Department of Computer Science and Engineering (CSE)
IIT Hyderabad

CS6450: Visual Computing

FEDERATED SEMI-SUPERVISED MEDICAL IMAGE CLASSIFICATION VIA INTER-CLIENT RELATION MATCHING

Quande Liu, Hongzheng Yang , Qi Dou, and Pheng-Ann Heng

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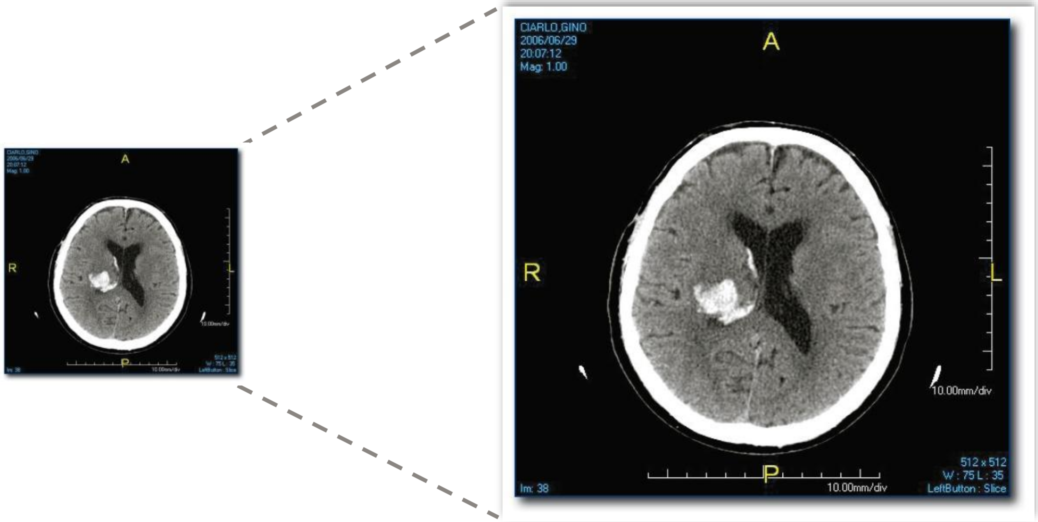
Instructor
Prof. C. Krishna Mohan

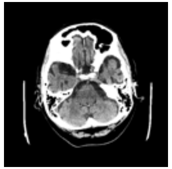
Teaching Assistant
Divya Peketi

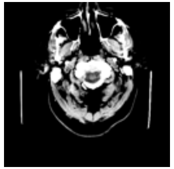
Presenter
Kamal Shrestha
cs21mtech16001

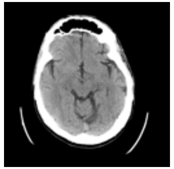
OVERVIEW

- Problem & Motivation
- Traditional Approach
- Proposed Approach
- Results & Conclusion









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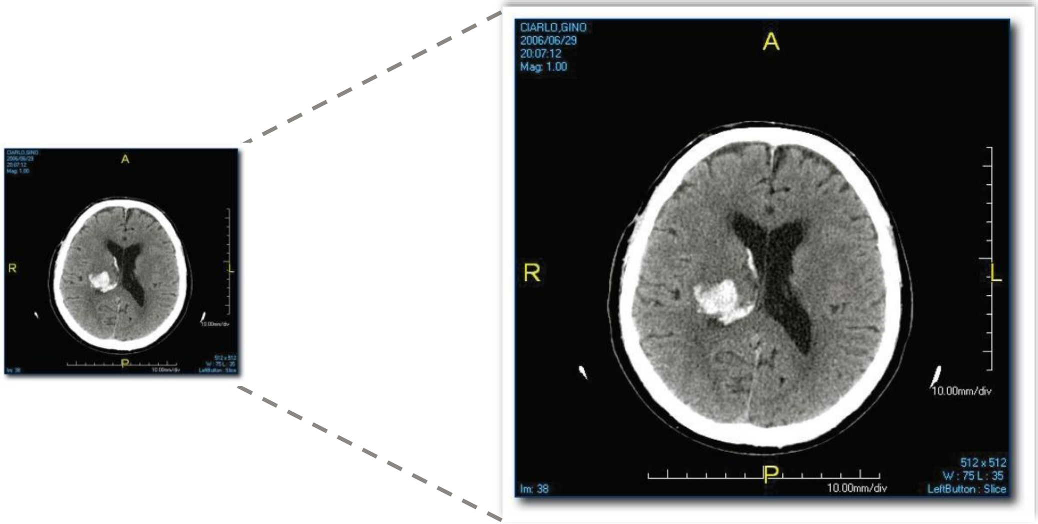
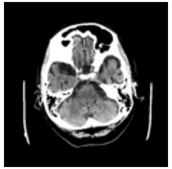
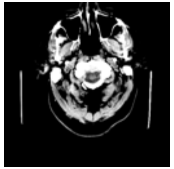
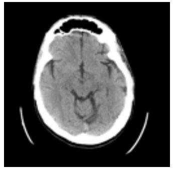
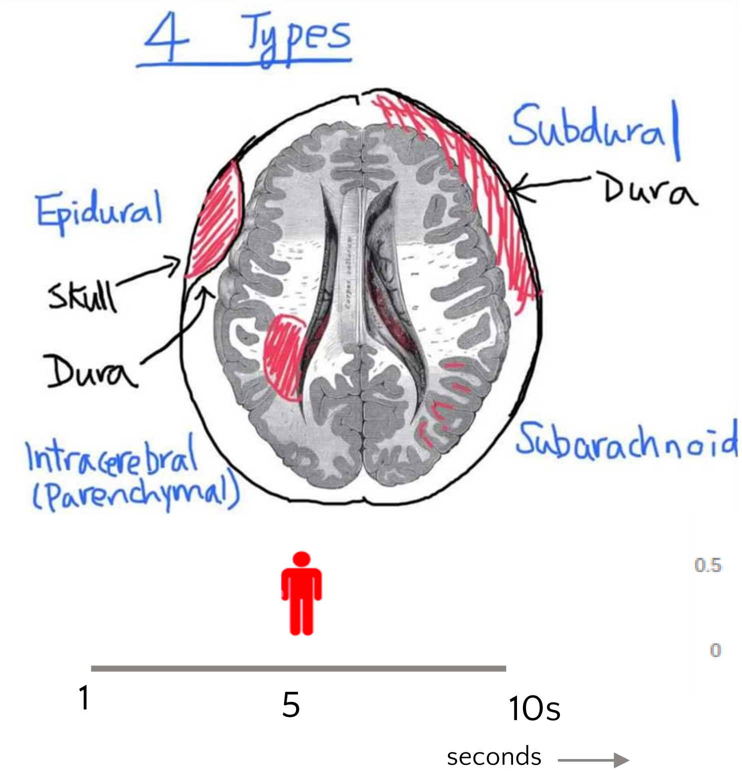


