Deep Learning for Medical Image Analysis

COMP5423

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Federated Learning in MIA

- Introduction
- Federated learning for predicting clinical outcomes
- Federated domain generalization
- Federated semi-supervised learning
- Challenge and future direction

Introduction

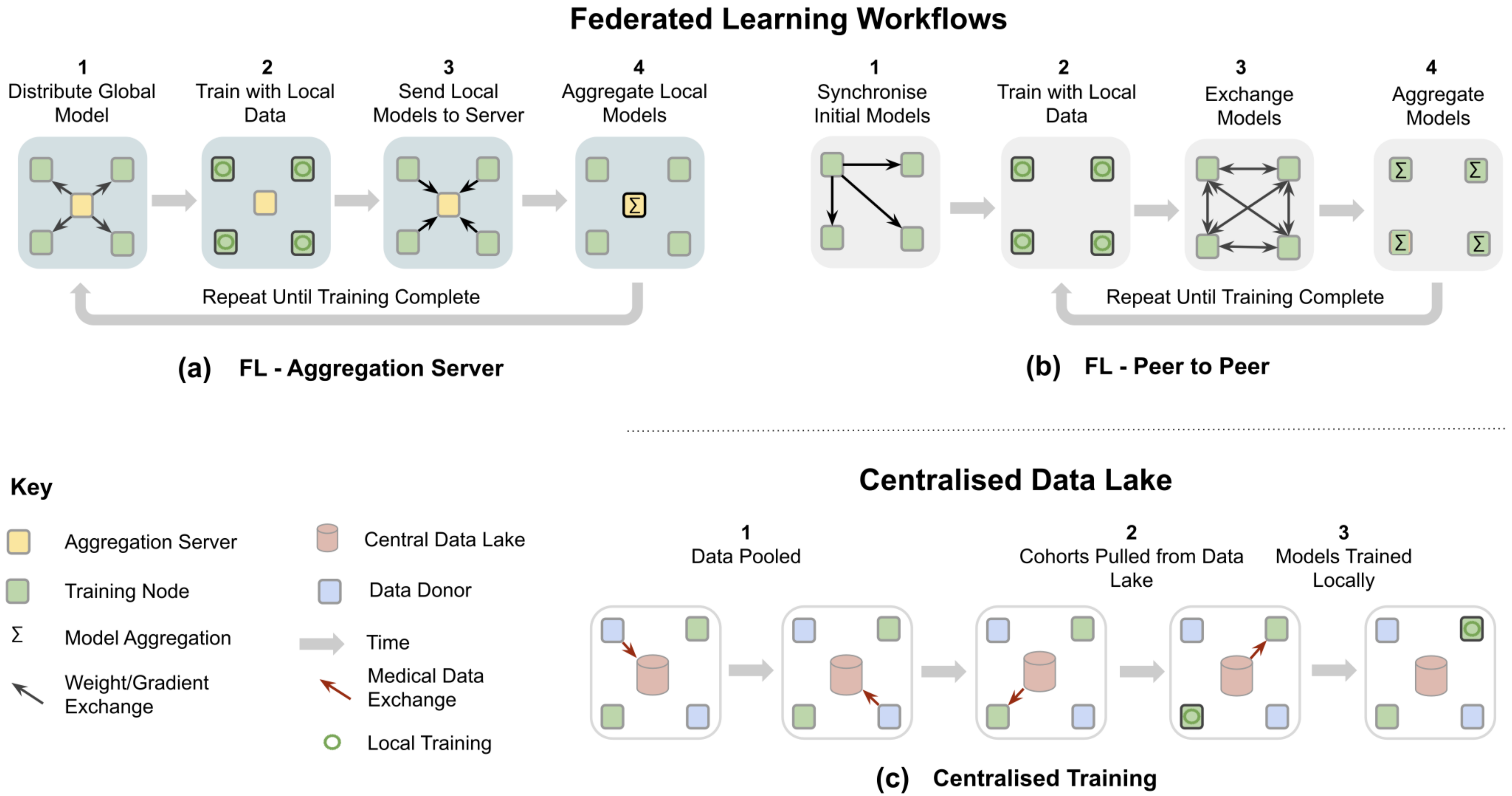
- Deep learning (DL) shows remarkable success in many domains but requires **large and diverse** datasets.
- Medical datasets are often difficult to obtain due to the complicated nature of healthcare system and processes.
- For example, different hospitals may only be able to access the clinical records of their own patient populations.
- An intuitive idea is to learn the model in a decentralized setting while keeping data localized.

Introduction

- **Federated learning** (FL) is a learning paradigm to address the problem of data governance and privacy.
- It trains learning models collaboratively without exchanging the data among sites.
- Originally developed for edge device user cases, it recently gained popularity in healthcare applications.
- FL enables gaining insights collaboratively without moving patient data beyond the firewalls of the institutions.

Rieke, et al. The future of digital health with federated learning. NPJ digital medicine, 2020.

