Balancing Privacy and Accuracy: A Federated Approach to Secure Message Classification

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August 19, 2025

Abstract

Privacy-preserving classification of sensitive communications, such as spam or intrusion detection, is essential across various domains including mobile messaging, Internet-of-Vehicles (IoV), and drone communications. In this work, we propose a federated learning-based message classification framework that enables decentralized training without exposing sensitive user data by incorporating differential privacy. We demonstrate this approach through an SMS spam classification use case, comparing its effectiveness against traditional centralized learning. Experimental results show that the non-private federated learning baseline achieved the highest performance (accuracy = 96.68%, F1-score = 0.88), with the Gaussian mechanism at $\sigma = 0.25$ providing the best trade-off between privacy and utility among differentially private methods (accuracy = 95.96%, F1-score = 0.85). In contrast, DP Logistic Regression with small ϵ values ($\epsilon \in \{1, 2\}$) yielded the poorest performance (accuracy = 13.36%). These findings highlight the significant impact of privacy parameters on utility, underscoring the necessity of careful mechanism and parameter selection in real-world secure communication systems.

1 Introduction

Effective classification of malicious or spam messages is crucial for maintaining security in modern communication systems, such as personal messaging apps, drone networks, and vehicle-to-vehicle communications in IoV. However, centralized data handling commonly poses significant privacy risks [1]. Federated Learning (FL) provides a decentralized alternative by training machine learning models directly on distributed user devices without centralizing sensitive data [2]. Nevertheless, FL alone is not sufficient to prevent potential data leakages, as model updates pose a threat to (differential) privacy. Specifically, the gradients or weight updates sent from client devices to the server still contain information about the underlying data, that can be retrieved by techniques like gradient inversion to potentially reconstruct private text data or determine if specific messages were part of the training set [3]. For that reason, it is useful to further add privacy-preserving techniques to federated learning approaches in order to mitigate the risk of data breaches [2].
In this paper, we investigate federated learning in conjunction with differential privacy as a privacy-preserving approach for secure message classification, illustrating our method through the practical scenario of SMS spam detection using the UCI spam collection dataset and a simple logistic regression classifier. Our primary goal is to provide a proof of concept demonstrating how these two techniques can work together effectively, rather than focusing on a highly sophisticated classification model. Additionally, we assess different noise mechanisms for differential privacy to highlight the resulting trade-offs between privacy and performance. Our demonstration illustrates the mechanics of federated learning with noise addition, provides a practical framework for exploring privacy-utility trade-offs, and serves as a foundation for implementing more advanced privacy-preserving techniques in the context of spam detection.

2 Related Work

2.1 Federated Learning (FL)

Federated learning is a distributed machine learning framework that has recently gained prominence as a privacy-preserving solution in areas such as healthcare, edge computing, IoV, and secure messaging systems [4–6]. In the FL approach, a global model is trained across devices (clients) which each locally hold a proportion of the data. Instead of training the centralized model by sending the joint data to the central server and updating the global model there, model updates are done locally. Afterwards, only these updates (e.g. gradients or weights) are shared with the server, which then aggregates them. Finally, the server sends the new global model back to the clients for further training [2, 3]. Although this approach is now widely applied and significantly supported privacy-sensitive applications, there remain several challenges. These include, for instance, statistical heterogeneity, which arises from the non-identically distributed data across

clients caused by differences in user behavior or data volume. This heterogeneity can hinder convergence or reduce model accuracy, as the often prevailing i.i.d. assumption in distributed optimization is violated. Furthermore, as already described above, there is the problem of vulnerability to adversarial attacks such as gradient inversion, which has to be addressed in order to ensure the security and privacy of the federated learning process (e.g. by the inclusion of differential privacy) [3, 7].