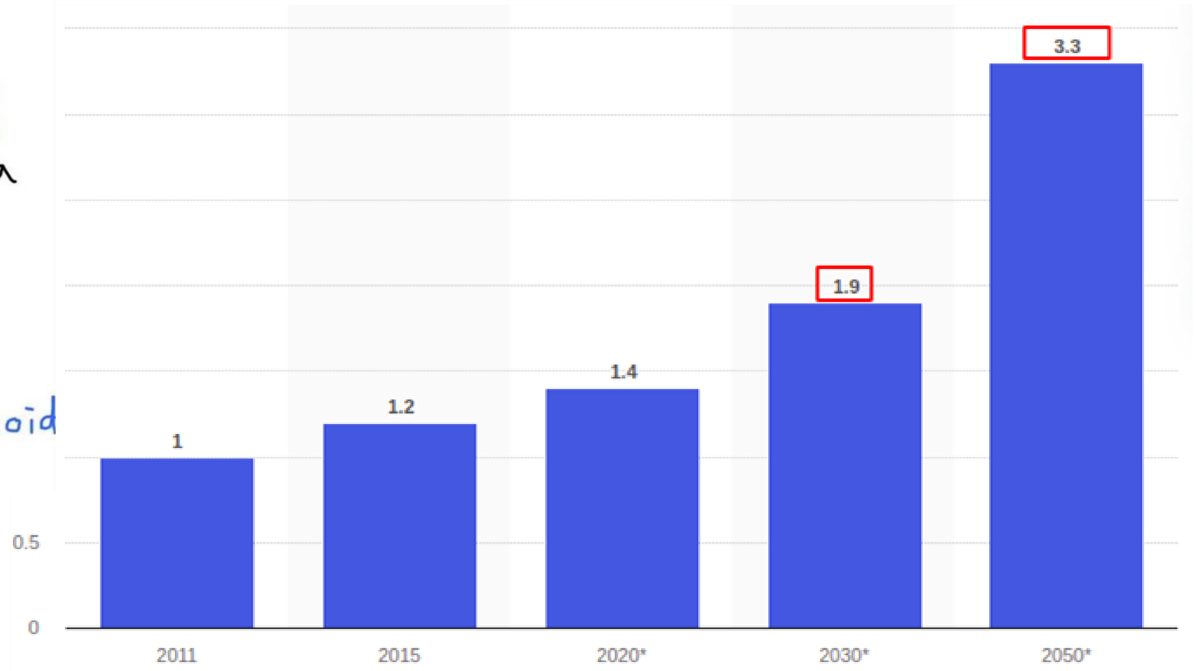






Brain Stroke or Brain Attack kills **more people than HIV, Tuberculosis, and Malaria combined.**





[Statista 2022]

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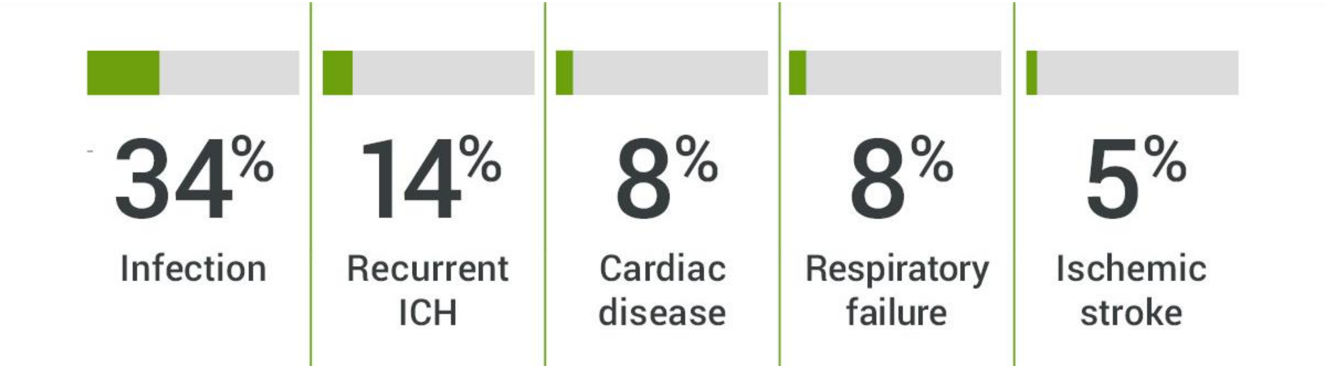
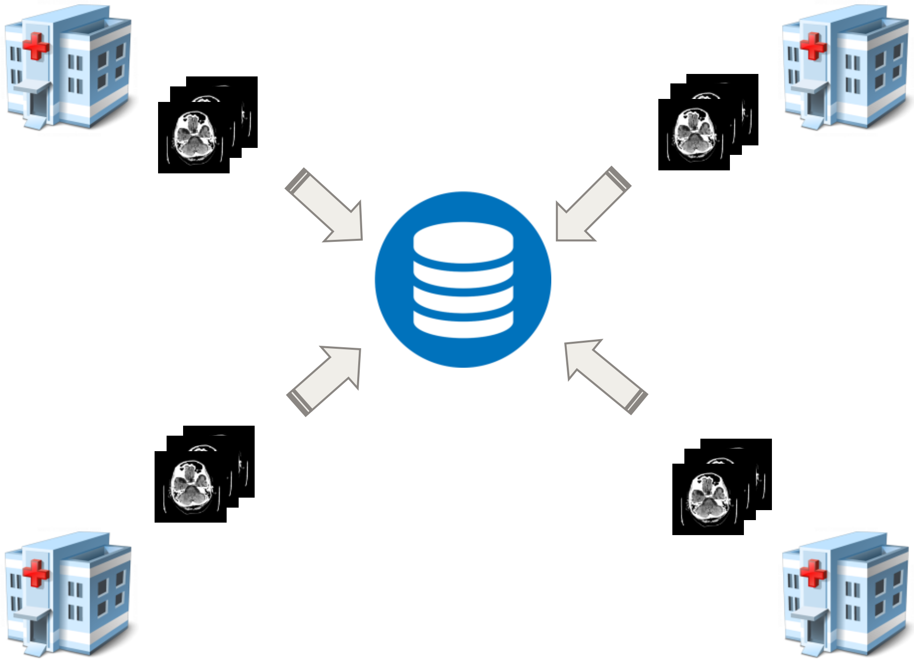


Healio

Data collaboration across medical institutions is increasingly desired to **mitigate the scarcity and distribution of medical images.**