Introduction



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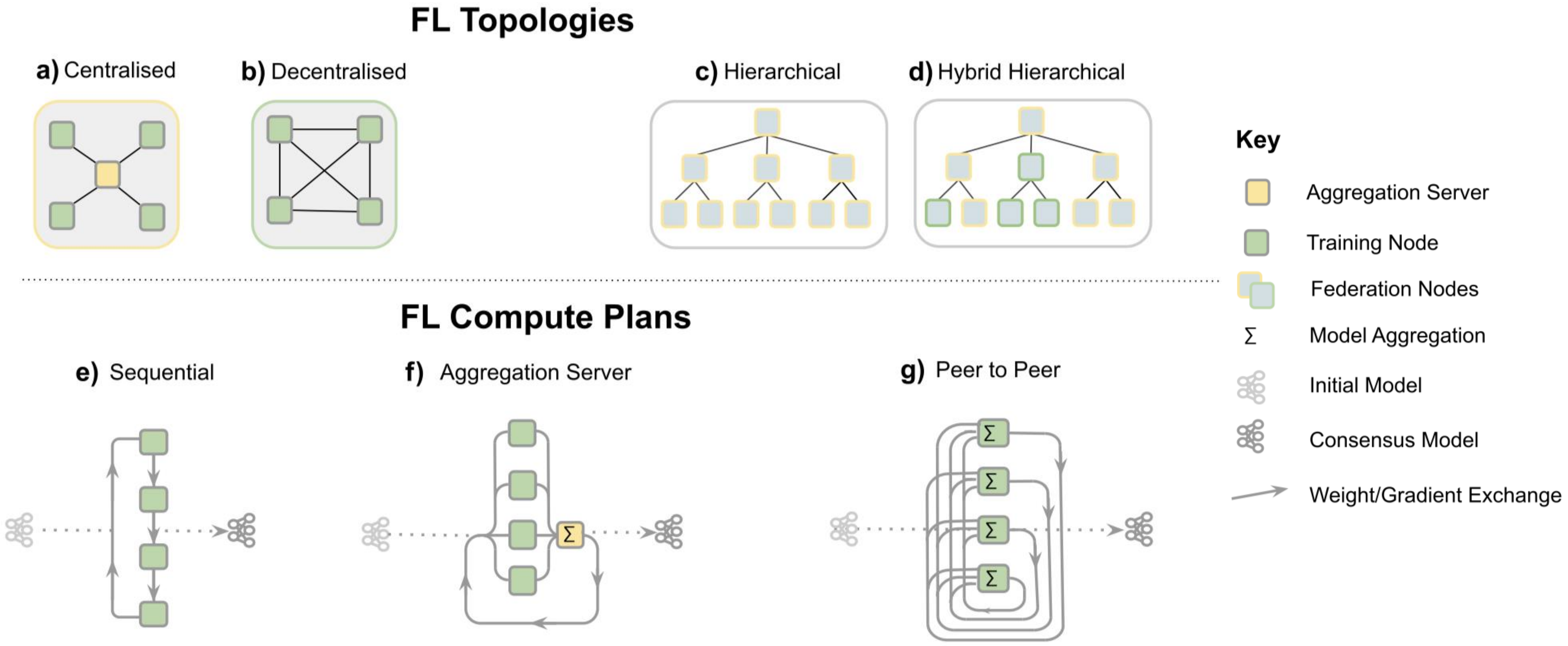
Introduction



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Introduction

- Let D_k denote the data distribution associated with client k, n_k is the number of samples available from client k, $n = \sum_{k=1}^{K} n_k$ is the number of total sample size.
- Federated learning is to solve an empirical risk minimization problem:

$$\min_{w} F(w) \coloneqq \sum_{k=1}^{K} \frac{n_k}{n} F_k(w), \qquad where\ \ F_k(w) \coloneqq \frac{1}{n_k} \sum_{x_i \in D_k} f_i(w)$$

where w is the model parameter to be learned, and f_i is specified via a loss function on the data pair $\{x_i, y_\mathrm{i}\}$.

Introduction

The promise of federated learning:

- To address data **privacy** and **governance** challenges by enabling machine learning from non-co-located data.
- To allow **large-scale**, **cross-institutional validation**, and enable novel research on rare diseases.
- High-dimensional and storage-intense medical data does not have to be **duplicated** from local institutions in a centralized pool.
- It can scale naturally with a potentially growing global dataset without **disproportionately** increasing data storage.

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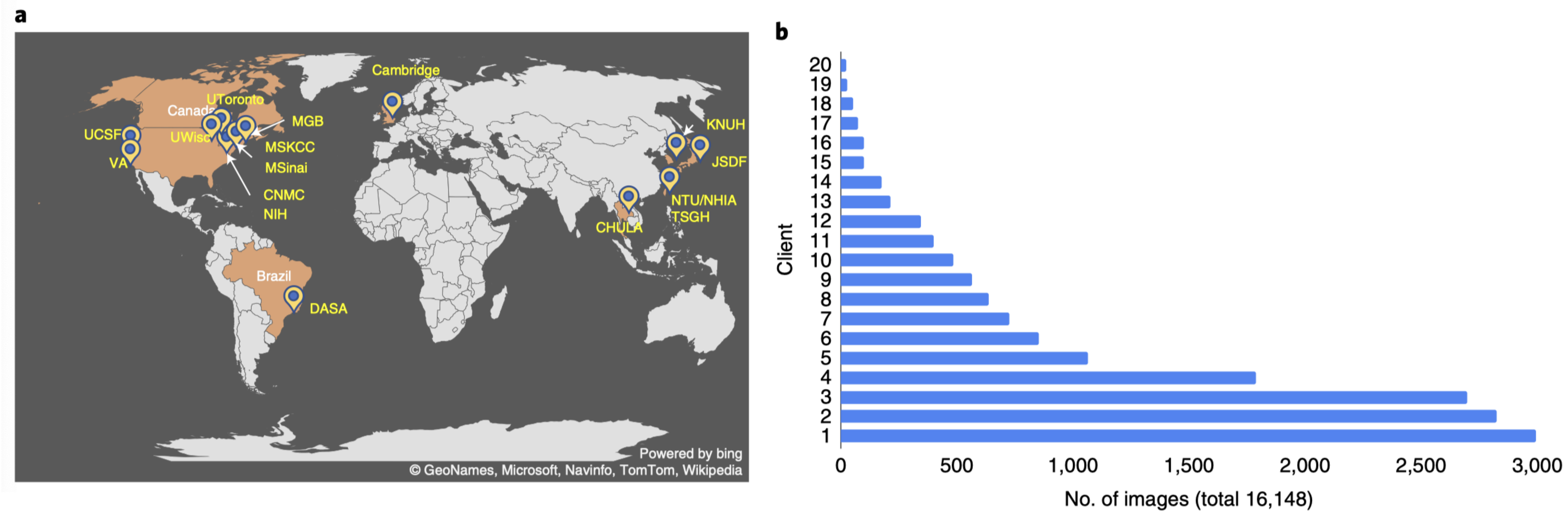
Federated Learning for Predicting Clinical Outcomes

- Federated learning potentially incentivizes data sharing and model training/testing without the usual privacy and data ownership hurdles of conventional collaborations.
- In this study, researchers train a federated learning model to predict future oxygen requirements of COVID-19 patients.
- The prediction model (i.e., EXAM model) takes multi-modality data as input, including laboratory results, vital signs, an imaging study and demographic information.

