

A Federated Learning Architecture for Prostate MRI Image Segmentation

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Abstract

Federated Learning (FL) has emerged as a key paradigm for addressing privacy-preserving machine learning across distributed environments, particularly in sensitive domains such as healthcare. In this work, we present the design and initial implementation of a FL-based pipeline for prostate cancer segmentation from MRI data within the context of the MUSA project. Leveraging the MUSA Cloud Platform, our architecture integrates hospital-level privacy constraints, decentralized training, and robust security measures. We describe the software stack, operational flow, and report preliminary results on a U-Net model trained in a real-world federated scenario. Our approach demonstrates the feasibility and potential of FL in large-scale clinical ecosystems, providing a foundation for the future development of secure and scalable AI-based healthcare solutions.

Keywords

Federated Learning, Deep Learning, Prostate Lesion Segmentation, Privacy preserving computation, NVFlare

1. Introduction

Prostate cancer is one of the most common cancers among men worldwide, making early and accurate diagnosis essential for effective treatment and prognosis. Magnetic Resonance Imaging (MRI), particularly in its multiparametric form (mpMRI), is the preferred imaging modality for the evaluation of prostate cancer due to its high soft tissue contrast. However, the resulting images often lack well-defined anatomical boundaries, which complicates visual interpretation.

Interpreting mpMRI typically requires manual annotation by radiologists to delineate key anatomical and pathological regions, such as the prostate gland, its central and peripheral zones, and any lesions. These annotations form segmentation masks that guide diagnosis and treatment planning. Although effective, this process is time-consuming, labor intensive, and dependent on expert knowledge.

Deep Learning offers a promising avenue for automating segmentation, potentially improving consistency, and reducing clinical workload [1]. Convolutional neural networks, especially U-Nets, have shown good performance in medical image segmentation [2]. However, training such models requires large volumes of annotated data: this poses a significant challenge, as most diagnostic centers have access to only small, privacy-sensitive data sets that cannot be easily shared. An effective solution to this limitation is Federated Learning. FL is a decentralized machine learning paradigm that enables the training of collaborative ML models on datasets distributed across multiple data sources, without the need to collect data in a single centralized location. As described by McMahan et al. in 2016 [3], the FL approach involves processing data directly on clients that share only the locally trained model

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parameters. Compared to traditional centralized approaches, in which data must be aggregated in one location for processing, FL reduces computation time, network traffic, and the risks associated with data security and privacy. This is particularly important in regulated sectors such as Healthcare, where patient privacy must be protected in accordance with regulations such as the GDPR for citizens of the European Union [5].

In this work, we report on the implementation of a Federated Learning architecture to train neural networks for automatic segmentation of prostate mpMRI, within a pilot of the PNRR project MUSA (Multilayered Urban Sustainability Action). The work is structured as follows: first we contextualize the work within the MUSA project (Section 2); then we describe the architecture (Section 3) and the experimental setup (Section 4); a discussion of the outcomes follows (Section 5), before outlining the conclusions and the planned future work (Section 6).

2. MUSA Project

The project involves collaboration between Milan University, the University of Milan-Bicocca, the proposing institution, the Polytechnic University of Milan, Bocconi University, and numerous public and private partners. MUSA was established in Milan as a response to the challenges that the metropolitan city faces in the transition to the different domains of sustainability. It is organized into six spokes (Urban Regeneration; Big-Data Open Data in Life Sciences; Deep Tech: Entrepreneurship and Technology Transfer; Economic Impact and Sustainable Finance; Sustainable fashion, luxury, and design; Innovation for Sustainable and Inclusive Societies). Spoke 2 focuses on developing technologies and processes for handling large amounts of health and Life Sciences data for the well-being and health of citizens.