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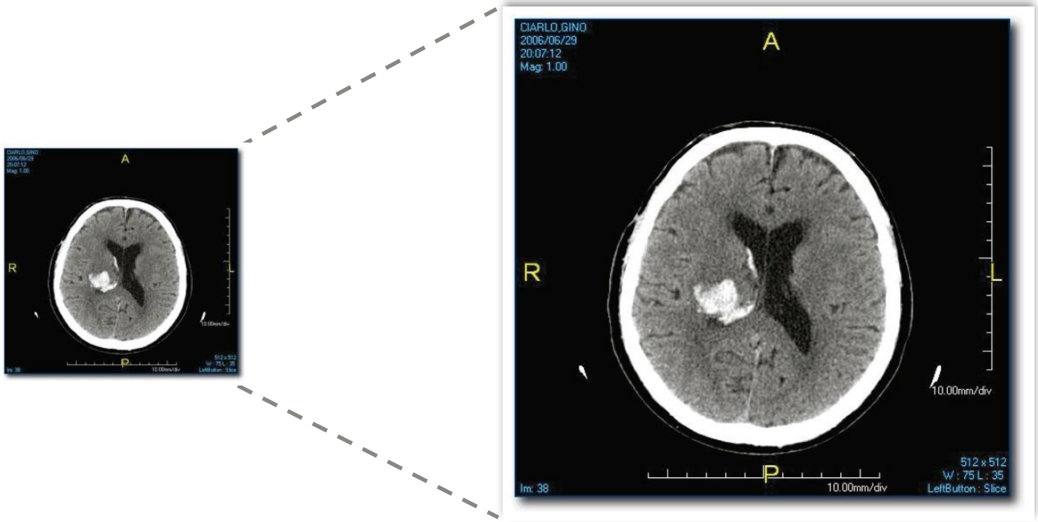
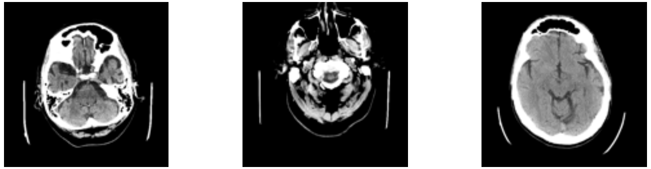
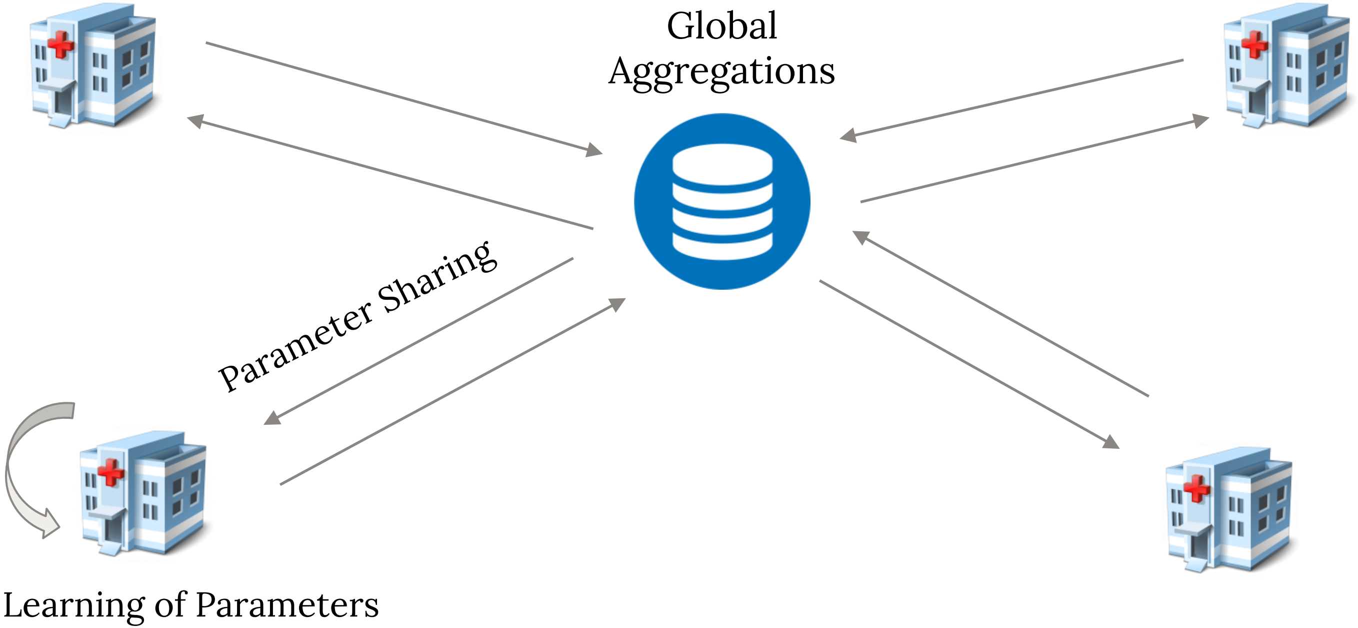