Dayan, et al. Federated learning for predicting clinical outcomes in patients with COVID-19. Nature medicine, 2021.

Federated Learning for Predicting Clinical Outcomes

Data used in this FL study:



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Federated Learning for Predicting Clinical Outcomes

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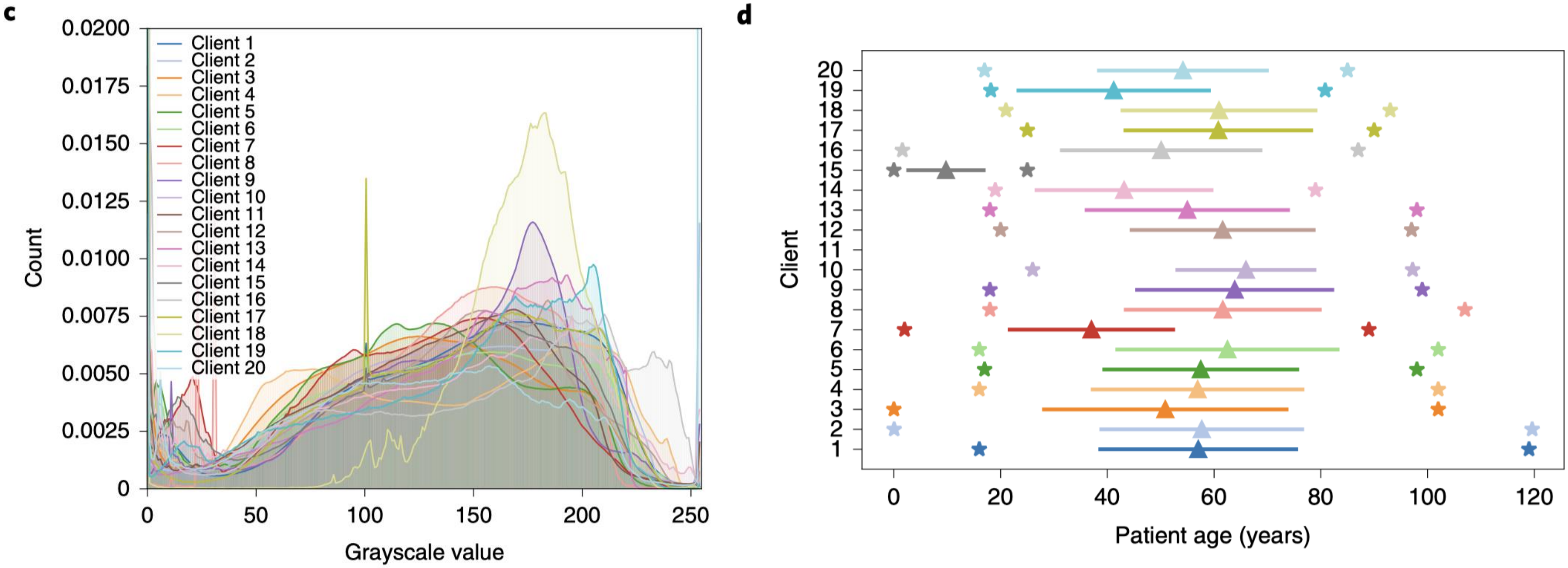

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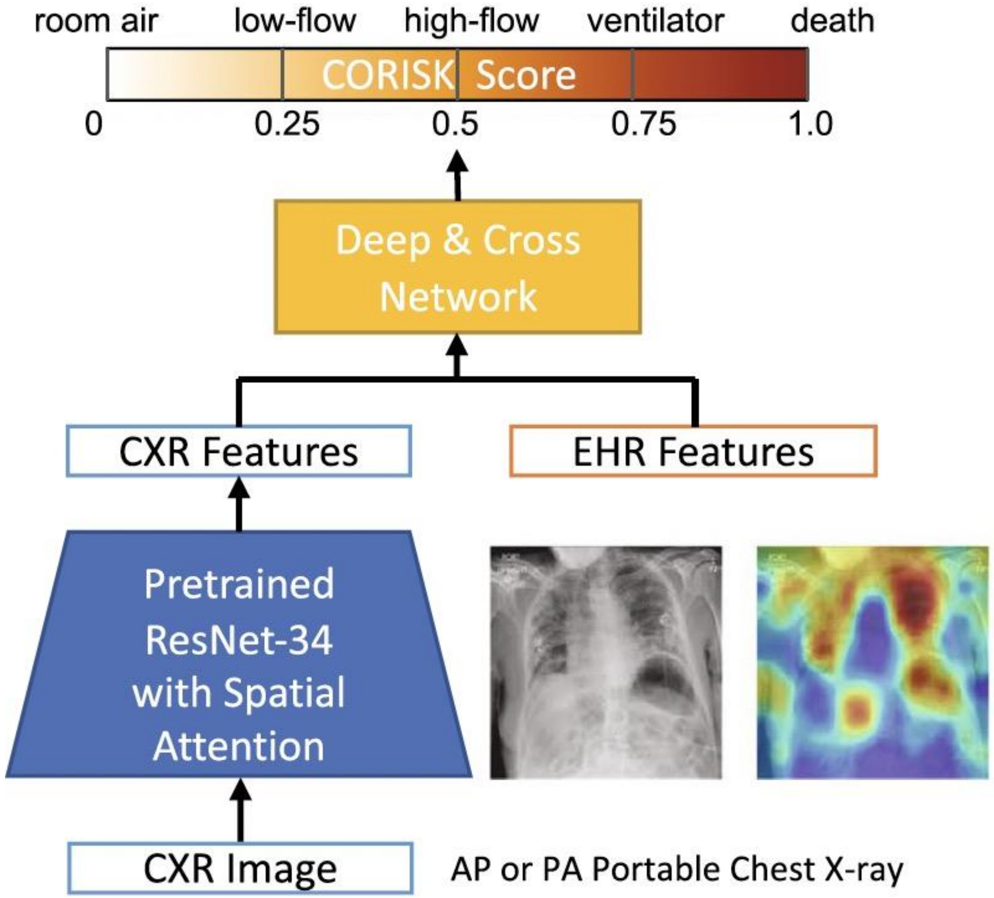
Federated Learning for Predicting Clinical Outcomes

