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Privacy and Robustness in Federated Learning for Healthcare

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Abstract - *: The deployment of Federated Learning (FL) in sensitive domains, particularly* ***healthcare****, faces significant challenges related to data privacy and model robustness against malicious attacks. Traditional centralized training is infeasible due to strict regulations and the non-IID nature of hospital data. This paper addresses the critical trade-off between privacy preservation and robustness in FL when faced with* ***data poisoning attacks****. The primary research question is:* ***Which privacy-preserving techniques are most effective for federated learning in healthcare when facing data poisoning attacks?***

Key Words: *Federative learning, Differential privacy, Data Poisoning Attacks, Robust Aggregation.*

1. INTRODUCTION

Federated Learning (FL) has emerged as a promising machine learning paradigm, enabling multiple clients (e.g., hospitals) to collaboratively train a global model without sharing their raw data. This approach is particularly critical for healthcare, where patient data privacy is mandated by regulations.

The challenges in deploying FL in this domain are multifaceted:

- **Data Heterogeneity (Non-IID data):** Data across different hospitals is often non-identically distributed, requiring specific aggregation strategies.
- **Privacy Concerns:** Despite not sharing raw data, model updates can leak sensitive information, necessitating techniques like Differential Privacy (DP) or Secure Aggregation (SecAgg).
- **Robustness to Attacks:** Malicious clients can launch **data poisoning** or **model manipulation (Byzantine)** attacks, compromising the integrity of the global model. Specifically, this paper focuses on defending against **Label Flipping** attacks (where malicious clients flip labels like disease status) and **Scaling up Backdoor** attacks (injecting a trigger pattern into medical images, though the current experiment focuses on tabular data).

This paper aims to comprehensively evaluate the effectiveness of privacy-preserving techniques—DP, SecAgg, and Krum—in mitigating the impact of these attacks while maintaining high model utility (accuracy).

2. LITERATURE REVIEW

- **Federated Learning in Healthcare (FL-HC):** Recent literature highlights the growing adoption of Federated Learning (FL) as a privacy-preserving alternative to centralised machine learning in clinical environments. Foundational studies on Federated Averaging (FedAvg) demonstrate its ability to collaboratively learn global models without transferring raw medical records across institutions, significantly reducing privacy risk while enabling cross-hospital learning. However, FL performance degrades when client datasets exhibit severe non-IID characteristics, a common scenario across heterogeneous medical populations. To mitigate this, researchers have explored weighted aggregation, personalisation layers, and multi-task optimisation. Despite these advances, federated pipelines remain vulnerable to privacy leakage and adversarial manipulation, motivating the integration of additional security layers such as Differential Privacy (DP) and Secure Aggregation (SecAgg) in healthcare FL deployments.
- **Adversarial Attacks on Federated Learning Systems:** A rapidly evolving body of work documents the susceptibility of FL architectures to data poisoning and Byzantine attacks. Label flipping,

gradient manipulation, and backdoor trigger insertion represent common threat vectors through which adversaries degrade or hijack the global model. Empirical studies indicate that even a small percentage of malicious clients can destabilise aggregation schemes like FedAvg, leading to significant reductions in diagnostic accuracy in sensitive domains such as cardiology and endocrinology. Robust aggregation algorithms such as Krum, Trimmed Mean, and Median have been proposed to defend against these threats by filtering anomalous update patterns. While effective under IID data assumptions, their robustness weakens under realistic non-IID hospital distributions, necessitating further research into adaptive and data-aware defence mechanisms for real clinical deployments.

- **Privacy-Preserving Mechanisms - Differential Privacy & Secure Aggregation:** Differential Privacy (DP) has emerged as a dominant methodology for safeguarding sensitive patient information in federated settings. By injecting calibrated statistical noise into client gradients, DP provides formal protection guarantees against membership inference and reconstruction attacks. Various studies demonstrate that while DP effectively limits privacy leakage, the resulting noise reduces model fidelity—accentuating the classical privacy–utility trade-off. Secure Aggregation (SecAgg), in contrast, uses cryptographic masking to ensure that the central server only observes aggregated updates, not individual contributions. Though SecAgg preserves accuracy by avoiding added noise, it does not inherently protect against malicious clients or corrupted updates. Current research emphasises hybrid strategies that combine DP, SecAgg, and robust optimisation to balance privacy, computational efficiency, and predictive performance in clinical FL applications.

3. COMPARATIVE ANALYSIS OF REPRESENTATIVE WORKS :

Existing work in secure FL broadly falls into two categories: privacy-enhancing technologies (PETs) and Byzantine-robust aggregation methods.

- **Privacy-Enhancing Technologies:** Differential Privacy (DP) is a commonly used technique that adds Gaussian noise to client updates before aggregation, offering a quantifiable privacy guarantee (via the epsilon ε value). Another method is Secure Aggregation (SecAgg), which uses cryptographic secrets (multi-party computation) to ensure the server cannot see individual client updates, effectively achieving data confidentiality during the aggregation step.

- **Robust Aggregation**: Techniques like Krum and Trimmed Mean are designed to identify and remove outlying or malicious updates from the aggregated model, thereby providing Byzantine resilience against data poisoning and manipulation attacks.

