MEDFL: A COLLABORATIVE FRAMEWORK FOR FEDERATED LEARNING IN MEDICINE

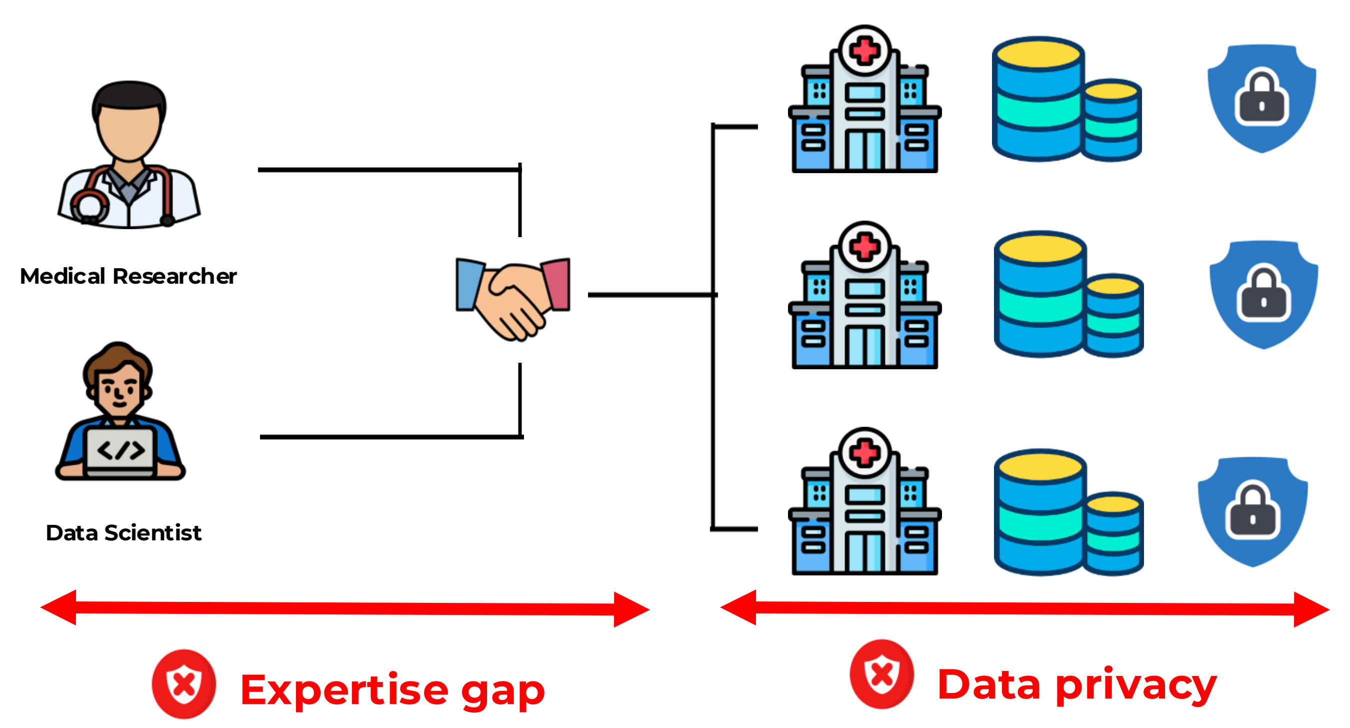
Ouael Nedjem Eddine SAHBI, Hithem Lamri, Bessam Abdulrazak, Martin Vallières. Faculty of Science, Université de Sherbrooke

CONTEXT

Collaboration between **medical researchers** and **data scientists** is essential to leverage AI for medical data analysis.