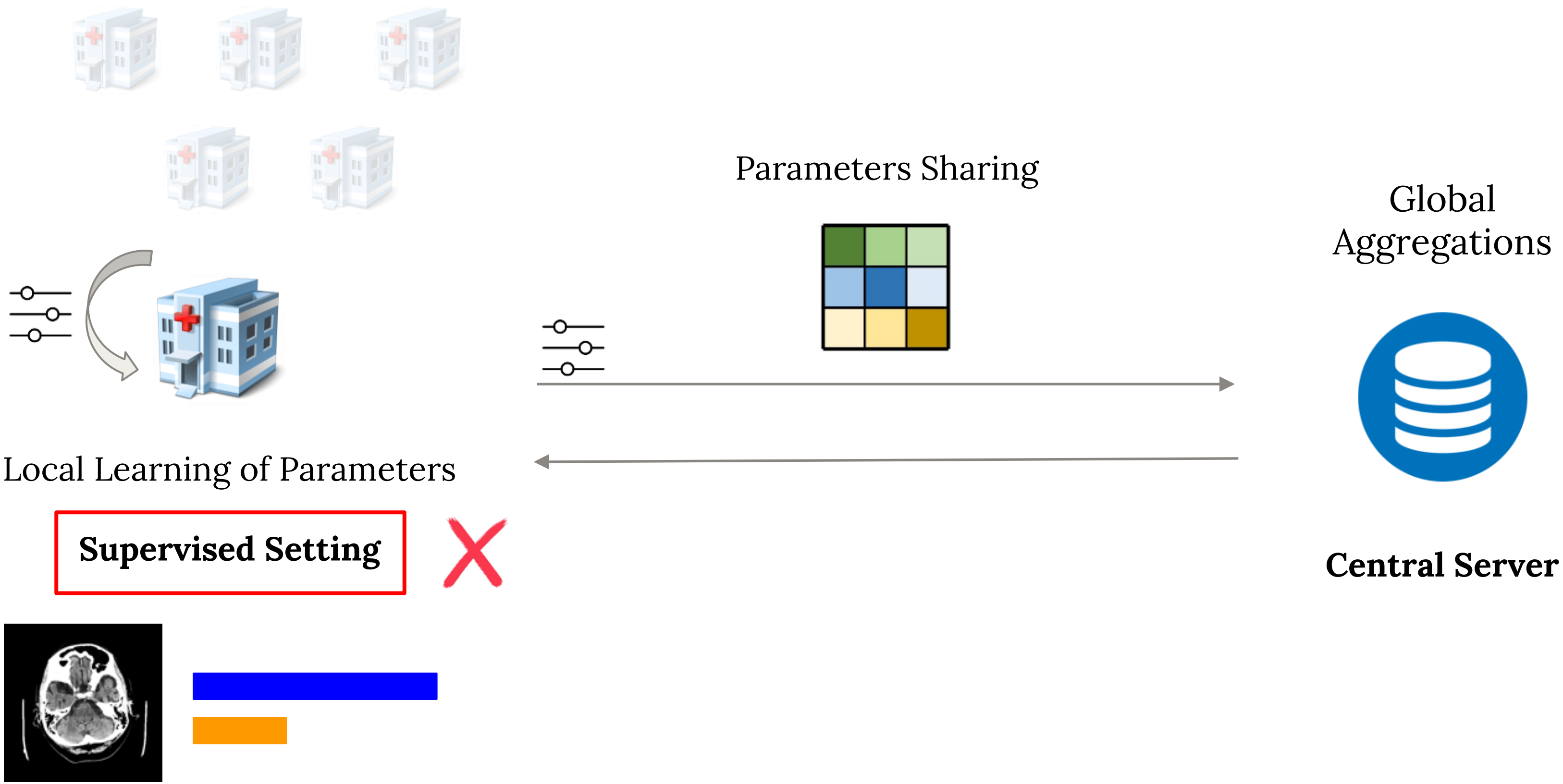


Federated learning (FL) has emerged as **a privacy-preserving solution** to learn models **without exchanging the sensitive health data.**

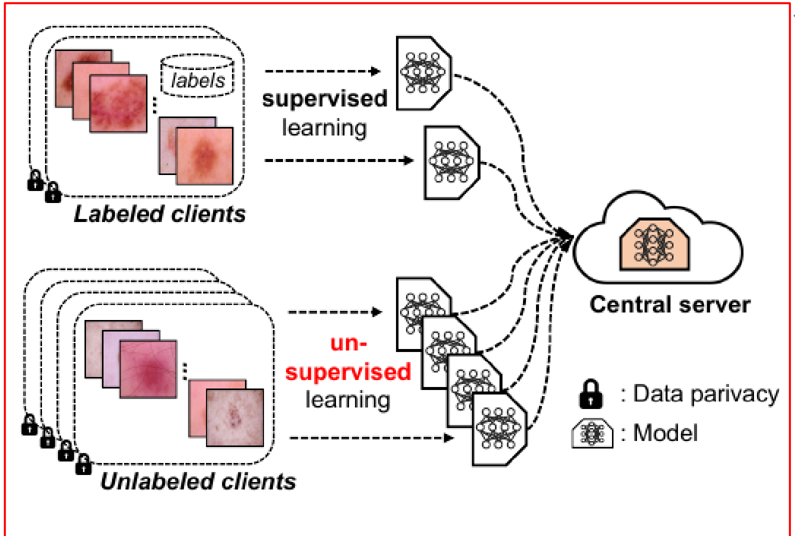


Supervised Setting

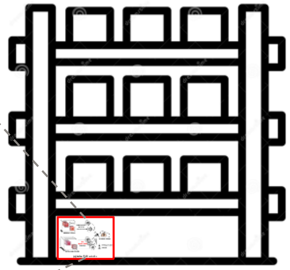
Existing FL algorithms typically **only allow the supervised training setting.**



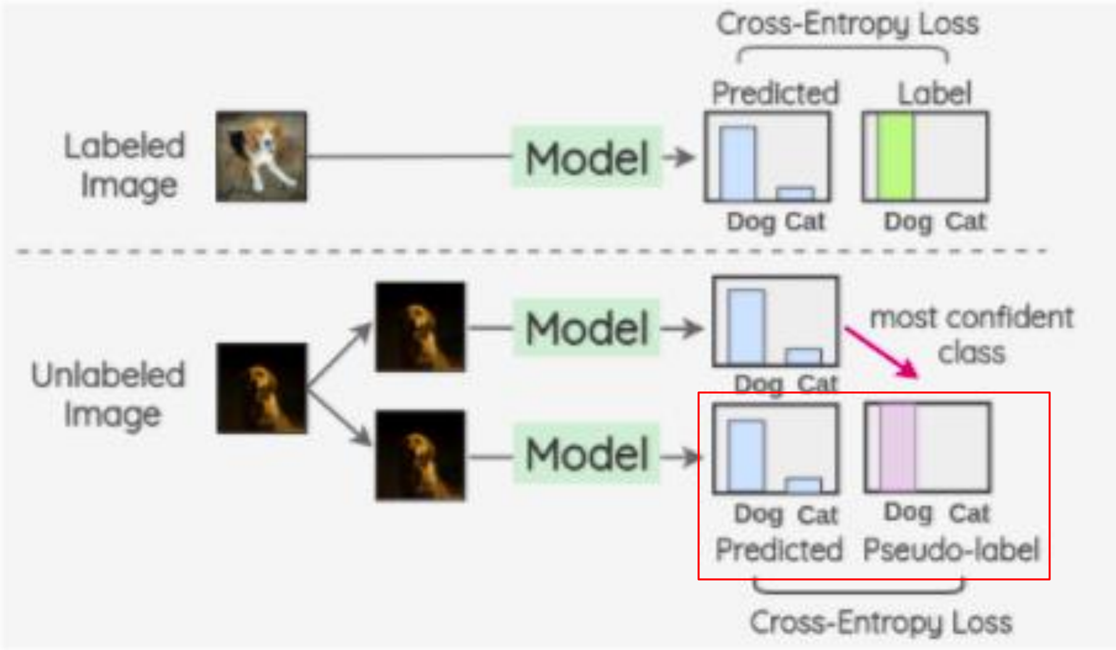
A naive FSSL, solution is to simply integrate the **off-the-rack semi-supervised learning (SSL) methods** onto the federated learning paradigm.



(a) Naive FSSL solution

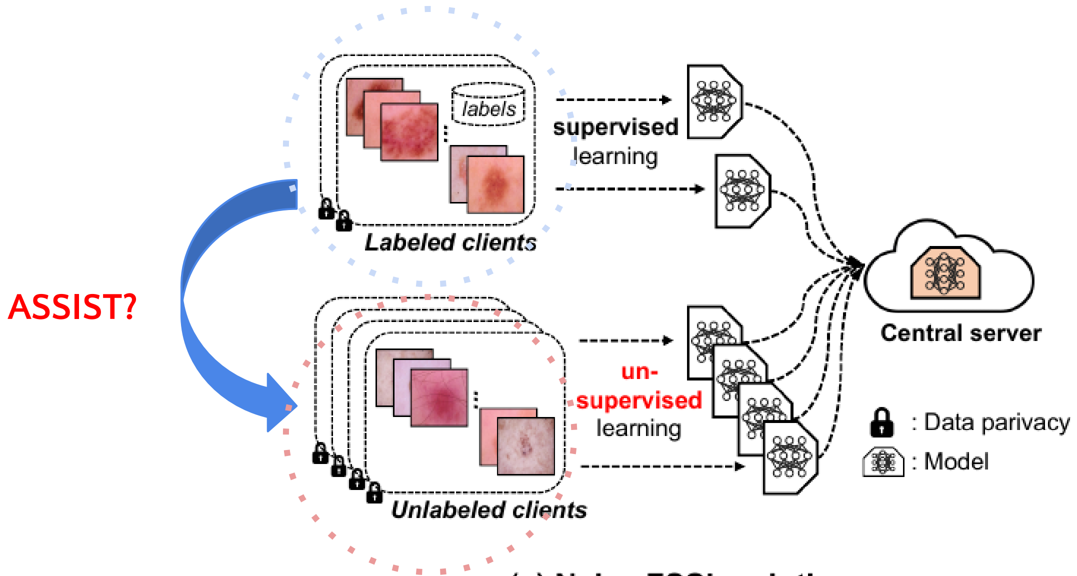


Semi supervised setting relies heavily on the assumption that the labeled data is **accessible** to provide necessary assistance.