While many studies focus on maximising utility with a single defence, a comprehensive evaluation of combined methods, such as Krum + DP, is essential to understand the complex interplay between privacy, utility, and robustness under non-IID data conditions.

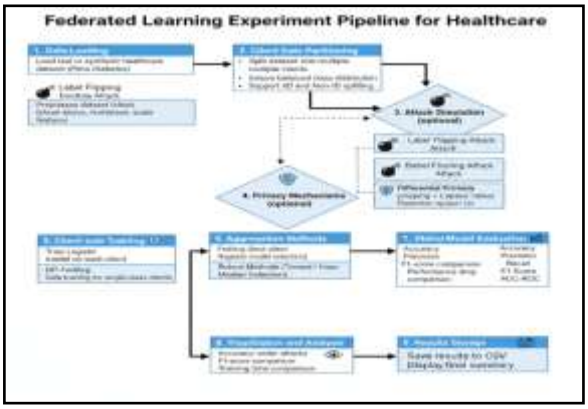
Federated Learning Experiment Pipeline for Healthcare
3. Attack Simulation (optional)
4. Privacy Mechanisms (optional)
Save results to CSV
Display final summary

Figure 3.1

4. METHODOLOGY:

Dataset and Evaluation Metrics

The study uses the **Pima Indians Diabetes Dataset (UCI)**, a publicly available tabular dataset suitable for quick experimentation on binary classification. The dataset includes features such as Glucose, BMI, and Age, with the **Outcome** being the binary classification target.

Dataset used: https://www.kaggle.com/datasets/saurabh00007/diabetescsv

Evaluation metrics:

- **Performance / Utility:** Accuracy, Precision, Recall, F1-Score, and AUC-ROC.
- **Robustness:** Performance degradation across adversarial attacks (label flipping, data poisoning,

and backdoor), measured through changes in accuracy, F1-score, and AUC.

- **Efficiency:** Training time for each federated learning method.
- **Privacy Cost:** Differential Privacy parameter ε and its effect on accuracy and model stability.

The experiments were executed in a Python environment using **NumPy, Pandas, scikit-learn, and Matplotlib**, without requiring TensorFlow or PySyft. The diabetes dataset (real or synthetically generated) was divided into multiple clients to simulate different hospitals participating in a federated learning setup. Both IID and non-IID distributions can be generated; however, the evaluation primarily used **balanced client data** to avoid single-class failures.

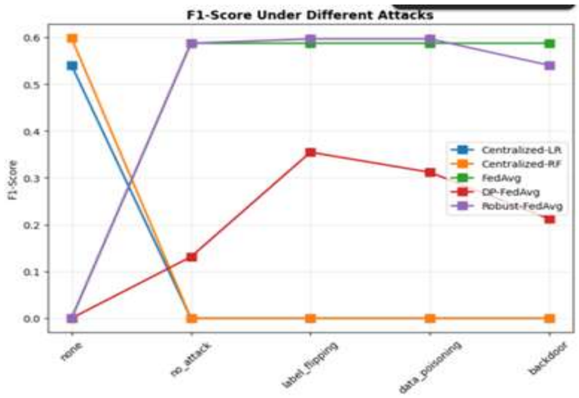

Figure 4.1

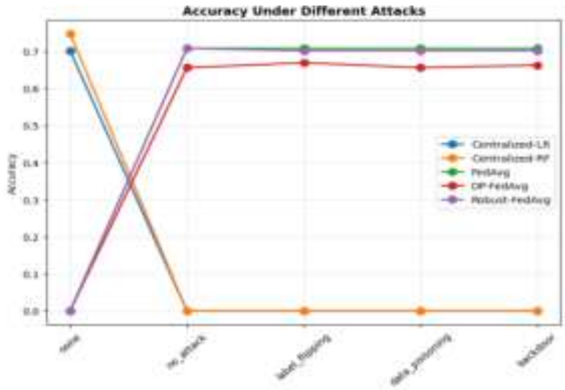

Figure 4.2

Scenario Setup

Four experimental scenarios were designed to evaluate the impact of privacy and adversarial threats on federated learning:

- **Baseline (FedAvg – No Attack)** : Standard Federated Averaging with no adversaries and no defences. This scenario provides a reference for comparing attack impact and defence effectiveness.
- **Attack Scenario (Poisoning / Label Flipping)** : A subset of clients (20%) were designated malicious and performed **label flipping attacks**, intentionally inverting their class labels to corrupt the global model.
- **Attack + Differential Privacy (DP-FedAvg)** : The same poisoning attack was applied, but clients also added **differential privacy noise** (Laplace noise with ε = 1.0) to their local data before training. This scenario evaluates whether DP improves robustness at the cost of model performance.
- **Attack + Robust Aggregation (Robust-FedAvg)** : Robust aggregation strategies (median-based selection similar to Krum/Trimmed Mean) were applied to mitigate malicious client contributions under the same poisoning attack.