Model:

The EXAM model is derived from a clinical decision support model (Buch, et al. 2021):

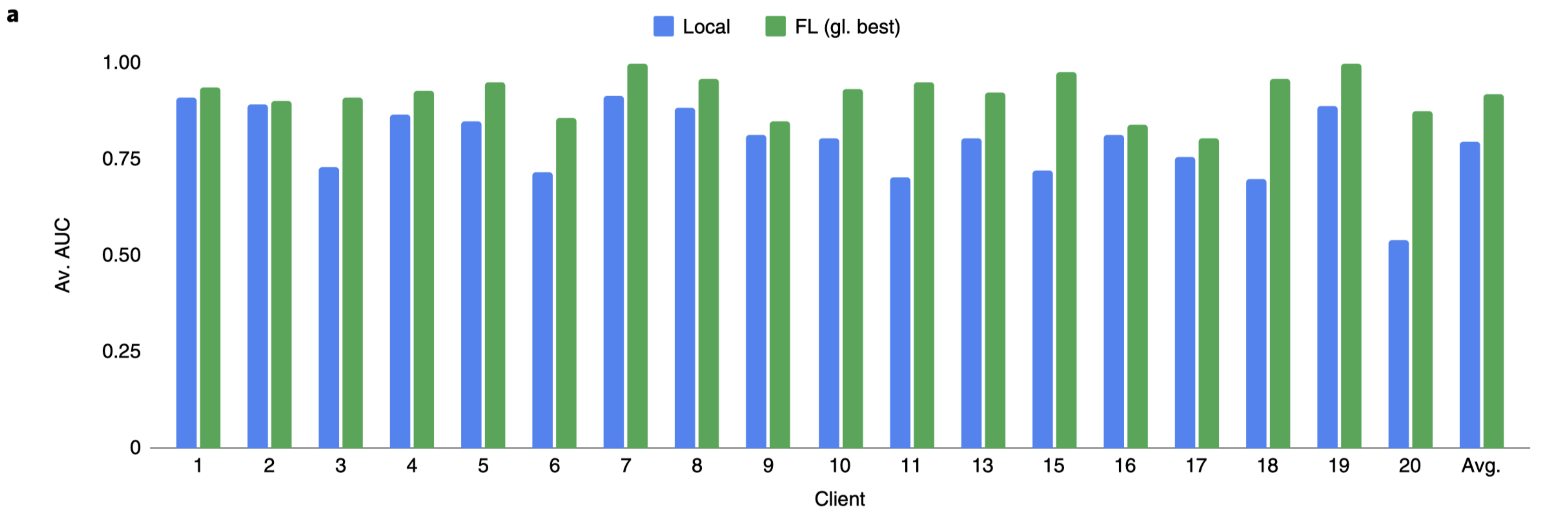
- 20 features (19 from EMR and one from CXR) were used as input to the model.
- The outcome labels were assigned based on patient oxygen therapy after 24- and 72-hour periods from initial admission to the emergency department (ED).



Dayan, et al. Federated learning for predicting clinical outcomes in patients with COVID-19. Nature medicine, 2021.
Buch, et al. Development and validation of a deep learning model for prediction of severe outcomes in suspected COVID-19 Infection. Arxiv, 2021.

Federated Learning for Predicting Clinical Outcomes

Results: Performance of FL versus local models



Client	1	2	3	4	5	6	7	8	9	10	11	13	15	16	17	18	19	20	Av.
Local	0.910	0.892	0.731	0.869	0.848	0.716	0.916	0.887	0.816	0.803	0.702	0.805	0.722	0.812	0.755	0.698	0.889	0.542	0.795
FL (gl. best)	0.938	0.902	0.912	0.929	0.950	0.857	1.000	0.961	0.849	0.935	0.950	0.925	0.979	0.839	0.806	0.958	1.000	0.875	0.920

Dayan, et al. Federated learning for predicting clinical outcomes in patients with COVID-19. Nature medicine, 2021.

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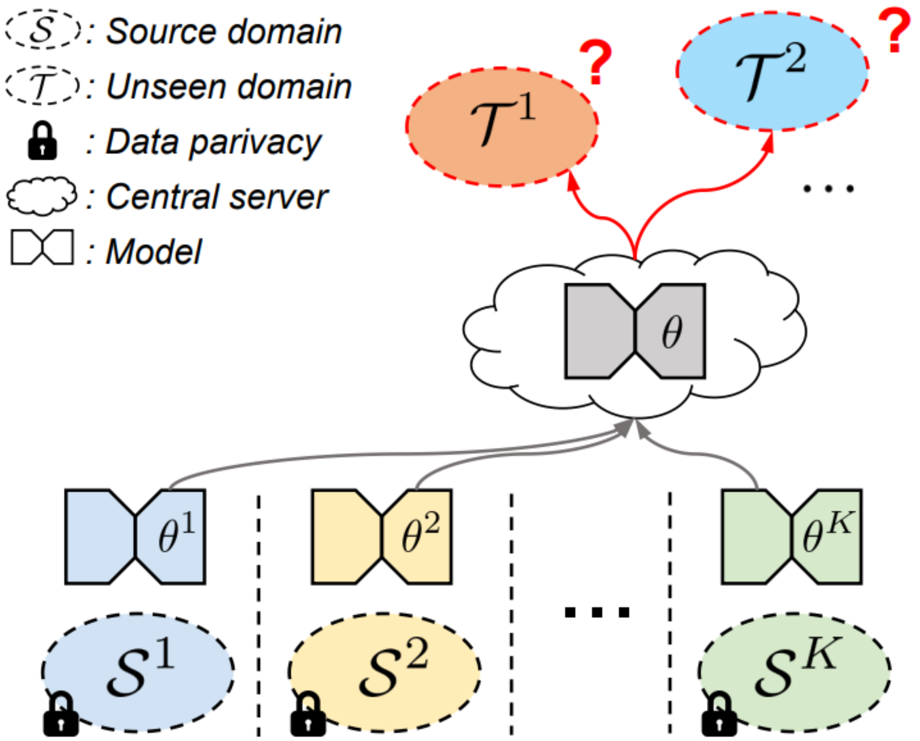
Federated Domain Generalization