2.1. The MUSA Cloud platform of Spoke 2

The MUSA Cloud platform of the Spoke 2 project focuses on the design and implementation of a secure, modular, and scalable digital infrastructure to support the acquisition, processing, and sharing of heterogeneous data in the life science domain. The objective is to promote the translation of biomedical and environmental research into real-world applications, enabling innovation in diagnostics, personalized medicine, and public health, while supporting the development of sustainable healthcare models. The MUSA Cloud Platform, developed within Work Package 1, represents the technical core of this vision. It is based on a federated architecture that integrates a central cloud hub, 5G edge nodes, and on-premise infrastructures provided by participating institutions. The platform supports multiple deployment models (cloud, edge, hybrid) and is built on key principles such as openness (through the use of open-source technologies), modularity, containerization, and compliance with FAIR data principles. The platform architecture includes the following core components:

- **MUSA DATA LAKE**, a distributed storage layer designed to manage various data formats - structured, semi-structured, unstructured, and binary - preserving data in its native form;
- **DATA & SERVICE CATALOG**, which semantically models data and services using ontologies, taxonomies, and metadata, supporting interoperability, traceability, and discoverability;
- **DATA INGESTION AND TRANSFORMATION LAYER**, enabling the extraction and processing of data from various sources (e.g., hospital systems, APIs, sensors) with scalable ETL capabilities;
- **SERVICE ORCHESTRATION ENGINE**, supporting the composition and automation of workflows for advanced analytics and AI/ML model execution;
- **GOVERNANCE AND PRIVACY FRAMEWORK**, ensuring compliance with data protection regulations (e.g., GDPR) via privacy-by-design mechanisms, risk assessment, and access control policies;
- **SERVICES ECOSYSTEM**, which delivers reusable and domain-specific services to researchers, clinicians, public institutions, and private actors across the life sciences landscape.

The platform follows a layered approach to data processing, advancing from raw data acquisition to application-ready data. This structure enables the creation of high-quality datasets for research and decision making while maintaining data provenance and security. Importantly, the MUSA Cloud Platform incorporates a business-oriented model to support data valorization and service reuse. Through the creation of a data and service marketplace, stakeholders can expose and consume data-driven services in a controlled, privacy-compliant environment. This facilitates the emergence of new business models in digital health, encourages investment in data-centric innovation, and enables public-private collaborations that generate both scientific and economic value.

2.2. Pilot on Federated Learning of Diagnostic Models

Among the objectives of this Spoke is the development of the Pilot 1.2.3 titled “Fusion of image-tabular data for federated learning of diagnostic models: creation of a repeatable approach for multi-centric diagnostic studies, based on federated learning and data of heterogeneous types.” The pilot will establish a repeatable AI pipeline that includes collection of highly heterogeneous data and their fusion with the purpose to maximize the accuracy of early diagnosis.

Within the scope of the present article, the focus is on image processing only.

3. The proposed Federated Architecture

The typical form of FL is the client-server architecture. In this setup, each client participating in the federation trains a shared model architecture, starting from a common set of initial weights provided by the server. Once enough clients have finished the local training on their own data and have submitted their results, these can be aggregated by the central server, using a specific aggregation algorithm, and redistributed to the clients to update the local models and initiate a new round of local training. This process continues until the global model converges, as shown in Algorithm 1, by minimizing a global loss function that can be defined as a weighted combination of local losses, each computed by different clients.

Algorithm 1 Client-Server Federated Learning with FEDERATEDAVERAGING [3, 4]. T is the number of federated learning rounds, n_k is the number of LocalTraining iterations minimizing the local loss $L_k(X_k; \phi^{(t-1)})$ for client k , and ϕ are the model parameters.

```

1: procedure FEDERATED LEARNING
2:   Initialize weights:  $\phi^{(0)}$ 
3:   for  $t \leftarrow 1 \rightarrow T$  do ▷  $T$  is the number of FL rounds
4:     for all clients  $k = 1 \dots K$  in parallel do
5:       Send  $\phi^{(t-1)}$  to client  $k$ 
6:       Receive  $(\Delta\phi_k^{(t)}, n_k)$  from client's LocalTraining( $\phi^{(t-1)}$ )
7:     end for
8:      $\phi_k^{(t)} \leftarrow \phi^{(t-1)} + \Delta\phi_k^{(t)}$ 
9:      $\phi^{(t)} \leftarrow \frac{1}{\sum_k n_k} \sum_k n_k \phi_k^{(t)}$ 
10:  end for
11:  return  $\phi^{(t)}$ 
12: end procedure