Pseudo-Label: The Simple and Efficient Semi-Supervised Learning Method for Deep Neural Networks

How to build the **interaction** between the learning at labeled and unlabeled clients, given the challenging constraint of data decentralization?



(a) Naive FSSL solution

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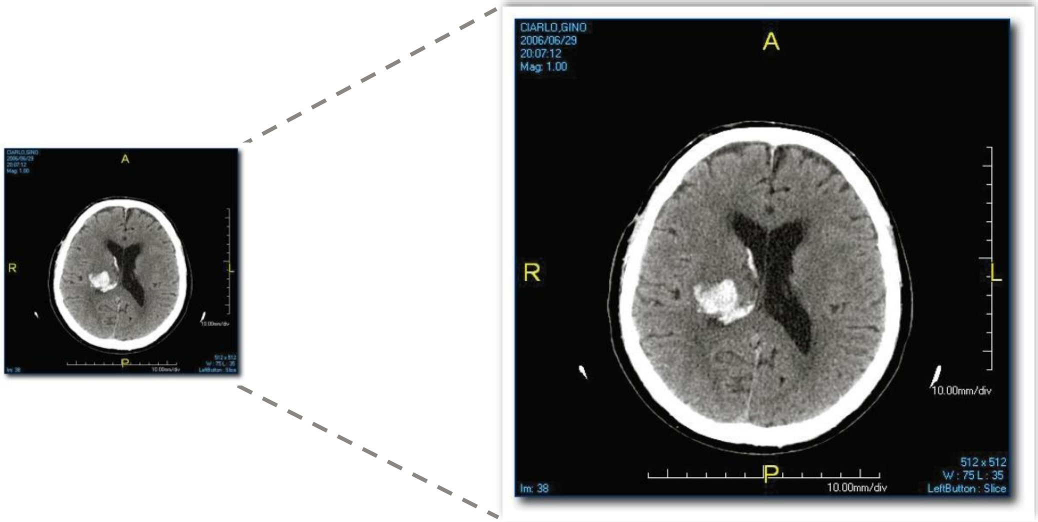
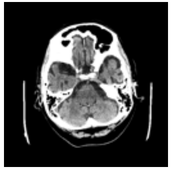
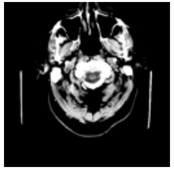
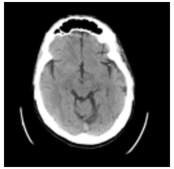
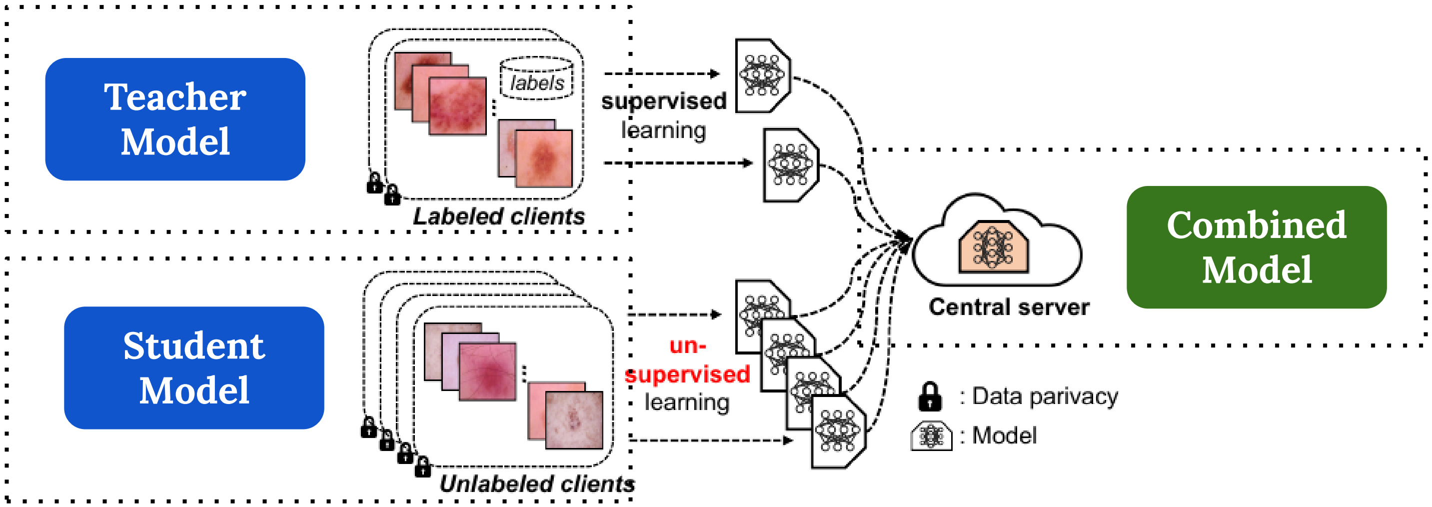






