# Maverick: *Collaboration-free* Federated Unlearning for Medical Privacy


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## Introduction

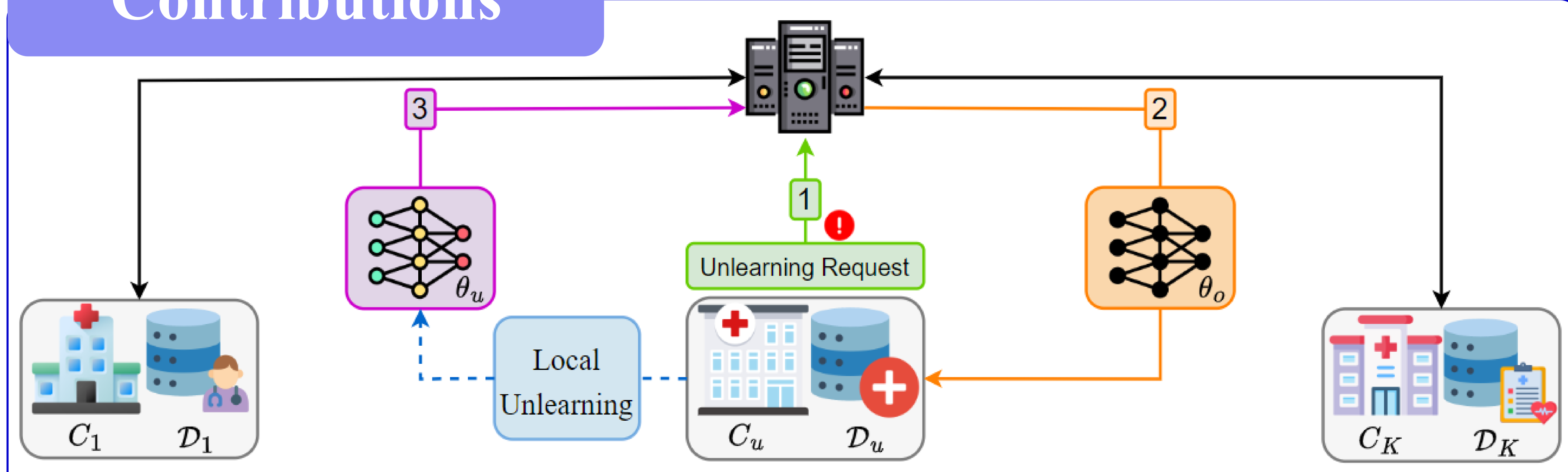
- **Federated Learning (FL)** enables collaborative model training across medical institutions without sharing raw data, preserving patient privacy.
- **Federated Unlearning (FU)** enables the removal of *sensitive* data from models, supporting the "*right to be forgotten*" established under **Article 17 of the GDPR**.
- As a result, FU strengthens privacy, supports legal compliance, and builds trust in medical AI.

## Motivation

**Limitations** of existing FU:

i. Require global client collaboration
ii. Increasing privacy risks
iii. High computational burden.
iv. Lack of a unified unlearning solution that can works across *sample*, *class* and *client* unlearning.