```

3.1. Software Selection

To define its final ecosystem architecture, MUSA adopts a methodological approach that balances the evolving needs of the research community with the continuous enhancement of platform services. The goal is to deliver a production-ready infrastructure that remains technologically up-to-date. Given the

rapid growth of FL, several frameworks have emerged—often with overlapping features—making it essential to carefully assess and select the most suitable solution for the intended use cases.

To guide the selection process, a set of key evaluation criteria was defined:

- **Reliability:** the ability to maintain a specified performance level under defined conditions over time.
- **Compatibility:** the extent to which the software supports different types of machine learning frameworks and models.
- **Security and Privacy Methods:** evaluated based on the presence of mechanisms such as TLS-based secure communication, secure aggregation, homomorphic encryption, differential privacy, role-based access control, and configurable data filtering.
- **Complexity:** reflects how easy the software is to learn, configure, and manage.
- **Commercial Support:** a strong indicator of software maturity, reliability, and production readiness.
- **Community and Update Frequency:** indicates the level of open-source activity, responsiveness to issues, and long-term sustainability.
- **Documentation Quality:** includes guides on how to use the system, extend or modify its functionality, and deploy it in production environments.

Based on the evaluation criteria, the following tools were considered: Flower, an open-source and flexible framework suited for research; NVFlare, a production-grade platform with strong security and GPU optimization; FATE, focused on vertical federated learning in the financial sector; and SubstraFL, designed for medical research with built-in governance and broad data support. In Table 1 is presented a summary of the key findings based on a comprehensive evaluation encompassing both qualitative assessment and quantitative benchmarks reported in recent literature [7, 6, 8, 11, 9, 10, 17, 19, 16, 18].

NVFlare emerged as the most suitable federated learning framework for MUSA's production infrastructure. Its strong alignment with enterprise requirements, high security standards, and proven performance in real-world healthcare applications position it as the preferred solution (see Fig 1)

3.2. The FL architecture adopted

NVFlare, developed by NVIDIA, is a production-ready FL platform designed for scalable, secure, and high-performance systems, with a particular focus on the healthcare domain. It is both model- and framework-agnostic, and supports model weight initialization and global model aggregation on both the server and client sides. Optimized for GPU-accelerated workloads, it integrates advanced security features and provides built-in mechanisms for monitoring, logging, and auditing, making it well-suited for enterprise-level applications.

Components NVIDIA FLARE (Federated Learning Application Runtime Environment) is a modular and open-source framework for implementing and executing federated learning workflows in distributed environments. Designed to support real-world, large-scale scenarios, FLARE provides a flexible infrastructure that clearly separates the federated training logic from the orchestration and communication mechanisms between client and server. On top of FLARE's core architecture, the framework includes advanced orchestration and monitoring mechanisms that facilitate communication between clients and server, ensuring proper coordination and tracking of the entire federated learning process. These components are essential for managing the distributed dynamics, initial provisioning, and synchronization of participants, ensuring that data and model updates flow efficiently and securely. In NVIDIA FLARE, collaborative computation is based on interactions between the Controller, which runs on the server and manages the execution of tasks, and the Executors, which are clients that carry

Table 1

Comparison of federated learning frameworks across multiple evaluation criteria.