2.2 Differential Privacy (DP)

Differential Privacy is a formal framework for privacy preserving data analysis that quantifies the extent to which the privacy of any individual in a dataset is protected when the output of an algorithm is released. In simpler terms, DP ensures that the inclusion or exclusion of any single individual's data in the dataset does not significantly affect the output, which in turn makes it difficult to determine whether their data was included in the computation or not. As a consequence, possible adversaries cannot infer sensible information about individuals based on the released output [8]. A common approach for implementing DP is the addition of random noise to the output of a function. However, this of course can distort the (predictive) performance of machine learning models, resulting in a trade-off between privacy and accuracy.
Formally, a computational algorithm $\text{alg} : \mathbb{R}^{N\times p} \to \text{Range(alg)}$, operating on a data matrix $Y \in \mathbb{R}^{N\times p}$, satisfies (ε, δ)-differential privacy, if for any measurable set

$$O \subseteq \{\text{alg}(Y + V) \mid Y \in \mathbb{R}^{N\times p}, V \in \mathbb{R}^{N\times p}\},$$

and for any pair of neighboring data matrices (Y, Y') differing in at most one element, the following holds:

$$\Pr[\text{alg}(Y + V) \in O] \leq e^{\varepsilon} \Pr[\text{alg}(Y' + V) \in O] + \delta.$$

In other words, changing a single element of Y by an amount that is upper-bounded by d only changes the distribution of the algorithms output by a factor of e^{ε} with probability at least $1 - \delta$, therefore limiting the influence of any individual data point on the algorithm's output [9].
Although DP is also preserved during post-processing and the outputs can therefore be denoised to improve accuracy again, a major problem remains: the iterative nature of machine learning models, which leads to an accumulation of privacy loss and thus requires a large amount of noise to be added [8]. While several techniques like optimized noise mechanisms exist in the literature to mitigate this problem [8], we do not focus on such technicalities as this would be beyond the scope of this paper. Our objective is instead to provide a basic demonstration of the combined implementation of differential privacy and federated learning in the context of SMS spam detection, comparing simple noise-based DP methods to illustrate their practical impact.

2.3 SMS Spam Detection

SMS spam comprises any unwanted messages, including unsolicited or malicious texts delivered through Short Message Service (SMS), that are often aimed at advertising, fraud, or phishing [10, 11]. As an increasing number of people are using their mobile devices for sensitive activities like online banking, the detection of SMS Spam Messages is of growing importance to prevent financial or personal harm [10, 12]. Although in recent years numerous architectures for the detection of such spam messages were published and employed, these "traditional" spam or malicious message detection models predominantly employ centralized training methods, leading to potential privacy issues because of the central aggregation of sensitive data which increases the risk of data breaches and unauthorized access [10, 13, 14]. To address these issues in the context of SMS spam detection, existing studies have also focused on secure aggregation protocols and privacy-preserving federated mechanisms to mitigate the associated privacy risks [10]. In this work, we extend these studies by employing federated learning integrated with differential privacy to demonstrate how user data can be protected throughout the training process of a machine learning classifier and illustrate the resulting trade-offs. As our dataset contains binary-labeled SMS messages, the task at hand can be defined as binary supervised classification problem. Therefore, we employ a simple logistic regression classifier in order to minimize computational cost while keeping the implementation straightforward and understandable. Finally, we perform a comparative analysis between our federated logistic regression models incorporating different differential privacy mechanisms and a traditional centralized baseline, evaluating trade-offs in convergence speed and accuracy.

3 Methodology

The proposed framework integrates *federated learning* (FL) with multiple *differential privacy* (DP) mechanisms to evaluate privacy-utility trade-offs in SMS spam classification. The experimental workflow mirrors the benchmarking implementation to ensure reproducibility.

3.1 Dataset and Preprocessing

We use the *SMS Spam Collection* dataset [15], which contains 5,574 labeled English SMS messages categorized as "ham" or "spam". The preprocessing steps are:

1. Convert text to lowercase.
2. Remove digits and punctuation using regular expressions.
3. Tokenize and remove English stopwords.
4. Apply TF-IDF vectorization with unigrams.

The resulting sparse feature matrix is used for all experiments.