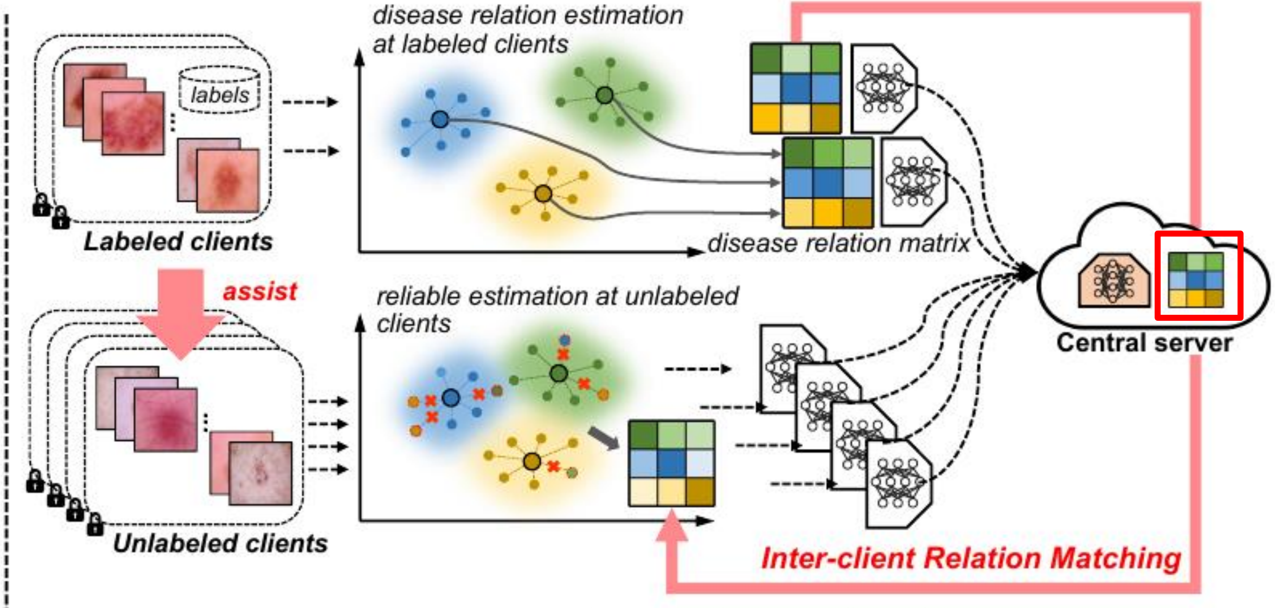


Challenges to the proposed model



(a) Naive FSSL solution

Inter-client Relation Matching scheme regularizes the unlabeled clients to capture **similar disease relationships as labeled clients** for preserving the discriminative task knowledge.



(b) Our FSSL solution (FedIRM)

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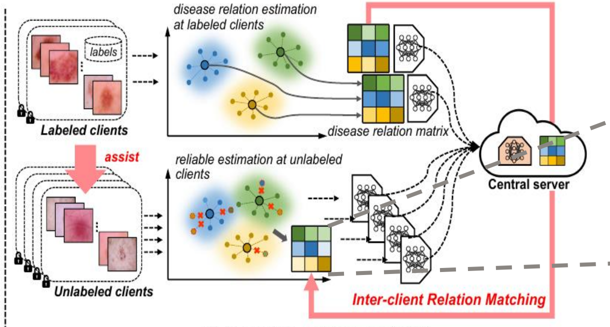
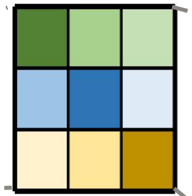
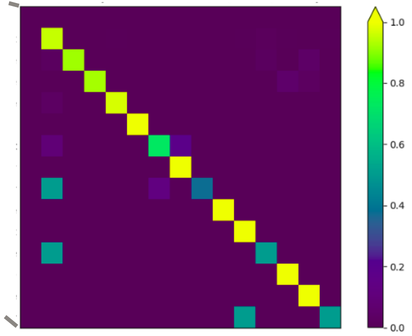


(b) Our FSSL solution (FedIRM)

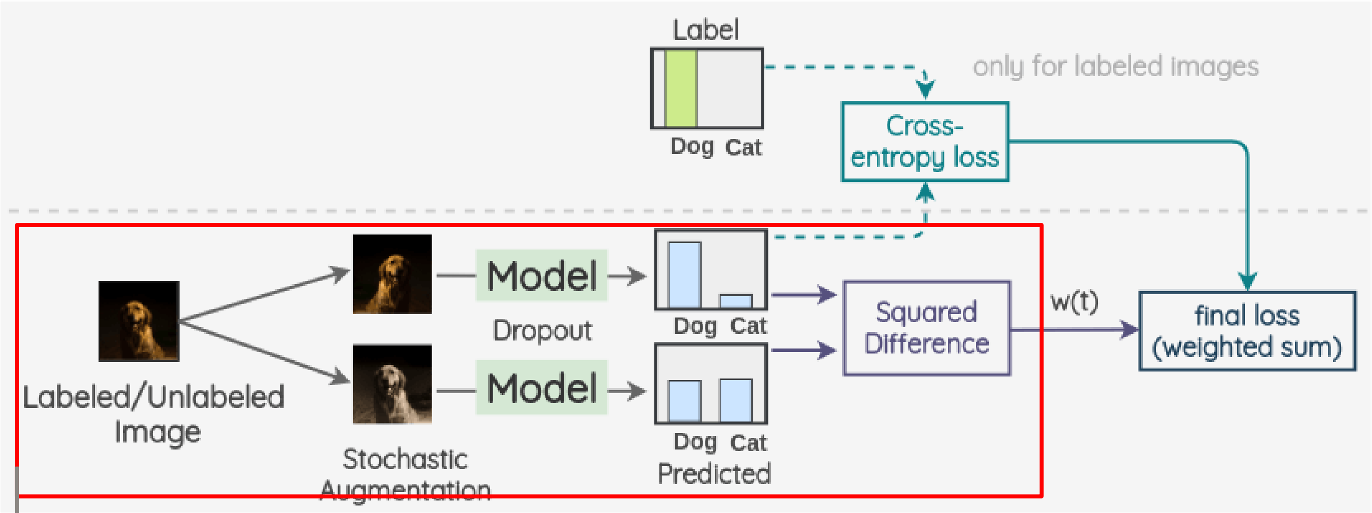


$$\mathbf{v}_c^l = \frac{1}{N_c^l}\sum_{i=1}^{N^l} \mathbb{1}_{[y_i^l = c]} \hat{f}_{\theta^l}(x_i^l)$$



DRM, labelled clients

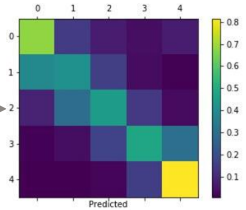
Proposed approach roots in **consistency regularization mechanism**, which enforces the prediction consistency under different **input perturbations** to exploit the unlabeled data.



$$\mathbf{w}^u = -\sum_{c=1}^{C} \bar{\mathbf{q}}^u_{(c)} \log(\bar{\mathbf{q}}^u_{(c)}), \text{ with } \bar{\mathbf{q}}^u_{(c)} = \frac{1}{T}\sum_{t=1}^{T} \mathbf{q}^u_{t(c)}$$

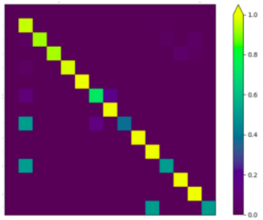
$$\mathbf{v}^u_c = \frac{\sum_{i=1}^{B} \mathbb{1}_{[(\mathbf{y}_i=c)\cdot(\mathbf{w}^u_i<h)]} \cdot \mathbf{p}^u_i}{\sum_{i=1}^{B} \mathbb{1}_{[(\mathbf{y}_i=c)\cdot(\mathbf{w}^u_i<h)]}}$$

DRM,
Un-labelled clients

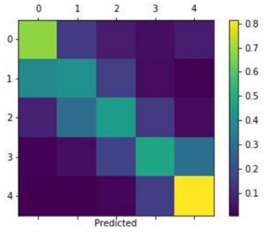


[Unsupervised data augmentation for consistency training]

Finally, the inter-client relation matching loss is designed by **minimizing the KL divergence** between disease relation matrix from labelled and unlabelled clients.