- Deep learning models suffer from domain shift issue between source domain and target domain.
- FL has witnessed some pilot progress on medical image analysis tasks, while neglecting model generalizability into unseen domains outside the federation. This is a crucial problem impeding wide applicability of FL models in real practice.
- Domain generalization (DG) is to study how to learn generalizable models with good performance on unseen target domains.

Federated Domain Generalization

Problem Definition:

- Standard federated learning paradigm involves the communication between a central server and K local clients.
- At each federated round t, every client will receive the same global model weights θ from the central server and update the model with their local data.
- How to learn a generalizable model with good performance on unseen domains?



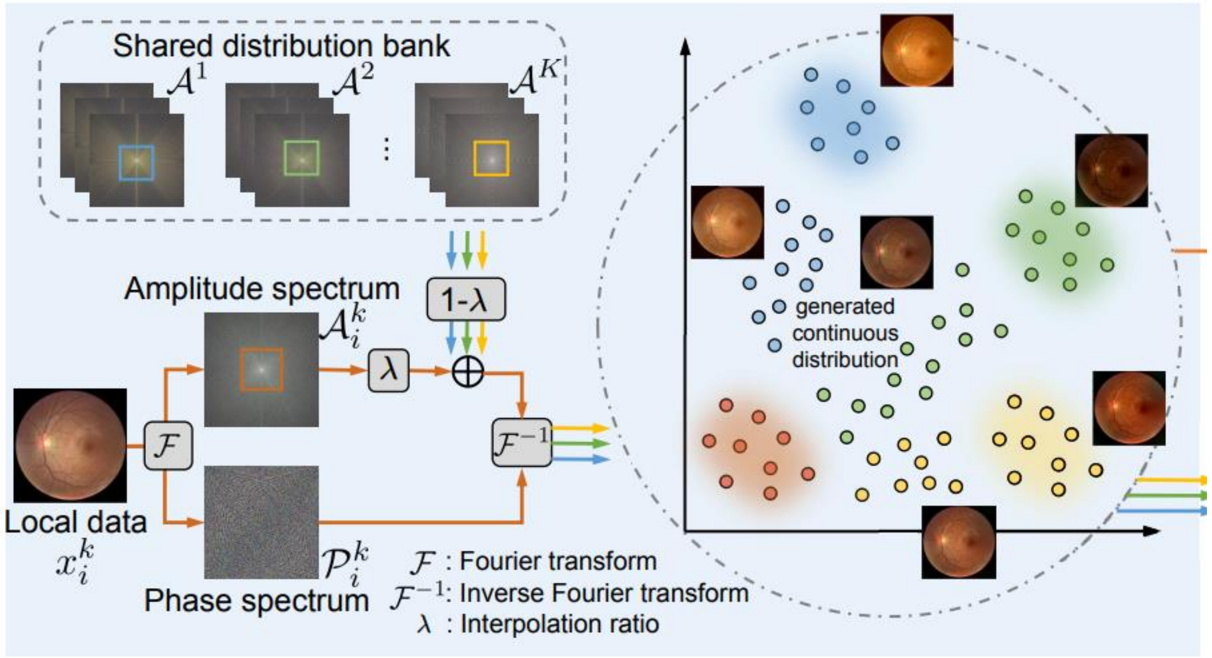
Liu, et al. Feddg: Federated domain generalization on medical image segmentation via episodic learning in continuous frequency space. CVPR 2021.

Federated Domain Generalization

Methodology:

- Continuous Frequency Space Interpolation:

- Extract amplitude spectrum bank $A = [A^1, \dots, A^k]$ via Fourier transformation on each client.
- Divide local images x^k into phases and amplitudes.
- Recombine local phases and amplitudes from A to generate images t^k of different distributions.



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Federated Domain Generalization

Methodology:

- Boundary-oriented Episodic Learning:

- Use raw input x^k as meta-train, generated t^k as meta-test.
- A meta-update is performed to virtually evaluate the updated parameters $\hat{\theta}_k$ on meta-test data t_i^k with a meta objective $\mathcal{L}_{meta}$. This optimization paradigm aims to train the model such that its learning on source domains can generalize on unseen domains.
- Regularize the boundary-related and background-related features with contrastive learning to enhance the intra-class cohesion and inter-class separation regardless of distribution.