3.2 Federated Data Partitioning

To emulate a cross-device federated learning setting, the dataset is randomly split into $N_c = 5$ disjoint client datasets $\{\mathcal{D}_1, \ldots, \mathcal{D}_{N_c}\}$, a 10% validation set, and a 20% test set. Each client retains a unique subset of the training data, with no raw samples exchanged between clients or transmitted to the server, thereby preserving data locality and mirroring the decentralized structure of federated learning.

3.3 Privacy Mechanisms

Four configurations are benchmarked.

1. **No Privacy:** FL without noise injection.
2. **Gaussian Mechanism:** Additive Gaussian noise $\mathcal{N}(0, \sigma^2)$ with $\sigma \in \{0.25, 0.5, 0.75, 1.0\}$.
3. **Laplace Mechanism:** Additive Laplace noise $\text{Lap}(0, b)$ with $b \in \{0.25, 0.5, 0.75, 1.0\}$.
4. **DP Logistic Regression:** (ε, δ)-DP logistic regression via `diffprivlib` with $\varepsilon \in \{1, 2, 5, 10, 20, 30, 50\}$ and $\delta = 10^{-5}$.

For Gaussian and Laplace mechanisms, the per-coordinate ε is computed as:

$$\varepsilon_{\text{Gauss}} = \frac{\Delta_2 \sqrt{2 \log(1.25/\delta)}}{\sigma}, \quad \varepsilon_{\text{Laplace}} = \frac{\Delta_1}{b}$$

where Δ_2 and Δ_1 denote ℓ_2 and ℓ_1 sensitivities.

3.4 Federated Training Procedure

We train a global logistic regression model using a simplified single-round *Federated Averaging* (FedAvg) procedure:

1. Initialize the global model parameters.
2. Distribute the model to all $N_c = 5$ clients.
3. Each client trains a local logistic regression model on its full dataset partition until convergence.
4. Clip each client's learned coefficients to a fixed bound `clip_value` $= 1.0$.
5. Apply the configured noise mechanism to the averaged model parameters:
    - **Gaussian mechanism**: add Gaussian noise to each parameter and compute the per-coordinate ϵ.

- **Laplace mechanism**: add Laplace noise to each parameter and compute the per-coordinate ϵ.
- **Differentially private logistic regression(diffprivlib)**: train each local model with built-in (ϵ, δ)-DP.

6. Aggregate the noisy coefficients across clients using FedAvg.
7. Evaluate the final model on the test set.

All runs fix $\delta = 10^{-5}$ for Gaussian and diffprivlib configurations.

3.5 Benchmarking and Parameter Sweeps

The benchmarking process iterates over all configurations, recording accuracy, precision, recall, F1-score, runtime, and privacy loss (ε) in JSON format. Parameter sweeps include:

- Gaussian: $\sigma \in \{0.25, 0.5, 0.75, 1.0\}$,
- Laplace: $b \in \{0.25, 0.5, 0.75, 1.0\}$,
- DP Logistic Regression: $\varepsilon \in \{1, 2, 5, 10, 20, 30, 50\}$.

3.6 Evaluation Metrics

We measure:

- **Utility:** Accuracy, Precision, Recall, and F1-score.
- **Runtime:** End-to-end training time.
- **Privacy:** Computed ε for noise-based configurations.

3.7 Code Availability

All source code, including preprocessing, FL training, DP mechanisms, and evaluation scripts, is available at:
`https://github.com/michaelkhany/FedSpamBenchmark`.

4 Results

4.1 Centralized Model Performance

The centralized baseline, trained on the complete dataset without any privacy noise, achieved an accuracy of 96.68%, precision of 84.15%, recall of 92.62%, and an F1-score of 88.18%. The confusion matrix shows low false-positive ($FP = 26$) and false-negative counts ($FN = 11$), resulting in an ROC-AUC of 0.9816 and PR-AUC of 0.9500. This serves as the upper-bound reference for privacy-preserving federated experiments.

