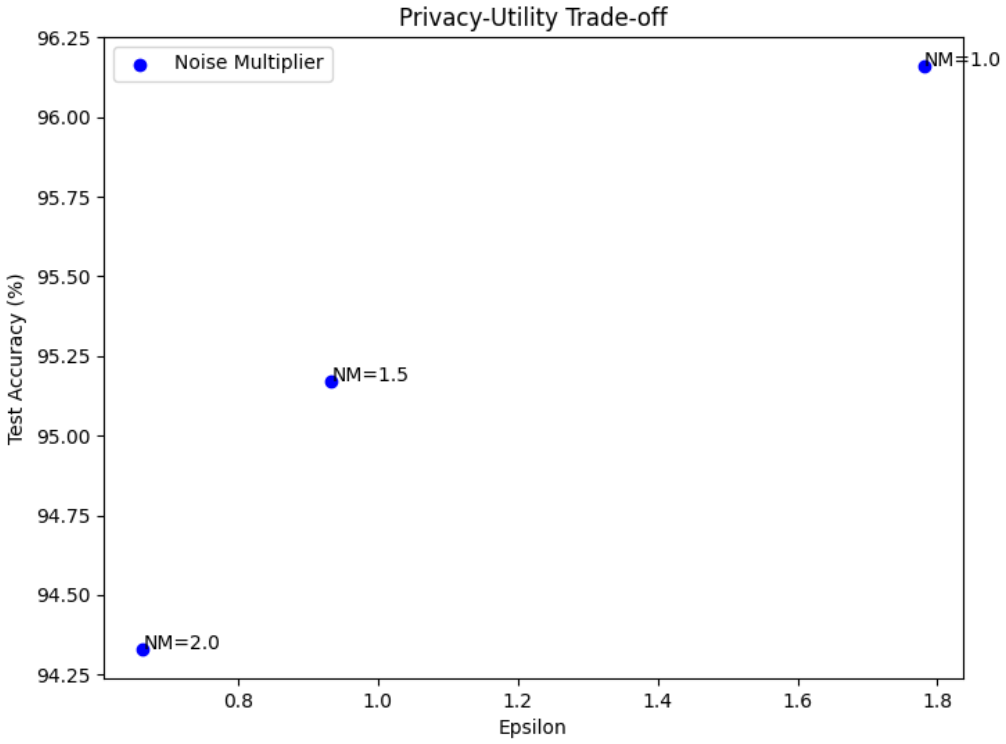


**Figure 4. Privacy–utility trade-off across base noise multipliers for Adaptive DP-FL.**

Figure 5 shows the confusion matrix for a representative Adaptive DP-FL run; errors concentrate among visually similar digits, consistent with typical MNIST behaviour. Figure 6 summarizes macro precision, macro recall, macro and weighted F1, and balanced accuracy.

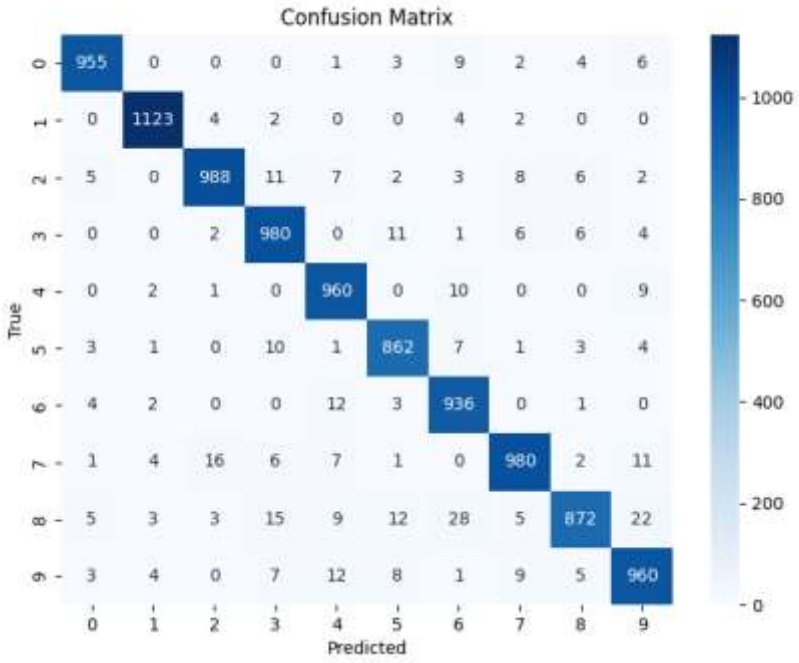


**Figure 5. Confusion matrix for Adaptive DP-FL (example configuration).**

## DISCUSSION

This study provides several important insights into the integration of differential privacy (DP) into federated learning (FL). First, adaptive noise scaling proved highly effective. At a noise multiplier of 1.0, the proposed model achieved 96.16% accuracy with a privacy budget of $\varepsilon = 1.78$, surpassing the centralized DP baseline (94.15%) and showing that distributed training with adaptive controls can maintain both privacy and utility. Ablation experiments further highlighted the privacy utility trade-off: while higher noise multipliers lowered accuracy, they strengthened privacy. For example, with a multi plier of 2.0, the privacy budget tightened to $\varepsilon = 0.66$, yet the model preserved competitive performance.