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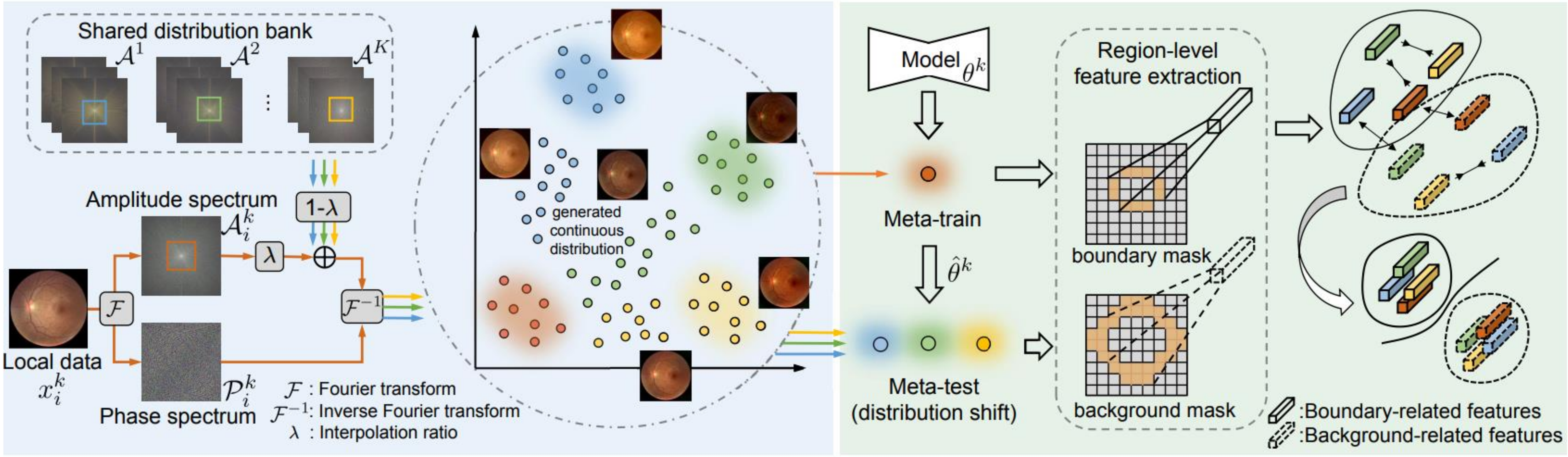
Federated Domain Generalization

Methodology:



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Federated Domain Generalization

Results:

Table 1. Comparison of federated domain generalization results on Optic Disc/Cup segmentation from fundus images.

Task	Optic Disc Segmentation					Optic Cup Segmentation					Overall	Optic Disc Segmentation					Optic Cup Segmentation					Overall
Unseen Site	A	B	C	D	Avg.	A	B	C	D	Avg.		A	B	C	D	Avg.	A	B	C	D	Avg.	
	Dice Coefficient (Dice) ↑											**Hausdorff Distance (HD) ↓**										
JiGen [3]	93.92	85.91	92.63	94.03	91.62	82.26	70.68	83.32	**85.70**	80.47	86.06	13.12	20.18	11.29	8.15	13.19	20.88	23.21	11.55	9.23	16.22	14.71
BigAug [60]	93.49	86.18	92.09	93.67	91.36	81.62	69.46	82.64	84.51	79.56	85.46	16.91	19.01	11.53	8.76	14.05	21.21	23.10	12.02	10.47	16.70	15.39
Epi-FCR [25]	94.34	86.22	92.88	93.73	91.79	83.06	70.25	83.68	83.14	80.03	85.91	13.02	18.97	**10.67**	8.47	12.78	19.12	21.94	11.50	10.86	15.86	14.32
RSC [17]	94.50	86.21	92.23	94.15	91.77	81.77	69.37	83.40	84.82	79.84	85.80	19.44	19.26	13.47	8.14	15.08	23.85	24.01	11.38	9.79	17.25	16.16
FedAvg [36]	92.88	85.73	92.07	93.21	90.97	80.84	69.71	82.28	83.35	79.05	85.01	17.01	20.68	11.70	9.33	14.68	20.77	26.01	11.85	10.03	17.17	15.93
ELCFS (Ours)	**95.37**	**87.52**	**93.37**	**94.50**	**92.69**	**84.13**	**71.88**	**83.94**	85.51	**81.37**	**87.03**	**11.36**	**17.10**	10.83	**7.24**	**11.63**	**18.65**	**19.36**	**11.17**	**8.91**	**14.52**	**13.07**

Table 2. Comparison of federated domain generalization results on prostate MRI segmentation.

Unseen Site	A	B	C	D	E	F	Average	A	B	C	D	E	F	Average
	Dice Coefficient (Dice) ↑							**Hausdorff Distance (HD) ↓**						
JiGen [3]	89.95	85.81	84.06	87.34	81.32	89.11	86.26	10.51	11.53	11.70	11.49	14.80	9.02	11.51
BigAug [60]	89.63	84.62	83.86	87.66	81.20	88.96	85.99	10.68	11.78	12.07	**10.66**	13.98	9.73	11.48
Epi-FCR [25]	89.72	85.39	84.97	86.55	80.63	89.76	86.17	10.60	12.31	12.29	12.00	15.68	8.81	11.95
RSC [17]	88.86	85.56	84.36	86.21	79.97	89.80	85.80	10.57	11.84	14.76	13.07	14.79	8.83	12.31
FedAvg [36]	89.02	84.48	84.11	86.30	80.38	89.15	85.57	11.64	12.01	14.86	11.80	14.90	9.30	12.42
ELCFS (Ours)	**90.19**	**87.17**	**85.26**	**88.23**	**83.02**	**90.47**	**87.39**	**10.30**	**11.49**	**11.50**	11.57	**11.08**	**8.31**	**10.88**

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Federated Semi-supervised Learning

- Label-efficient learning is an open problem for FL.
- Typically, DL suffers from data issues:

\- Lack of data, heterogenous data, unlabeled data, noisy data, etc.

- Learning a robust model under a non-fully supervised setting is still challenging.

\- Semi-supervised learning, Self-supervised learning, Un-supervised learning, etc.

Federated Semi-supervised Learning

COVID-19 Lesion Segmentation from CT Images

- The availability and quality of local labels varies due to heterogeneity in equipment and limited medical resources across the globe.
- Federated semi-supervised learning to solve such a challenge.

- FL could handle the problem of data privacy and utilization.
- Semi-supervised learning can ensure effective training when sites have only limited amount of labeled data but large amount of unlabeled data.

Yang, et al. Federated semi-supervised learning for COVID region segmentation in chest CT using multi-national data from China, Italy, Japan. Medical image analysis, 2021.