However, this collaboration faces **two major challenges**:

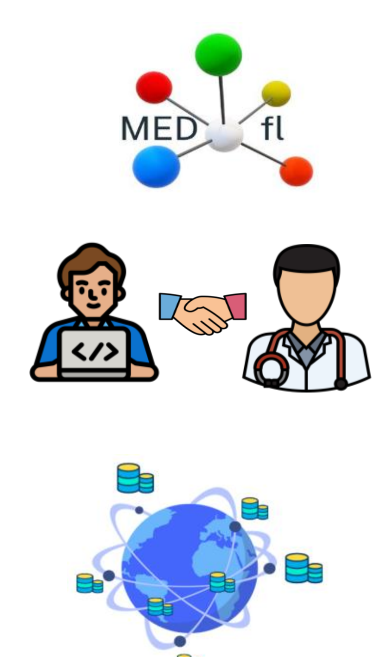
- A **gap in expertise** between domain specialists and data experts, which complicates communication and workflow integration.
- The **privacy constraints** of hospital data, which prevent direct data sharing and centralized model training.



OBJECTIVES

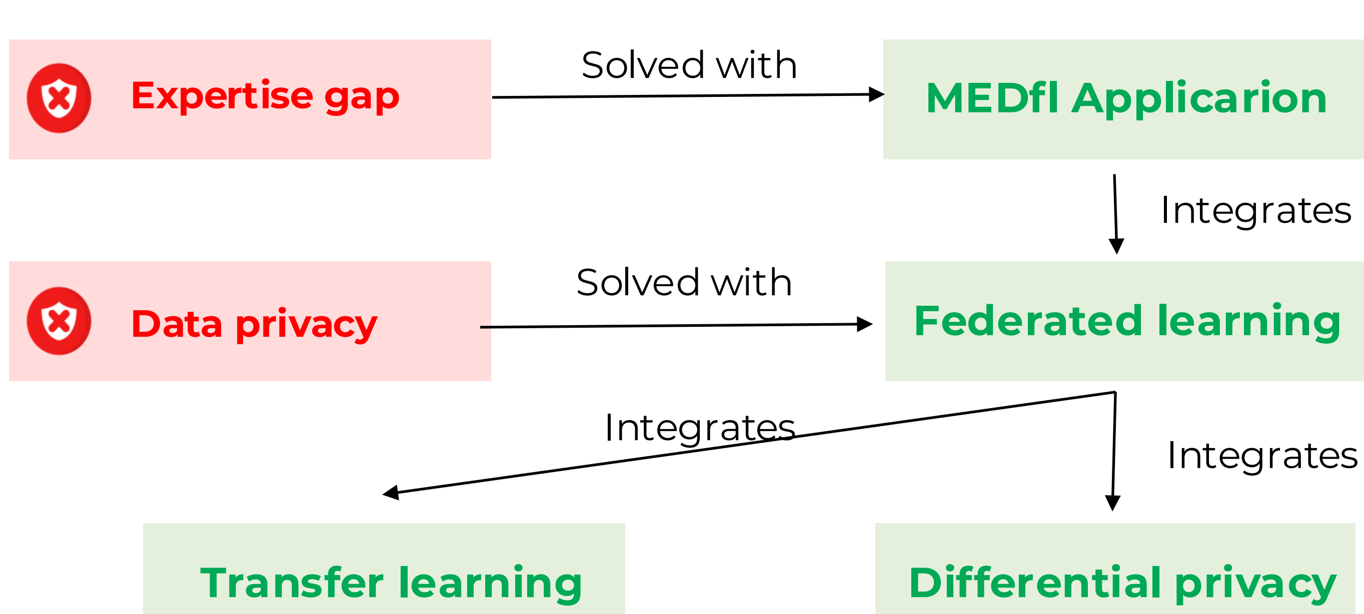
This project seeks to tackle two key challenges that limit effective collaboration between medical researchers and data scientists:

- **Bridging the expertise gap** between medical and technical domains, enabling effective communication, understanding, and workflow alignment between healthcare specialists and AI researchers.
- **Preserving data privacy and security,** ensuring that sensitive medical data distributed across hospitals can be analyzed collaboratively without being shared or centralized.