DRM, labelled clients



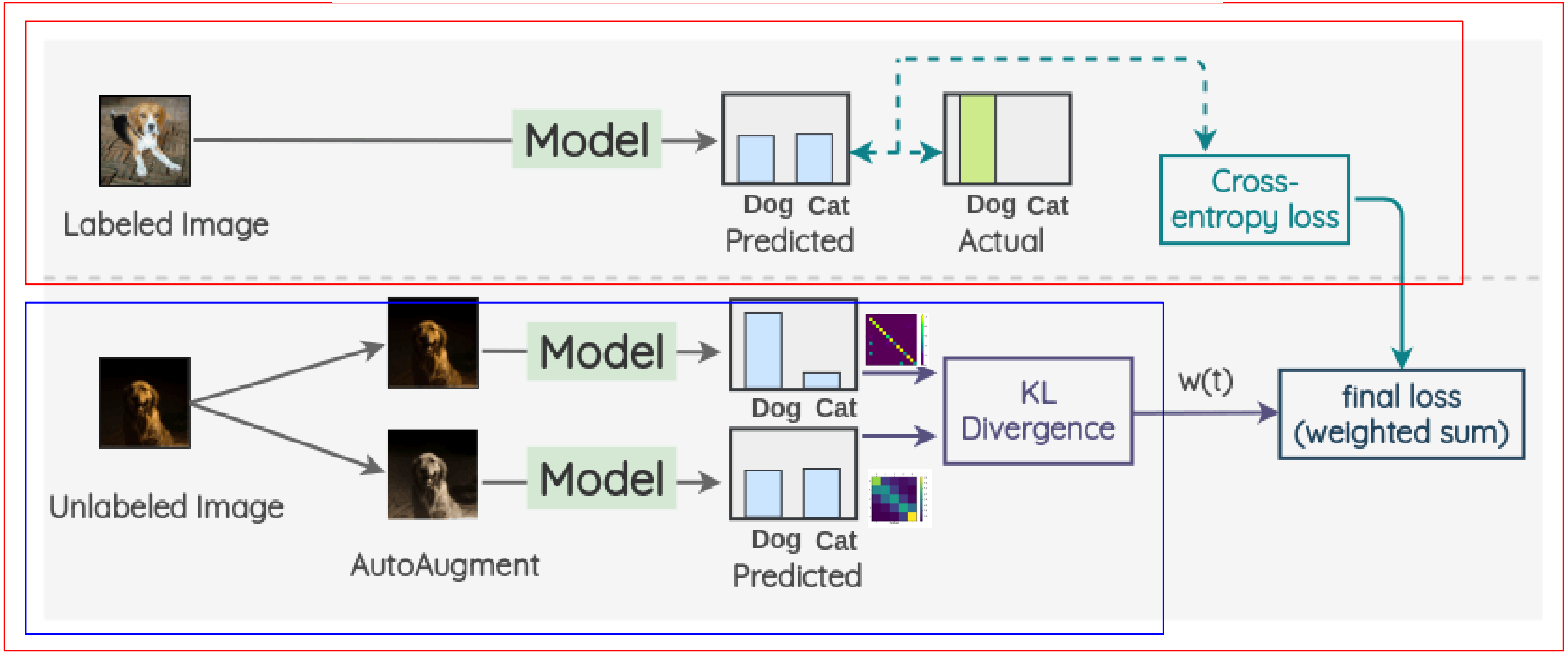
DRM, Un-labelled clients

$$\mathcal{L}_{\text{IRM}} = \frac{1}{C}\sum_{c=1}^{C}(\mathcal{L}_{\text{KL}}(\mathcal{M}_c||\mathcal{M}_c^u) + \mathcal{L}_{\text{KL}}(\mathcal{M}_c^u||\mathcal{M}_c)),$$

$$\text{with } \mathcal{L}_{\text{KL}}(\mathcal{M}_c||\mathcal{M}_c^u)) = \sum_j \mathcal{M}_{c(j)} \log \frac{\mathcal{M}_{c(j)}}{\mathcal{M}_{c(j)}^u}$$

The **local learning objectives** at labeled and unlabeled clients are respectively expressed as:

$$\boxed{\mathcal{L}^l = \mathcal{L}_{ce}(\mathcal{D}^l, \theta^l)} \text{ and } \boxed{\mathcal{L}^u = \lambda(\omega)(\mathcal{L}_c + \mathcal{L}_{\text{IRM}})}$$



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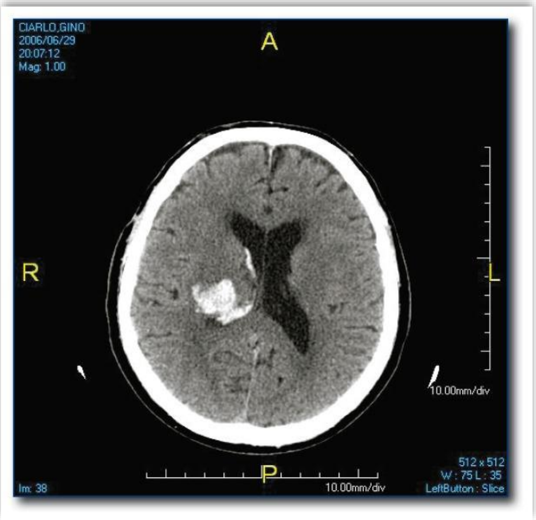
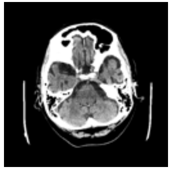
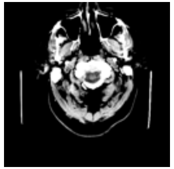
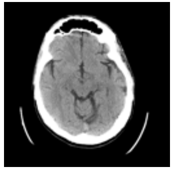
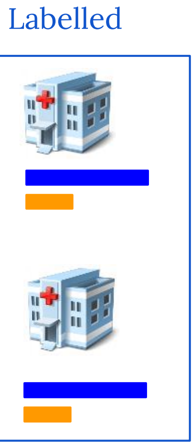








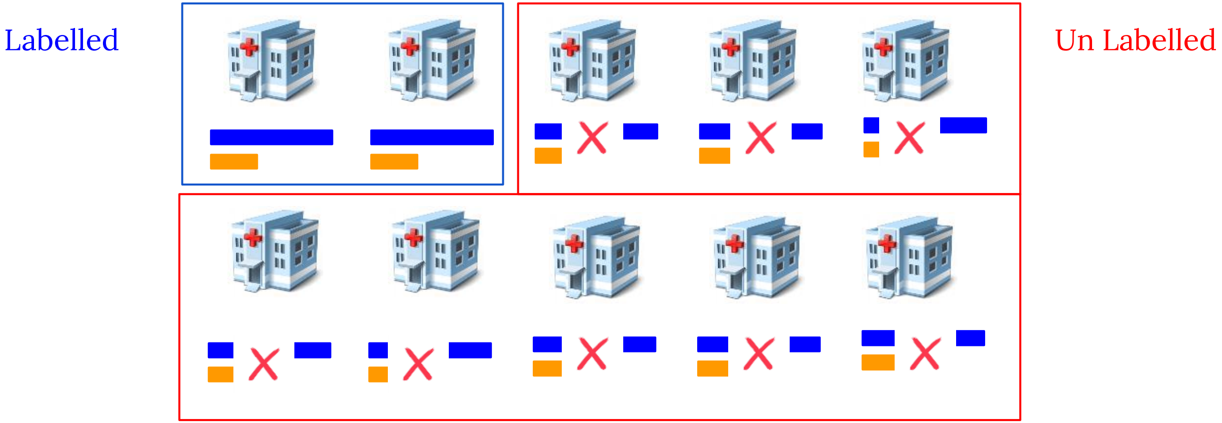
FedAvg, Federated Averaging (Weighted Averaging)