Federated Semi-supervised Learning

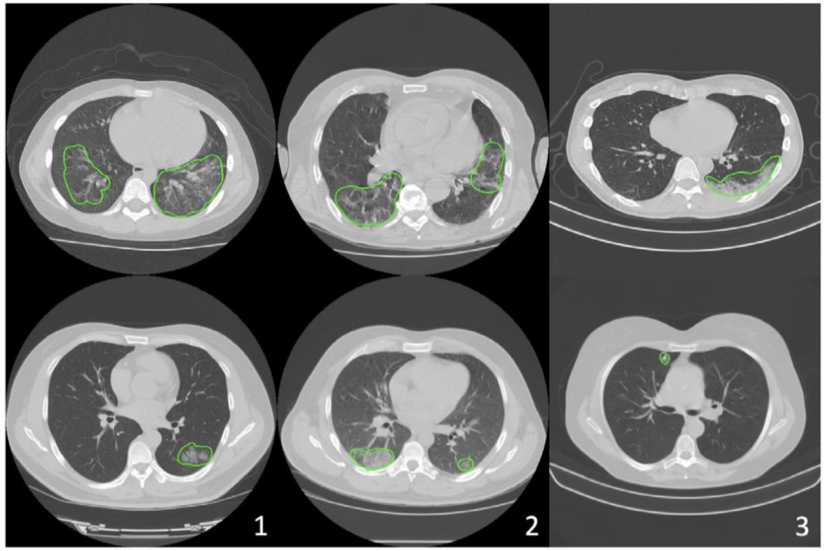
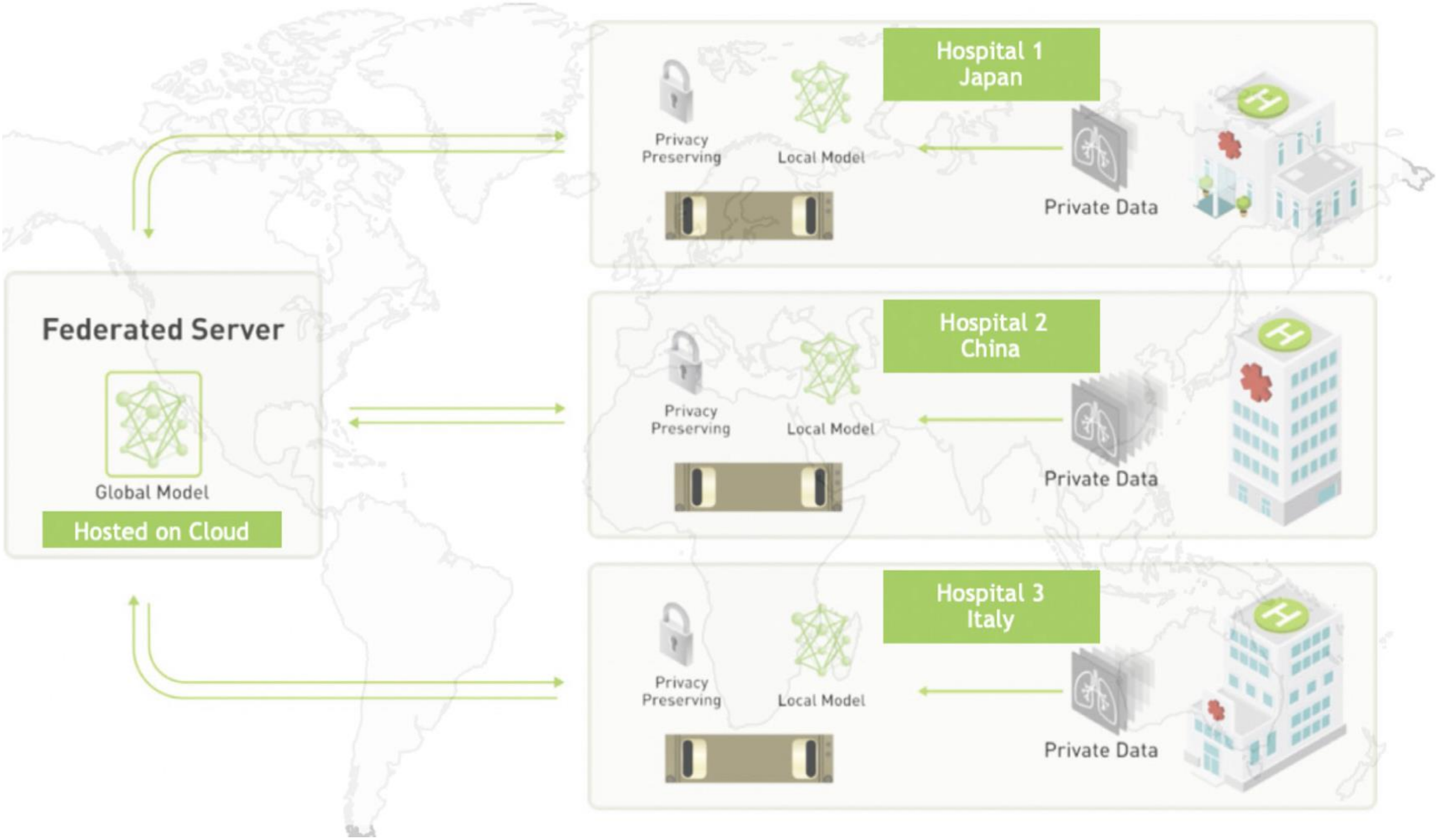


Fig. 2. The axial planes of chest CT scans from three different sites. Areas inside green contours represent COVID-19 affected regions annotated by radiologist. The appearance of the affected region identified as "infiltrates" range from diffused ground glass opacity (COVID, upper row) to focal nodules (lower row). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