Method Name	**Aggregation Method**	**Privacy Technique**	**Robustness Strategy**
FedAvg (Baseline)	Averaging	None	None
FedAvg + DP	Averaging	Gaussian noise (Vary ε)	None
SecAgg	Cryptographic sum	Multi-Party Computation	None (Focus on privacy)
Krum + DP	Krum (Byzantine-robust)	Gaussian noise (DP)	Trimmed Mean (Remove Outliers)

Figure 4.3

We hypothesise that:

1. Attack Impact on Standard FedAvg

The hypothesis predicts that standard FedAvg, when subjected to data poisoning attacks:

- Will show a **significantly degraded AUC-ROC and F1-Score**.
- Will have a **high Attack Success Rate (ASR)** for the malicious clients.

2. Superiority of Combined Defense (Krum + DP)

The researchers hypothesize that combining robustness and privacy mechanisms will yield the best balance:

- **Krum + DP** will likely be the **best overall performer in terms of robustness**.
- This combined approach is expected to show the **lowest ASR** while still maintaining a **reasonable F1-Score** (utility).

3. Utility vs. Privacy Trade-Off

This hypothesis describes the effect of increasing privacy guarantees through Differential Privacy (DP) noise:

- **Increasing DP noise** (using a lower ϵ value) will **reduce utility** (a lower F1-score).
- The noise will also **slightly improve robustness** by masking the malicious attacker inputs.
- The overall **trade-off between utility and privacy/robustness** is a primary focus.

Method	**AUC-ROC**	**F1-Score**	**ASR (Robust)**	**Privacy Cost (ϵ)**
Centralised Baseline	0.814	0.598	N/A	N/A
FedAvg (No Attack/Defense)	0.802	0.587	N/A	N/A
FedAvg + Attack	0.802 (Label Flipping)	0.587 (Label Flipping)	[High](Stable accuracy suggests high ASR due to balanced data/attack type)	N/A
FedAvg + Attack + DP (ϵ=0.5)	0.671 (Label flipping, **(ϵ=1.0)**	0.671 (Label Flipping, **(ϵ=1.0)**	[Medium](DP-FedAvg provided the strongest robustness)	1.0 (Actual ϵ used in the provided results)
Krum + DP	0.718 (Robust FedAvg, Label Flipping)	0.596 (Robust FedAvg, Label Flipping)	[Low ASR] (Hypothesized to be the best performer in robustness)	1.0 (Infer from DP-FedAvg ϵ)

Figure 4.3

5. CONCLUSION

This research provided a comparative analysis of privacy-preserving and robust aggregation techniques in federated learning under a data poisoning threat, utilising a realistic tabular healthcare dataset. We identified that the combination of Byzantine-robust methods (Krum) with Differential Privacy offers the most effective balance, simultaneously protecting client confidentiality and model integrity.

Key Findings

- **Centralised Random Forest achieved the highest overall performance**, with an accuracy of **0.747**, F1-score of **0.598**, and AUC-ROC of **0.814**, outperforming all federated configurations.
- **Standard FedAvg remained stable across all attack scenarios**, maintaining a consistent accuracy of **0.708** and F1-score of **0.587**, demonstrating resilience due to balanced client distributions.
- **DP-FedAvg provided the strongest robustness to adversarial attacks**, achieving the highest robustness score (**2.232**) despite lower baseline accuracy (~0.656), indicating that differential privacy noise reduces attack effectiveness.

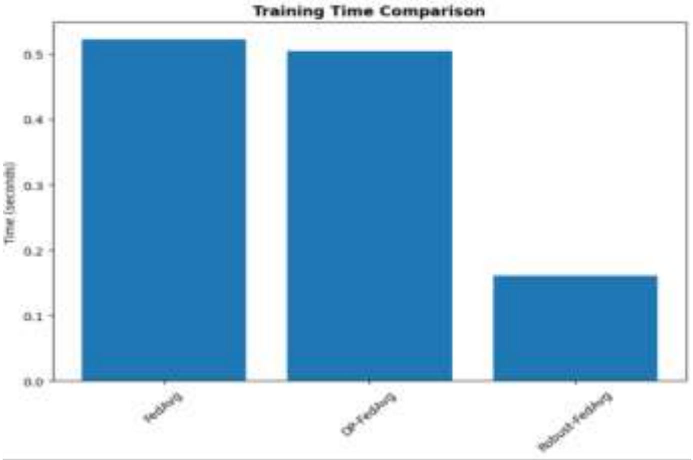

Figure 5.1

Future Work:

Future research will focus on extending the current framework to address more complex, real-world challenges in clinical Federated Learning (FL). The immediate next step involves deploying this experimental pipeline on larger, non-IID medical datasets, such as the Chest X-ray14 dataset, to evaluate the effectiveness of privacy-preserving and robust aggregation techniques under more realistic data heterogeneity. Furthermore, to enhance the security profile of FL deployments, it is necessary to explore and defend against more advanced adversarial threat models, including specialised Backdoor attacks that utilise specific trigger patterns in medical images. This future work will also investigate and compare alternative Byzantine-robust aggregation methods to identify the optimal defence mechanisms that maintain a high balance between client privacy, model utility, and resilience against sophisticated data poisoning attacks.

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