Criteria	FLOWER	NVFLARE	FATE	SUBSTRA FL
Reliability	High bug rate.	Low bug rate.	High bug rate.	Low bug rate.
Compatibility	Tabular and image data. Framework agnostic. No vertical FL.	Tabular, image, and text data. Model/framework agnostic. Vertical FL supported.	Only tabular data. Regression models. Vertical FL supported.	Data/model and framework agnostic. No vertical FL.
Security and Privacy methods	SSL/TLS, Differential Privacy.	SSL/TLS, Secure Aggregation, Homomorphic Encryption, DP, RBAC, Data Filters.	Homomorphic Encryption, Multi-party Computation.	RBAC, Traceability, Protection from metadata poisoning.
Rediness for commercial usage	Mainly for research.	Production-ready.	Production-ready.	Production-ready.
Community	100 contributors, high rate commitment.	32 contributors, high rate commitment.	84 contributors, high rate commitment.	34 contributors, low rate commitment.
Documentation	High quality and accessible.	High quality, goal-based.	Lacking.	Good but incomplete.
Cloud Support	Mentioned in Q&A. Not documented.	Detailed in documentation. Hybrid setups supported.	Fate-Cloud exists. Not documented.	Mentioned in documentation.
Complexity	Easy to use.	Deploy and configuration can be complex.	Medium complexity	Medium complexity

out the tasks assigned by the Controller. Overseeing both is the Admin, the entity responsible for configuring and supervising the entire federated workflow, including the coordination and definition of tasks distributed to clients.

Security components. NVFlare provides a robust solution requirements, aligning well with the stringent security requirements of the MUSA ecosystem, through a comprehensive, multi-layered security framework that includes authentication, authorization, data privacy protection, auditing, and local client policies.

- **AUTHENTICATION AND COMMUNICATION SECURITY:** NVFlare authenticates all participants using mutual TLS, with each entity receiving a startup kit containing credentials and endpoint information to ensure secure and authorized communication.
- **FEDERATED AUTHORIZATION:** The system implements a role-based user authorization model, allowing each site to define its own policies. This approach enables granular control over user permissions and supports dynamic addition of new users and sites without necessitating server-side updates.
- **DATA PRIVACY PROTECTION:** NVFlare enhances data privacy by allowing clients to define local policies, including data filters and computing resource management. These policies can be modified at runtime without re-provisioning, providing flexibility while maintaining security.
- **AUDITING:** All user commands and job events are automatically recorded in audit files on both server and client sides, facilitating transparency and accountability throughout the federated learning workflow .

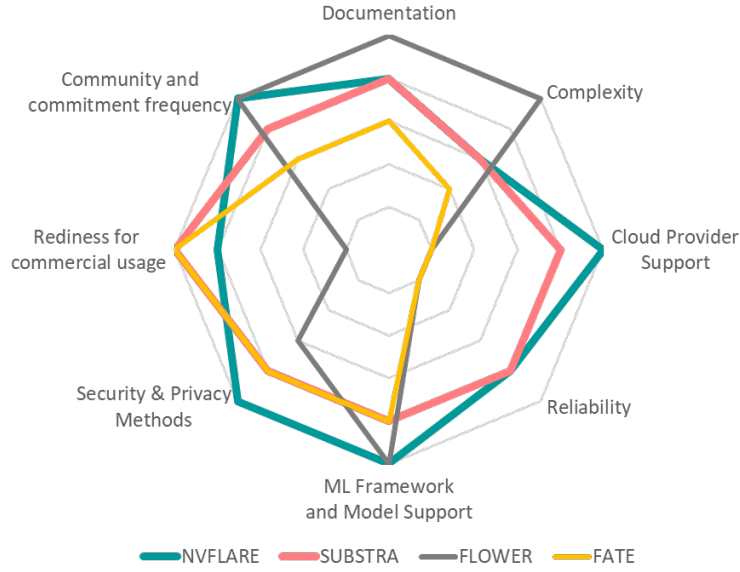


Figure 1: This illustration summarizes the results of the software selection process, based on the key features listed above.