METHOD

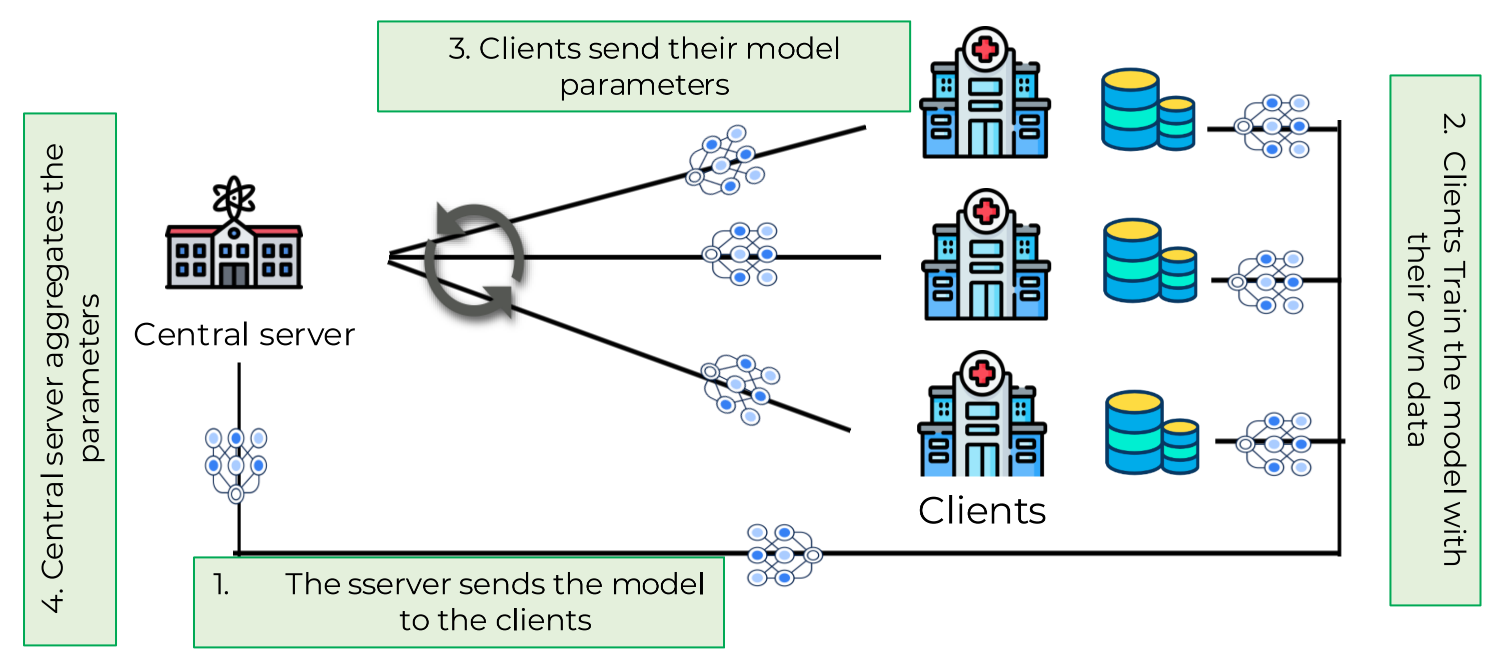
To address the challenges, this project develops the **MEDfl application**, a platform that integrates **Federated Learning** and provides an accessible interface to facilitate collaboration between medical and technical researchers.



1. Federated learning

Federated Learning (FL) is a decentralized approach that allows multiple institutions to **train a shared model without exchanging raw data**.