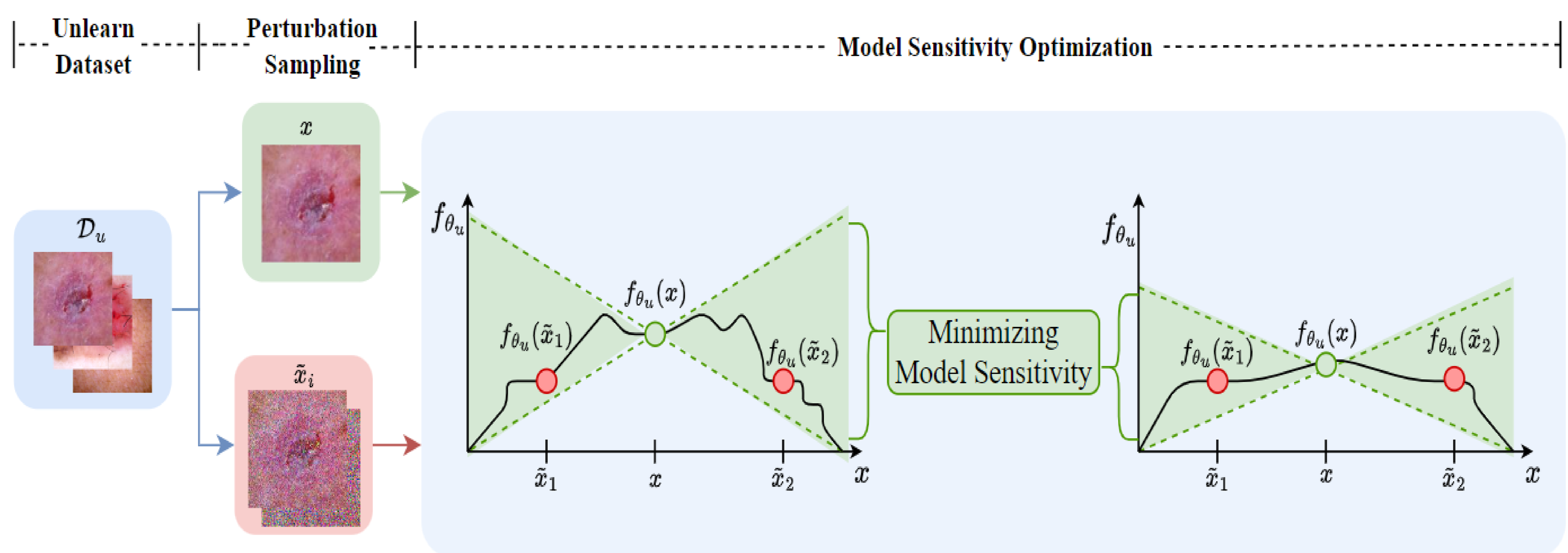
## Contributions




1. ***Collaboration-Free FU Framework***
   Local unlearning without needing collaboration from other clients.
2. ***Model Sensitivity Minimization***
   Introduces a Lipschitz-based metric to reduce memorization.
3. ***Theoretical & Empirical Validation***
   Validated on medical datasets for *sample*, *class,* and *client* unlearning.

## Proposed Method

***Maverick*** enables local unlearning at the target client **without requiring** collaboration from other, ensuring privacy and efficiency.




1. **Perturbation Sampling**: Add Gaussian noise to input samples

$$\tilde{x} = x + \delta, where\ \delta \sim \mathcal{N}(0, \sigma^2)$$

2. **Model Sensitivity Approximation:** Monte Carlo sensitivity estimation.

$$\mathbb{E}_{\delta} \frac{\left\| f_{\theta_o}(x) - f_{\theta_o}(\tilde{x}) \right\|_2}{\|x - \tilde{x}\|_2} \sim \frac{1}{N} \sum_{i=1}^{N} \frac{\left\| f_{\theta_o}(x) - f_{\theta_o}(\tilde{x}_i) \right\|_2}{\|\delta_i\|_2}$$

3. **Local Optimization:** Reduce model's output response to the target data.

$$\theta_u = argmin \mathbb{E}_{(x,y)\in D_u} \frac{1}{N} \sum_{i=1}^{N} \frac{\left\| f_{\theta_o}(x) - f_{\theta_o}(\tilde{x}_i) \right\|_2}{\|\delta_i\|_2}$$

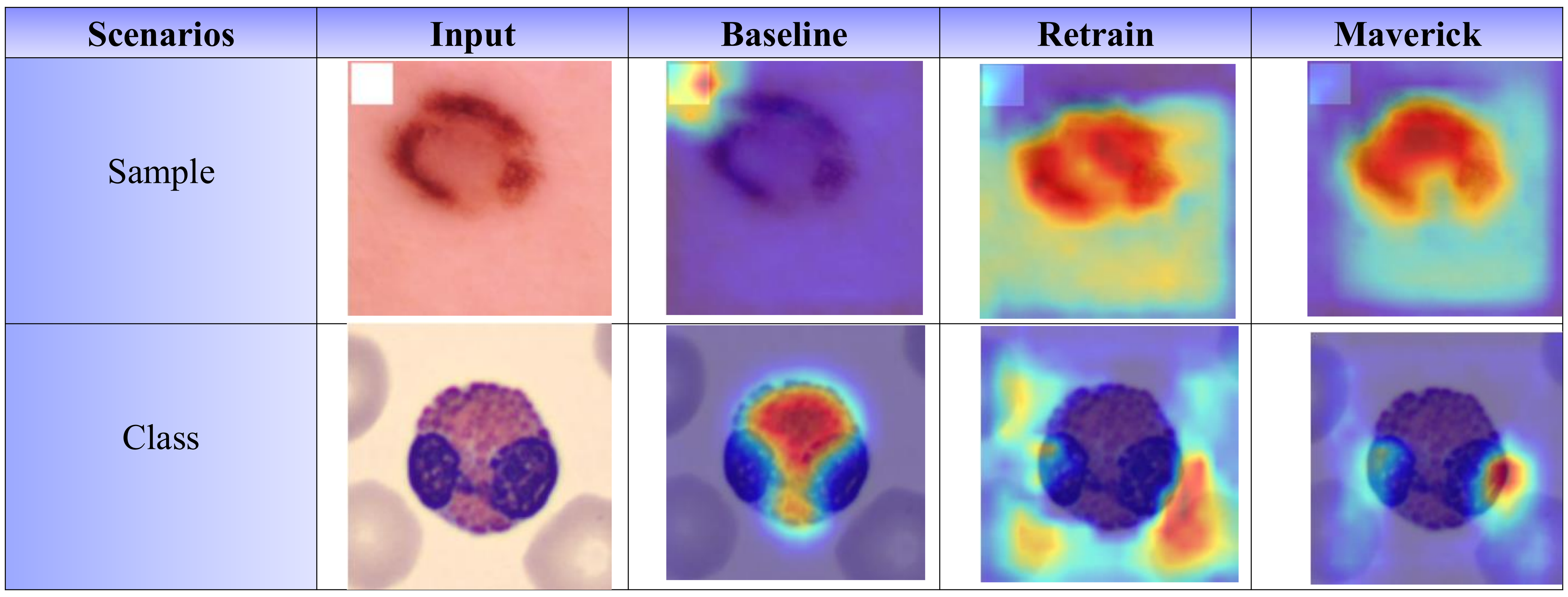
## Scenarios Definition

i. **Sample Unlearning -** Removes *specific patient records* (e.g., one patient's scan) when an individual withdraws consent.
ii. **Class Unlearning -** Removes *all data from an entire medical institution* (e.g., a hospital exits the collaboration).
iii. **Client Unlearning -** Eliminates *a specific data class* (e.g., all CT scans of a certain disease) from the model.