4. Experimental Setup

The following sections describe the dataset, the infrastructure, and the model training configuration used in the experiment.

Datasets and Data Distribution To evaluate our approach, we performed experiments using three open-source datasets for prostate tumor segmentation MRI scans, released as part of international challenges, specifically: PROSTATEX [13], PROSTATE158 [14], and PI-CAI [15]. These datasets provide a diverse set of MRI acquisitions along with pixel-wise segmentation masks, where each pixel is labeled as either background or tumor nodule, enabling robust evaluation of prostate tumor segmentation models. To simulate a realistic medical scenario, data were distributed across three clients using a non-IID (non-Independent and Identically Distributed) partitioning strategy to reflect real-world heterogeneity. To address the class imbalance, we implemented an additional preprocessing step that excluded all image slices lacking tumor annotations. Background-only slices are common in MRI due to the sequential acquisition process. This is explained by the entry slice phenomenon, where initial slices capture areas outside the target anatomy, and by the dead time between acquisitions of consecutive slices, which can result in additional non-informative slices. This filtering procedure effectively removed these background-only slices, thereby reducing the dominant occurrence of non-informative pixels and enhancing the training on tumor-related regions.

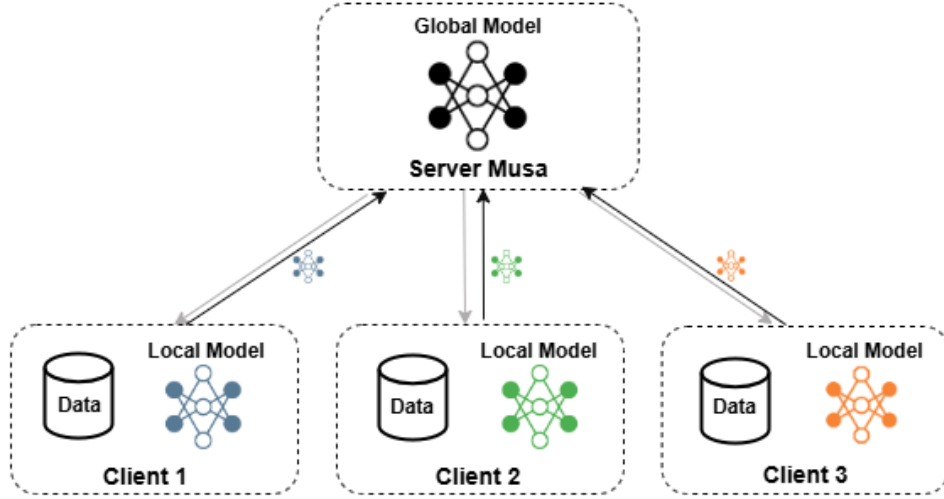
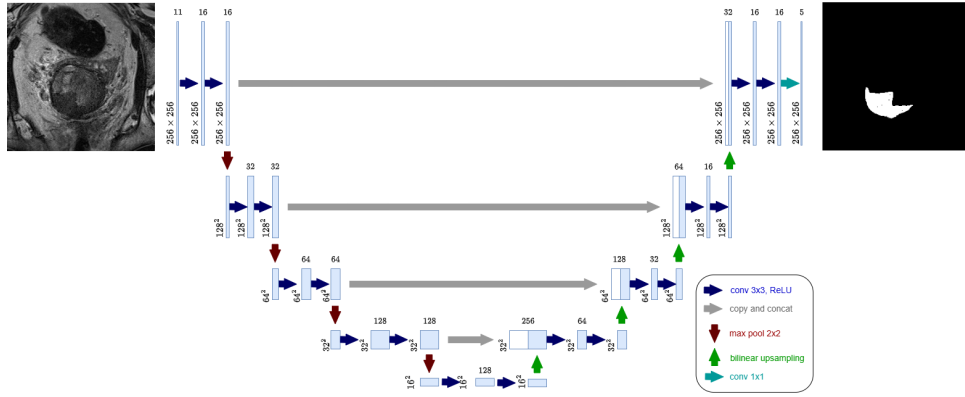
The distribution of cases across training, validation, and test sets for each client is reported in Table 2.