Table 1: Centralized Model Metrics (No Privacy Noise)

Acc	Prec	Rec	F1	ROC-AUC	PR-AUC	RT (s)
0.9668	0.8415	0.9262	0.8818	0.9816	0.9500	0.01

4.2 Federated Model Performance with Gaussian Mechanism

Gaussian noise was applied at different scales (σ), with ε decreasing proportionally to the noise magnitude. At $\sigma = 0.25$, the model retained 95.96% accuracy with $\varepsilon \approx 7.75$. Increasing noise to $\sigma = 1.0$ reduced accuracy to 85.74% and ROC-AUC to 0.8219.

Table 2: Federated Model with Gaussian Mechanism

Scale	Acc	Prec	Rec	F1	ROC	PR	ε
0.25	0.9596	0.8377	0.8658	0.8515	0.9683	0.9178	7.75
0.50	0.9121	0.6281	0.8389	0.7184	0.9473	0.8334	3.88
0.75	0.9022	0.6724	0.5235	0.5887	0.8961	0.6931	2.58
1.00	0.8574	0.4745	0.6242	0.5391	0.8219	0.5871	1.94

4.3 Federated Model Performance with Laplace Mechanism

Laplace noise showed a steeper decline in performance with higher scales. At $b = 0.25$, accuracy was 93.90% with $\varepsilon = 1.6$, but at $b = 1.0$, accuracy dropped to 76.32% and PR-AUC to 0.3377.

Table 3: Federated Model with Laplace Mechanism

Scale	Acc	Prec	Rec	F1	ROC	PR	ε
0.25	0.9390	0.7425	0.8322	0.7848	0.9564	0.8652	1.60
0.50	0.8834	0.5576	0.6174	0.5860	0.8589	0.5901	0.80
0.75	0.8762	0.5311	0.6309	0.5767	0.8487	0.5361	0.53
1.00	0.7632	0.3051	0.6040	0.4054	0.7688	0.3377	0.40

4.4 Federated Model with DP Logistic Regression (Diffprivlib)

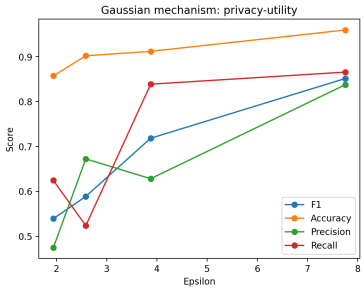
For DP Logistic Regression, performance was near-random for $\varepsilon \leq 5$, with PR-AUC close to the class prior. Accuracy only became competitive at $\varepsilon \geq 30$, reaching 78.57% with PR-AUC 0.3402.

Table 4: Federated Model with DP Logistic Regression

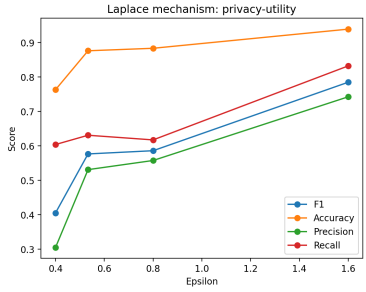
ε	Acc	Prec	Rec	F1	ROC	PR	RT (s)
1	0.1336	0.1336	1.0000	0.2358	0.5000	0.1336	2.54
5	0.1381	0.1336	0.9933	0.2355	0.5608	0.1773	1.26
10	0.5157	0.1439	0.5302	0.2264	0.5232	0.1422	1.25
30	0.7022	0.2348	0.5436	0.3279	0.6791	0.2504	1.04
50	0.7857	0.3282	0.5772	0.4185	0.7602	0.3402	1.37

4.5 Privacy-Utility Trade-offs

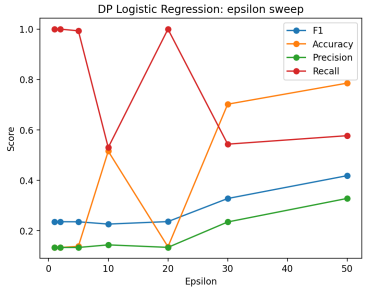
Figures 1a-1c visualize the privacy-utility relationship for each mechanism. For the Gaussian mechanism, $\sigma = 0.25$ retains most accuracy with $\varepsilon \approx 7.75$, whereas $\sigma \geq 0.75$ results in a steep decline in utility. For the Laplace mechanism, values of $b \leq 0.5$ offer a better trade-off between privacy and performance, while higher noise levels quickly diminish PR-AUC. In the case of the diffprivlib logistic regression, performance remains consistently low until $\varepsilon \geq 30$, indicating a high sensitivity to privacy constraints.