## Experiments

| Scenarios | Datasets | Metrics | Accuracy (%) | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Baseline | Retrain | FT | FedCDP | FedRecovery | Maverick |
| Sample | Path | $D_r$ | 91.37 | 92.50 | **93.04** | 70.19 | 90.14 | 89.43 |
| | | $D_u$ | 90.48 | 0.00 | 46.13 | 22.61 | 2.35 | **0.71** |
| | | MIA | 92.51 | 8.69 | 55.49 | 38.05 | 13.43 | **10.04** |
| Class | Derma | $D_r$ | 82.52 | 80.39 | **81.38** | 79.31 | 55.51 | 79.18 |
| | | $D_u$ | 80.88 | 0.00 | 53.69 | 0.51 | 31.40 | **0.18** |
| | | MIA | 90.62 | 2.60 | 40.44 | 5.17 | 34.16 | **0.49** |
| Client | Blood | $D_r$ | 91.21 | 91.90 | **93.38** | 79.58 | 89.54 | 88.33 |
| | | $D_u$ | 92.83 | 0.00 | 43.38 | 25.29 | 1.95 | **0.53** |
| | | MIA | 96.71 | 5.78 | 52.57 | 39.85 | 10.95 | **6.73** |

## Qualitative Results

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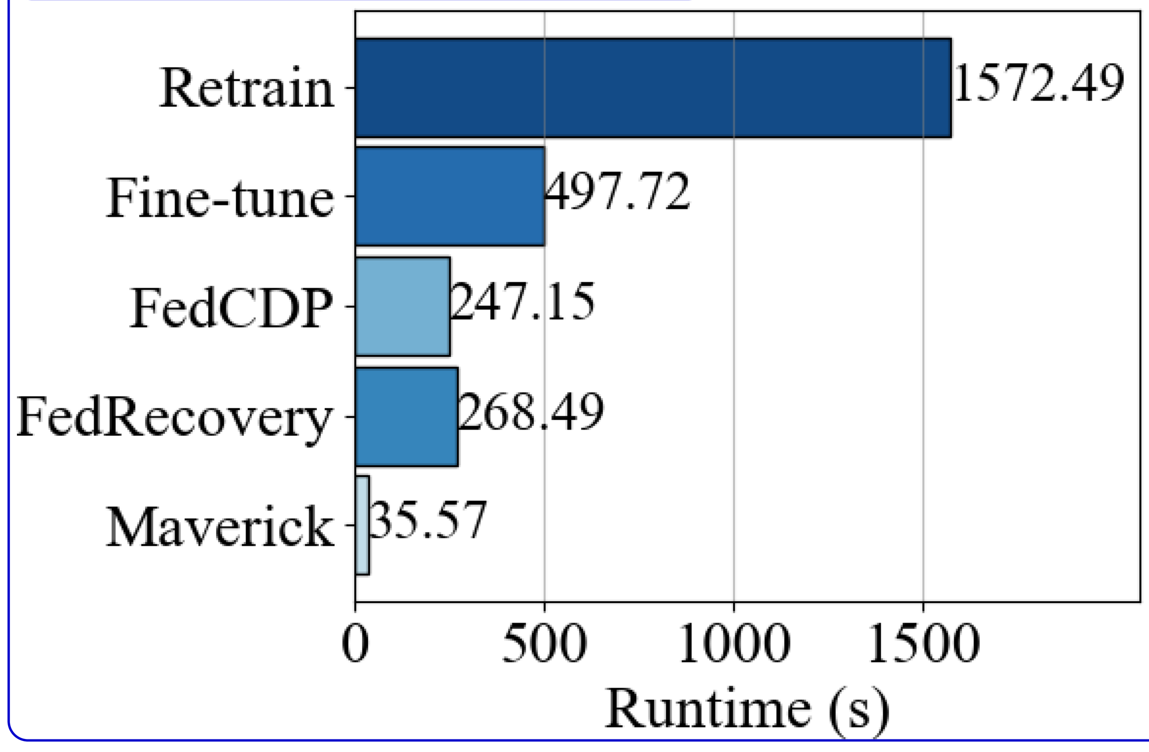
## Time Efficiency




## Conclusion

- **Maverick** is the first *collaboration-free* federated unlearning method for medical AI.
- Enables local unlearning without disturbing other clients.
- Demonstrates strong results in privacy, efficiency, and fidelity.
- Well-suited for real-world healthcare and privacy-critical domains.