FL Setup We adopted a cross-silo FL configuration, where each client simulates a distinct data-holding entity. The central server, acting as the aggregator, is represented by the MUSA platform server, while the hospital nodes are simulated by clients that train local models on private data (see Fig. 2). Model updates are periodically sent to the server, which synchronously aggregates them using the Federated Averaging (FedAvg) algorithm. Specifically, the global model \mathbf{w}_{global} is updated as the weighted average of the local models \mathbf{w}_i from each client, where the weight for each model update is proportional to the

Table 2

Number of cases per client and split.

	Client1	Client2	Client3
Dataset	ProstateX	Prostate158	PI-CAI
Training	346	321	57
Validation	121	92	16
Testing	51	46	9
Total no black	518	459	82
Total	2090	2066	219

**Figure 2:** An illustration of the logic of training the global model through local training on client data.**Figure 3:** Unet architecture on which it has been designed the proposed solution.

size of the local dataset n_i :

$$\mathbf{w}_{global} = \frac{\sum_{i=1}^N n_i \cdot \mathbf{w}_i}{\sum_{i=1}^N n_i}$$

where N is the total number of clients and n_i is the number of data points held by the i -th client.

For the segmentation task, we employed the U-Net architecture, widely used in medical image analysis due to its strong performance on pixel-wise classification tasks (see Fig. 3).

Each client was configured with the following training parameters:

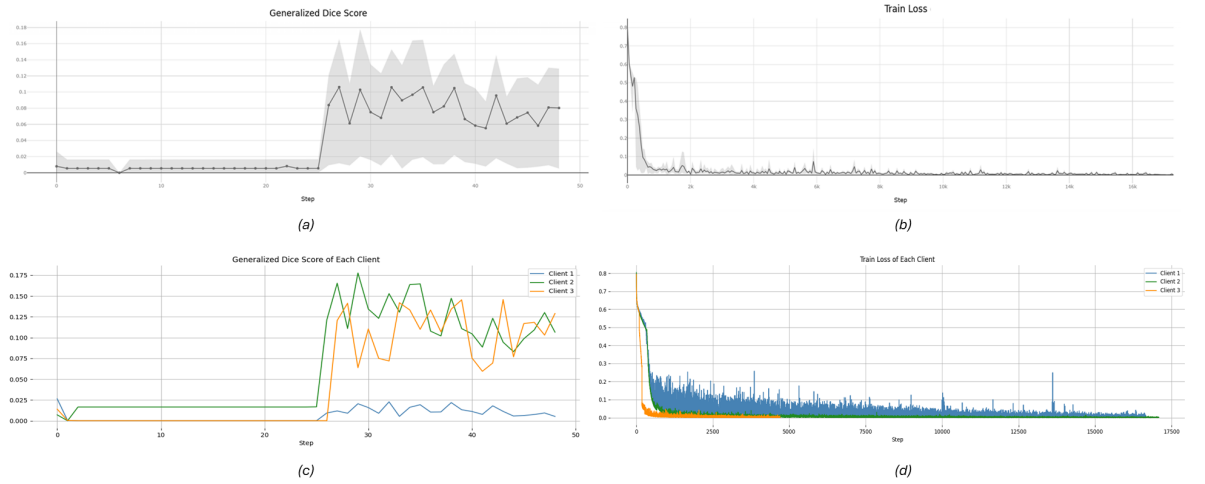


Figure 4: Metrics tracked with MLflow. (a) and (b) show the global Generalized Dice Score and Binary Cross Entropy Loss; (c) and (d) show the corresponding local metrics for individual clients.