(a) Gaussian mechanism



(b) Laplace mechanism



(c) DP logistic regression

Figure 1: Privacy-utility trade-offs for different differential privacy mechanisms in the federated logistic regression setting

4.6 Runtime Impact

Gaussian and Laplace mechanisms introduce negligible overhead ($\approx 0.01\,\mathrm{s}$ per round), while DP Logistic Regression incurs 1–2.5 s due to per-coordinate clipping and noise application. Note, however, that these measurements correspond to a single communication round.

4.7 Federated vs. Centralized Comparison

Federated training without noise closely matches centralized performance, confirming that performance degradation is primarily due to noise injection rather than the federated setup itself. Well-tuned Gaussian ($\sigma = 0.25$) and Laplace ($b = 0.25$) mechanisms preserve over 95% of centralized accuracy while providing moderate ε privacy guarantees.

5 Privacy Implications

Federated learning inherently enhances privacy by ensuring that model training occurs locally on client devices, with only model updates being shared for aggregation. This design eliminates the direct transfer of raw message data, reducing the risk of data breaches and aligning closely with regulatory frameworks such as the GDPR. Furthermore, this approach supports the principles of *data minimization*, *transparency*, and *informed user consent* [1]. However, the privacy guarantees depend heavily on the aggregation protocol and the degree of protection applied to model updates. As demonstrated in our results, integrating differential privacy mechanisms introduces measurable trade-offs between utility and privacy, which must be balanced according to the sensitivity of the underlying data.

6 Limitations

While our DP federated learning framework demonstrates the general feasibility and trade-offs of integrating simple noise mechanisms into federated model aggregation, there are several limitations. First, due to the simplified implementation, clipping and adding Gaussian or Laplace noise to aggregated model parameters provides only basic privacy protection, and there is no tracking of the cumulative privacy loss across multiple communication rounds, as it would be in a full iterative DP framework. Additionally, while our approach using (diffprivlib) DP logistic regression provides local privacy guarantees, it also does not account for composition effects over multiple federated rounds.
Beyond privacy, our approach also faces typical federated learning challenges, such as high computational demands on local devices and non-IID data distributions that can slow down convergence and reduce accuracy.

7 Conclusion and Future Work

This work demonstrated and evaluated the integration of federated learning into a privacy-preserving SMS spam classification pipeline, benchmarking multiple differential privacy mechanisms (Gaussian, Laplace, and DP logistic regression), across a range of parameter settings. The results confirm that federated learning inherently reduces privacy risks by avoiding raw data transfer, yet additional guarantees through differential privacy introduce measurable utility losses. The degree of this trade-off depends strongly on the choice of noise mechanism and parameter values, as reflected in the privacy-utility curves (Figures 1a, 1b, and 1c) and in the detailed performance tables presented earlier.

The analysis shows that Gaussian noise generally maintained better predictive utility than Laplace at comparable privacy budgets, while DP logistic regression proved highly sensitive to the value of ε, often leading to severe degradation at stricter privacy levels. These findings offer actionable guidance for deploying privacy-preserving decentralized message classification in domains such as the Internet of Vehicles, drone-based communication, and other latency-sensitive applications where both accuracy and privacy are critical. The non-private federated baseline achieved the highest overall performance, with the Gaussian mechanism at $\sigma = 0.25$ emerging as the most effective privacy-preserving variant. Conversely, DP Logistic Regression with small ϵ values suffered drastic performance degradation, making it unsuitable for practical deployments.