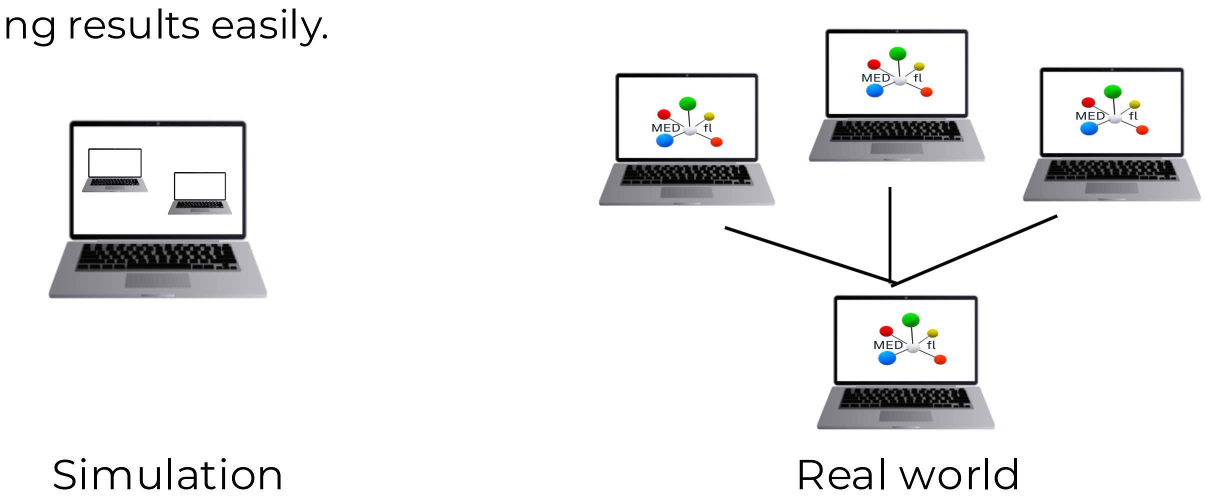
Each client (e.g., hospital) trains locally on its private dataset and sends **model parameters** to a **central server**, which aggregates them to update the global model.



2. MEDfl application

MEDfl is a federated learning framework designed for **both simulation and real-world deployment**.

It provides a graphical interface that allows researchers to **configure, pipelines, execute experiments and visualize** federated learning results easily.

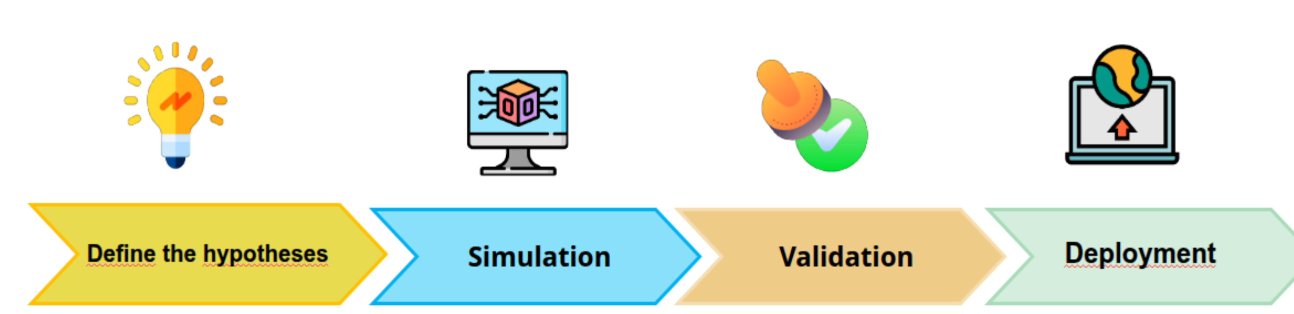


RESULTS

- **MEDfl package** is now available on **PyPI** https://pypi.org/project/MEDfl/ , It supports **both simulation and real-world federated learning** environments, and it's integrated to **the desktop application.**
- **Open-source repositories:**
  - **Python package:** github.com/MEDomicsLab/MEDfl
  - **Desktop application:** github.com/MEDomicsLab/MEDomics/tree/dev_medfl_sqllite
- A complete **YouTube playlist** guides users through installation, configuration, and experiment execution https://www.youtube.com/playlist?list=PLEPy2VhC4-D7Y4lkGMRpHG8ydVZQonkMJ
- Detailed documentation and usage examples are provided to help researchers **install, configure, and run** experiments easily.

CONCLUSION

With **MEDfl**, researchers can first validate their hypotheses through **simulation**, then move to **real-world deployment,** facilitating collaboration, ensuring data privacy, and reducing costs.



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