- **Optimizer:** Adam
- **Learning Rate:** 1×10^{-3}
- **Loss Function:** Binary Cross-Entropy with Logit
- **Epochs per round:** 1
- **Federated rounds:** 50
- **Evaluation Metric:** Generalized Dice Score

The simulated client nodes were hosted on separate instances, each equipped with an NVIDIA T4 GPU (16 GB), 4 vCPUs, and 16 GB of RAM. This setup ensured adequate computational resources for local training of the U-Net models in each federated round.

Preliminary Results and System Monitoring To monitor the progress of federated training, the MLflow tracking component was integrated into the NVFlare pipeline, enabling real-time visualization of key metrics such as Binary Cross Entropy (BCE) and Dice Score. BCE quantifies the discrepancy between predicted probabilities and true binary labels, serving as an indicator of classification performance. The Dice Score, widely used in medical image segmentation tasks, measures the overlap between predicted and ground-truth regions, making it especially effective in scenarios involving imbalanced data. Although optimizing model performance was not the primary goal of this study, the tracked metrics showed a consistent decrease in loss and an improvement in Dice Score over the course of training, indicating that the federated learning process was functioning effectively even in the presence of heterogeneous data. (see Fig. 4).

Equally important, detailed inspection of NVFlare’s log files confirmed the correct and reliable communication between the clients and the central server across all federated rounds. This validation step is crucial, as it demonstrates the technical feasibility and robustness of the overall setup — a prerequisite for real-world deployment in sensitive domains like healthcare.

5. Discussion

This work demonstrated the feasibility of a cross-silo FL pipeline in healthcare, focusing on system architecture rather than pure model performance. A key takeaway was the value of integrating tools

like MLflow into the NVFlare framework, which allowed transparent, real-time tracking of training metrics and enhanced reproducibility. Furthermore, the ability to monitor the logs and the health status of the nodes round by round proved crucial to ensuring stable communication and identifying potential issues early, thus enhancing the robustness of the federated training process.

The federated approach provides significant advantages in healthcare by enabling institutions to collaboratively train models without sharing raw data, ensuring privacy compliance. It also facilitates the democratization of access to advanced technological tools, enabling smaller or resource-constrained institutions to leverage cutting-edge AI models without requiring extensive computational infrastructure. This latter aspect is essential for the effective scalability of the system, as it enables the inclusion of new institutions that meet only the minimal requirements for model execution, thereby facilitating streamlined onboarding and integration into the federated network.

Despite data heterogeneity, the global model demonstrated good generalization, proving the potential of FL to handle decentralized medical data.

Overall, the successful integration of training orchestration, real-time monitoring, and inter-node communication within this federated setup confirms its scalability and transferability to real hospital environments, where privacy concerns and infrastructure variability are paramount. These results highlight the potential for FL to make advanced AI technologies more accessible across healthcare institutions, fostering a more inclusive and equitable approach to medical innovation.

6. Conclusions and Future Work

Future developments within the scope of this project will focus on extending the current pipeline into real hospital environments. This involves validating the proposed architecture under realistic conditions, including the presence of heterogeneous IT systems, strict data governance rules, and cross-organizational security requirements.

Moreover, future work will focus on enhancing both training efficiency and model accuracy through further optimization of the architecture, advanced training techniques, and adaptive learning strategies.

An important direction for future research involves the integration of Fully Homomorphic Encryption (FHE) during inference. This would enable external healthcare institutions — not directly involved in the training process — to securely query the global model without accessing or downloading it, thus ensuring the protection of intellectual property and patient confidentiality while still leveraging the model's insights.