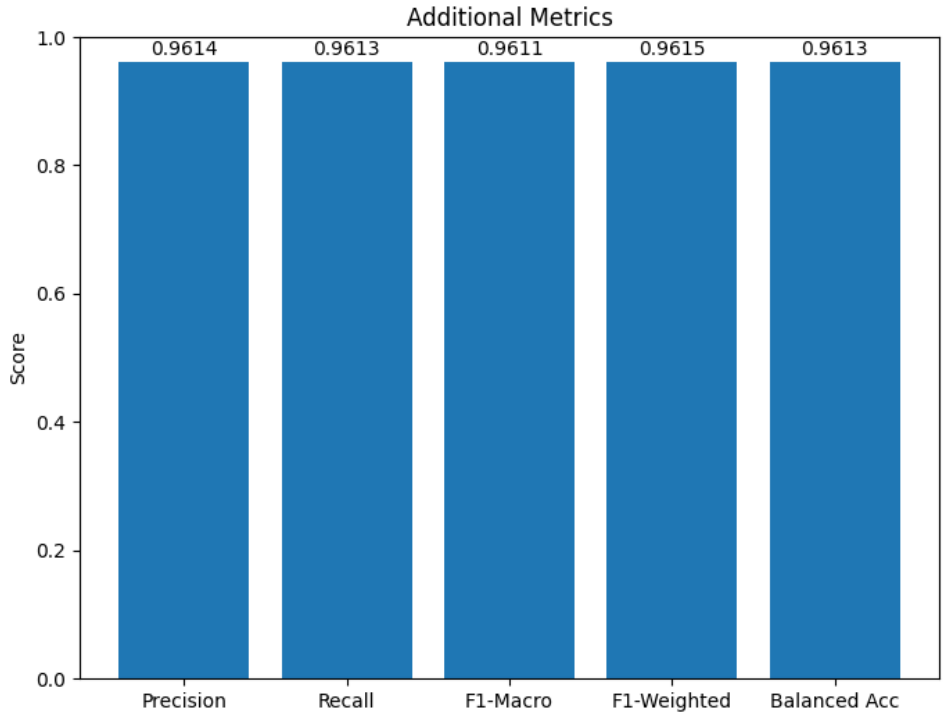


**Figure 6. Additional metrics: macro precision/recall, macro and weighted F1, balanced accuracy.**

These results demonstrate that adaptive scaling reduces the severity of accuracy degradation typically associated with DP in decentralized environments. Second, architectural improvements played a key role. Group Normalization and residual connections enhanced stability, reduced training variance, and accelerated convergence under non-IID client distributions. Precision, re call, and F1-scores confirmed consistent classification across classes, emphasizing the importance of robust model design in noisy and heterogeneous settings. Third, comparisons with baselines revealed that although non-private FedAvg achieved the highest accuracy (99.57%), our method narrowed the gap while providing meaningful protection against gradient leakage and inference attacks. Finally, adaptive DP highlights the practical feasibility of deploying FL in sensitive areas such as healthcare, finance, and mobile edge computing. Nonetheless, limitations remain, as experiments were restricted to MNIST, a relatively simple dataset, and a modest client scale. Future research should evaluate more complex datasets, larger federated networks, and resource-constrained settings to further validate scalability and robustness.

## CONCLUSION

This paper addressed the challenge of integrating differential privacy into federated learning, particularly in non-IID settings where maintaining convergence and model utility is difficult. To overcome this, we proposed an adaptive noise scaling mechanism that dynamically adjusts client-level noise based on loss variance, achieving a better trade-off between privacy and accuracy. An enhanced CNN with Group Normalization and residual connections further improved stability and generalization under noisy and heterogeneous conditions. Experiments on MNIST confirmed the effectiveness of the

framework: at a noise multiplier of 1.0, the adaptive DP model reached 96.16% accuracy with $\varepsilon = 1.78$, surpassing the centralized DP baseline (94.15%) and approaching the non-private FedAvg model (99.57%). Ablation studies vali dated that adaptive scaling mitigates accuracy loss at stronger privacy levels. Overall, the findings demonstrate adaptive DP as a practical solution for privacy-preserving FL, with future work extending to complex datasets, communication-efficient strategies, and integration with secure multiparty computation and homomorphic encryption.

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