Future research should focus on optimizing computational efficiency to reduce on-device training time and communication costs, mitigating the effects of non-identically distributed data through personalization and improved aggregation strategies, and incorporating more advanced privacy-preserving technologies such as fully homomorphic encryption and secure multi-party computation. Furthermore, extending the experimental validation to real-world (multi-round) cross-device settings with heterogeneous hardware and realistic network conditions will provide a more comprehensive assessment of the proposed framework's robustness and scalability.

References

[1] V. S. K. Mothukuri, R. M. Parizi, S. Pouriyeh, Y. Huang, A. Dehghantanha, and G. Srivastava, "A survey on security and privacy of federated learning," *Future Generation Computer Systems*, vol. 115, pp. 619–640, 2021.

[2] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS)*. PMLR, 2017, pp. 1273–1282.

[3] C. Meijer, J. Huang, S. Sharma, E. Lazovik, and L. Y. Chen, "Ts-inverse: A gradient inversion attack tailored for federated time series forecasting models," 2025. [Online]. Available: https://arxiv.org/abs/2503.20952

[4] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 10, no. 2, pp. 1–19, 2019.

[5] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, "Federated learning in mobile edge networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 2031–2063, 2020.

[6] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings *et al.*, "Advances and open problems in federated learning," *Foundations and Trends® in Machine Learning*, vol. 14, no. 1-2, pp. 1–210, 2021.

[7] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated learning: Challenges, methods, and future directions," *IEEE Signal Processing Magazine*, vol. 37, no. 3, p. 50–60, May 2020. [Online]. Available: http://dx.doi.org/10.1109/MSP.2020.2975749

[8] M. Kumar, M. Rossbory, B. Moser, and B. Freudenthaler, "An optimal (,) - differentially private learning of distributed deep fuzzy models," *Information Sciences*, vol. 546, 08 2020.

[9] M. Kumar, M. Rossbory, B. A. Moser, and B. Freudenthaler, "Deriving an optimal noise adding mechanism for privacy-preserving machine learning," in *Proceedings of the 3rd International Workshop on Cyber-Security and Functional Safety in Cyber-Physical (IWCFS 2019)*, G. Anderst-Kotsis, A. M. Tjoa, I. Khalil, M. Elloumi, A. Mashkoor, J. Sametinger, X. Larrucea, A. Fensel, J. Martinez-Gil, B. Moser, C. Seifert, B. Stein, and M. Granitzer, Eds. Linz, Austria: Springer International Publishing, Aug. 2019, pp. 108–118.

[10] Y. Li, R. Zhang, W. Rong, and X. Mi, "Spamdam: Towards privacy-preserving and adversary-resistant sms spam detection," 2024. [Online]. Available: https://arxiv.org/abs/2404.09481

[11] X. Liu, H. Lu, and A. Nayak, "A spam transformer model for sms spam detection," *IEEE Access*, vol. 9, pp. 80 253–80 263, 2021.

[12] D. Timko, D. H. Castillo, and M. L. Rahman, "A quantitative study of sms phishing detection," 2024. [Online]. Available: https://arxiv.org/abs/2311.06911

[13] T. A. Almeida, J. M. G. Hidalgo, and A. Yamakami, "Contributions to the study of sms spam filtering: new collection and results," *Proceedings of the 11th ACM Symposium on Document Engineering*, pp. 259–262, 2011.

[14] H. Q. Anh, P. T. Anh, P. S. Nguyen, and P. D. Hung, "Federated learning for vietnamese sms spam detection using pre-trained phobert," in *Intelligent Data Engineering and Automated Learning – IDEAL 2024*, ser. Lecture Notes in Computer Science. Springer, 2024, vol. 15346, pp. 254–264.

[15] U. M. L. Repository, "SMS Spam Collection Data Set," https://archive.ics.uci.edu/ml/datasets/sms+spam+collection, 2012, accessed: 2025-07-04.