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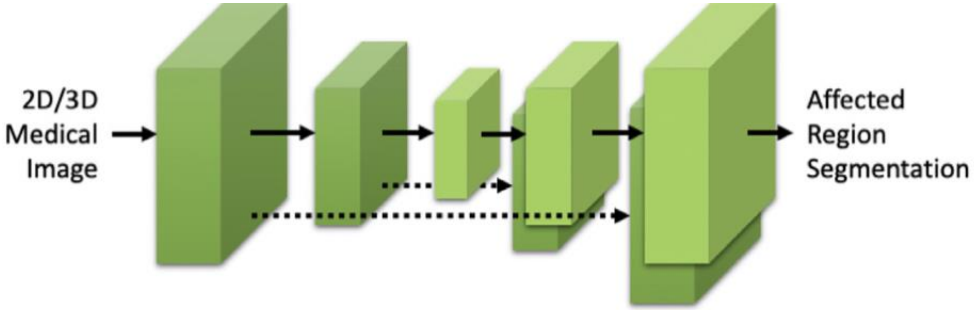
Federated Semi-supervised Learning

Methodology:



- Supervised federated learning
- Baseline model: 3D U-shape FCN.
- Utilize weight aggregation.
- Federated semi-supervised learning
- For client with unlabeled data, they introduced a new consistency loss function.

$$\hat{y} = \begin{cases} 1, & H(u) > 0.5 \\ 0, & otherwise \end{cases}$$

$$L_{consistency} = L(\hat{y}, H(g(u)))$$

where *u* is an image sample, *g* is augmentation function and *H* is the global model.

Yang, et al. Federated semi-supervised learning for COVID region segmentation in chest CT using multi-national data from China, Italy, Japan. Medical image analysis, 2021.

Federated Semi-supervised Learning

Experiments:

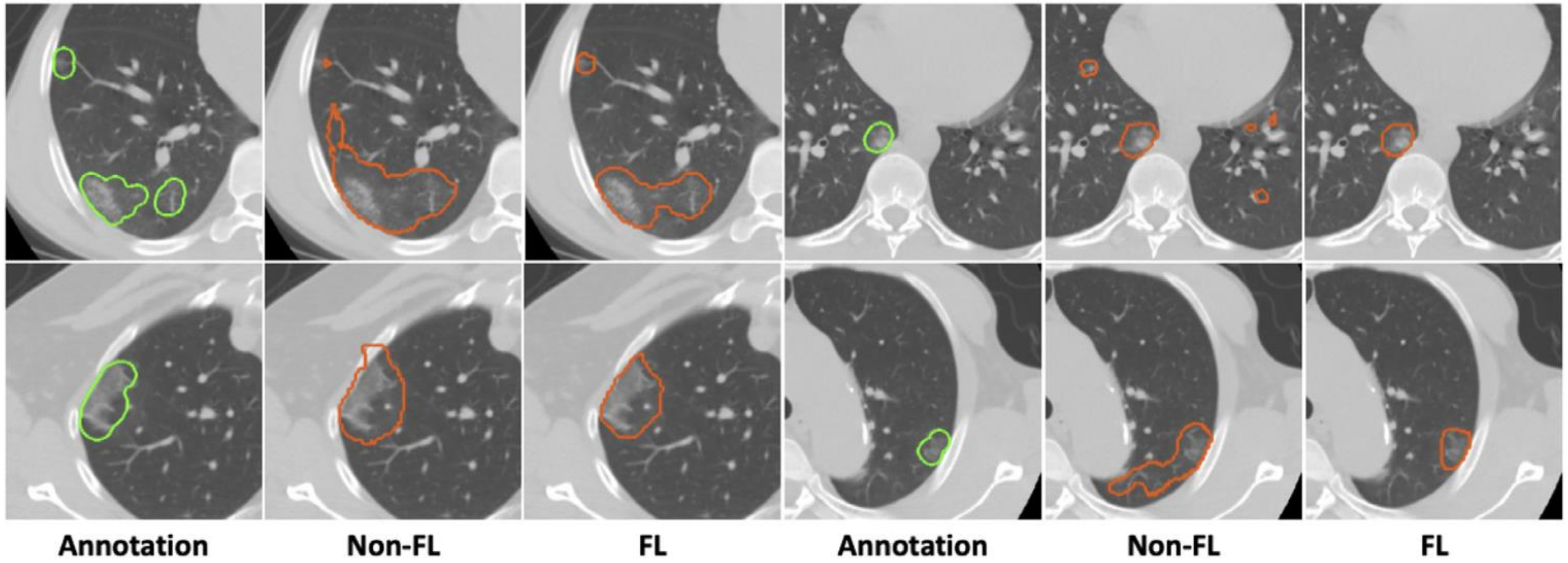


Fig. 5. Visualizations of federated semi-supervised segmentation of COVID regions in 3D CT (from the testing set of unsupervised client **Image_2**). "Non-FL" indicates results from the model trained with Image_1 along, and "FL" denotes results from the model trained with federated semi-supervised learning on Image_1 and Image_2. The segmentation results using the proposed framework captures the ground truth shapes better and has less false positives.

Yang, et al. Federated semi-supervised learning for COVID region segmentation in chest CT using multi-national data from China, Italy, Japan. Medical image analysis, 2021.

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Challenge and Future Direction

The FL faces a few challenges, such as

- **Statistical Challenge**:

- The data distribution among all clients differ greatly; Local data may be far from being a representative sample of the overall distribution.

- **Communication Efficiency**:

- The number of clients K is large and may be much bigger than the average number of training samples stored in the local clients.

- **Privacy and Security**:

- Additional privacy protections, e.g., differential privacy, are needed.
- It is impossible to ensure all clients are equally reliable.

Xu, et al. Federated learning for healthcare informatics. Journal of Healthcare Informatics Research, 2021.

Challenge and Future Direction

There are many FL related topics in medical image analysis:

- **Real-world application**: How to deploy FL in the real world?
- **Personalization**: How to personalize the global model to fit locally?
- **Label-efficient**: How to learn robustly and efficiently under different types of supervision?
- **Privacy and Security**: How to preserve privacy and promise security?
- **System design**: How to design a robust, low-latency and safe system?
- Others.