References

- [1] S. Fouladi, L. Di Palma, F. Darvizeh, D. Fazzini, A. Maiocchi, S. Papa, G. Gianini, and M. Ali, "Neural Network Models for Prostate Zones Segmentation in Magnetic Resonance Imaging," *Information*, vol. 16, no. 3, p. 186, 2025.
- [2] S. Fouladi, G. Gianini, D. Fazzini, A. Maiocchi, E. Damiani, S. Papa, and M. Ali, "Advanced Prostate MRI Analysis: UNET-based Models for Zonal and Lesion Segmentation," in *Proceedings of the International Conference on Management of Digital EcoSystems (MEDES)*, 2024.
- [3] H.B. McMahan, E. Moore, D. Ramage, S. Hampson, and others: Communication-efficient learning of deep networks from decentralized data. *arXiv:1602.05629* (2016)
- [4] H. R. Roth, D. Yang, W. Li, A. Myronenko, W. Zhu, Z. Xu, X. Wang, and D. Xu, *Federated Whole Prostate Segmentation in MRI with Personalized Neural Architectures*, arXiv:2107.08111 [eess.IV], 2021.
- [5] P. Voigt and A. von dem Bussche: *The EU General Data Protection Regulation (GDPR): A Practical Guide*. 1st ed., Springer, Cham (2017)
- [6] D.J. Beutel, T. Topal, A. Mathur, X. Qiu, T. Parcollet, P.P. de Gusmão, and N.D. Lane: Flower: A friendly federated learning research framework. *arXiv:2007.14390* (2020)

- [7] Y. Liu, T. Fan, T. Chen, Q. Xu, and Q. Yang: FATE: An industrial-grade platform for collaborative learning with data protection. *Journal of Machine Learning Research* **22**(226), 1–6 (2021)
- [8] M. Galtier and C. Marini: Substra: A framework for privacy-preserving, traceable and collaborative machine learning. *arXiv:1910.11567* (2019)
- [9] I. Kholod, E. Yanaki, D. Fomichev, E. Shalugin, E. Novikova, E. Filippov, and M. Nordlund: Open-source federated learning frameworks for IoT: A comparative review and analysis (2023)
- [10] C. Vlad-Andrei: Federated learning: A comparison of methods. Master's thesis, Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS), Delft University of Technology, The Netherlands (2023)
- [11] H.R. Roth, Y. Cheng, Y. Wen, I. Yang, Z. Xu, Y.-T. Hsieh, K. Kersten, A. Harouni, C. Zhao, K. Lu, Z. Zhang, W. Li, A. Myronenko, D. Yang, S. Yang, N. Rieke, A. Quraishi, C. Chen, D. Xu, N. Ma, P. Dogra, M. Flores, and A. Feng: NVIDIA FLARE: Federated learning from simulation to real-world. *arXiv:2210.13291* (2022)
- [12] H.R. Roth, Z. Xu, Y.-T. Hsieh, A. Renduchintala, I. Yang, Z. Zhang, Y. Wen, S. Yang, K. Lu, K. Kersten, C. Ricketts, D. Xu, C. Chen, Y. Cheng, and A. Feng: Empowering Federated Learning for Massive Models with NVIDIA FLARE. *arXiv:2402.07792* (2024)
- [13] S. G. Armato III, H. Huisman, K. Drukker, et al.: PROSTATEx Challenges for computerized classification of prostate lesions from multiparametric magnetic resonance images. *Journal of Medical Imaging*, **5**(4):044501 (2018). <https://doi.org/10.1117/1.JMI.5.4.044501>
- [14] Prostate158 Challenge: Grand Challenge dataset for prostate MRI segmentation. (2022). Available at: <https://prostate158.grand-challenge.org/data>. Accessed: June 2, 2022. <https://doi.org/10.5281/zenodo.6481141>
- [15] PI-CAI Challenge: Public Training and Development Dataset. (2022). Available at: <https://doi.org/10.5281/zenodo.6517398>. Accessed: June 2, 2022.
- [16] <https://github.com/NVIDIA/NVFlare>
- [17] <https://github.com/Substra>
- [18] <https://github.com/adap/flower>
- [19] <https://github.com/FederatedAI/FATE>

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.