Method	Client num		Metrics				
	Label	Unlabel	AUC	Sensitivity	Specificity	Accuracy	F1
FedAvg [20]	10	0	90.48 ± 0.31	64.33 ± 1.13	92.68 ± 0.43	89.94 ± 0.92	63.94 ± 1.20

[Mean teachers are better role models]

FedAvg, Federated Averaging with 2 supervised clients



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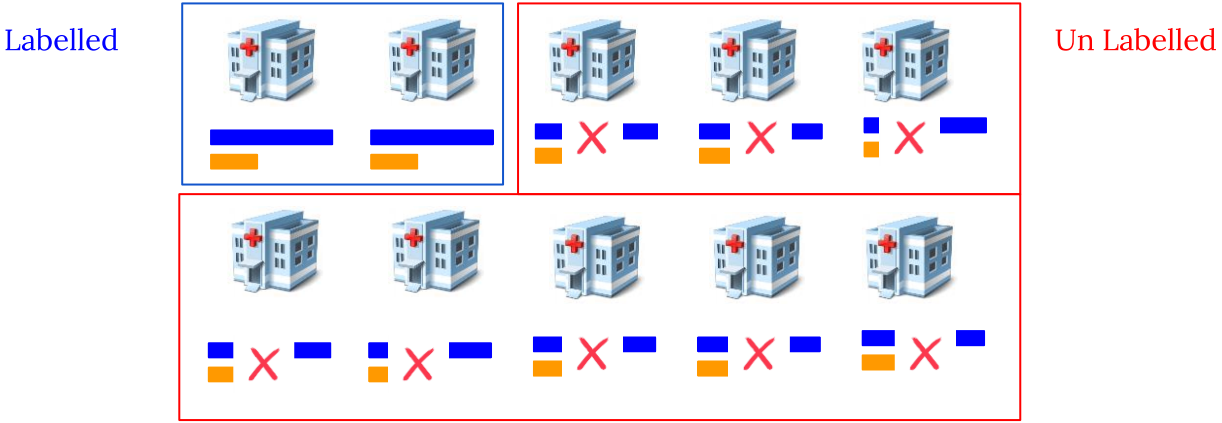
FedAvg [20]	2	0	83.40 ± 0.87	57.88 ± 1.68	90.48 ± 0.79	87.45 ± 1.08	57.10 ± 1.29

Fed-Self Training, Federated learning with Pseudo labels



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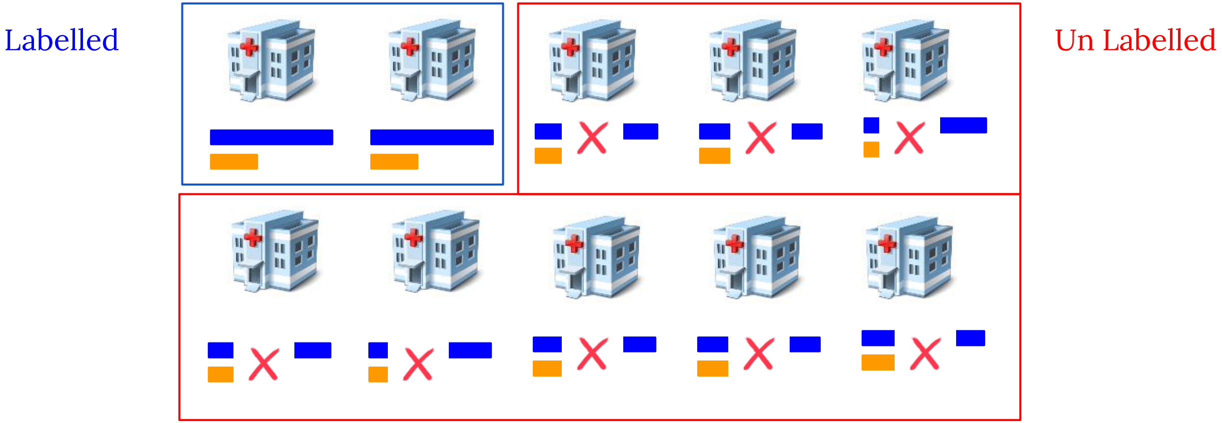
Fed-SelfTraining [33]	2	8	84.32 ± 0.82	57.94 ± 1.66	90.22 ± 0.74	87.90 ± 1.81	57.48 ± 1.14
Fed-Consistency [31]	2	8	84.83 ± 0.79	57.26 ± 1.93	90.87 ± 0.62	88.35 ± 1.32	57.61 ± 1.08

Fed-Consistency, Federated Learning with Consistency Loss



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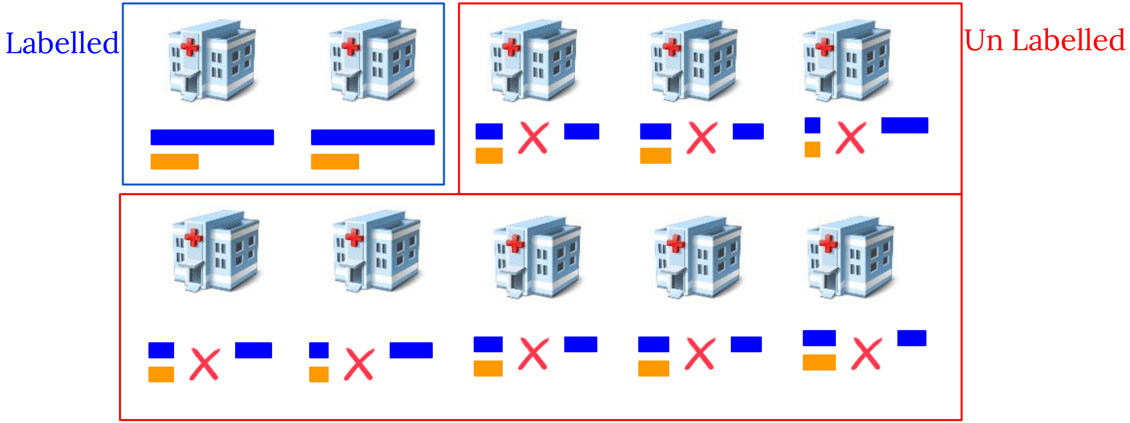
FedIRM, Federated Learning with Inter Client Relation Matching **(Proposed)**



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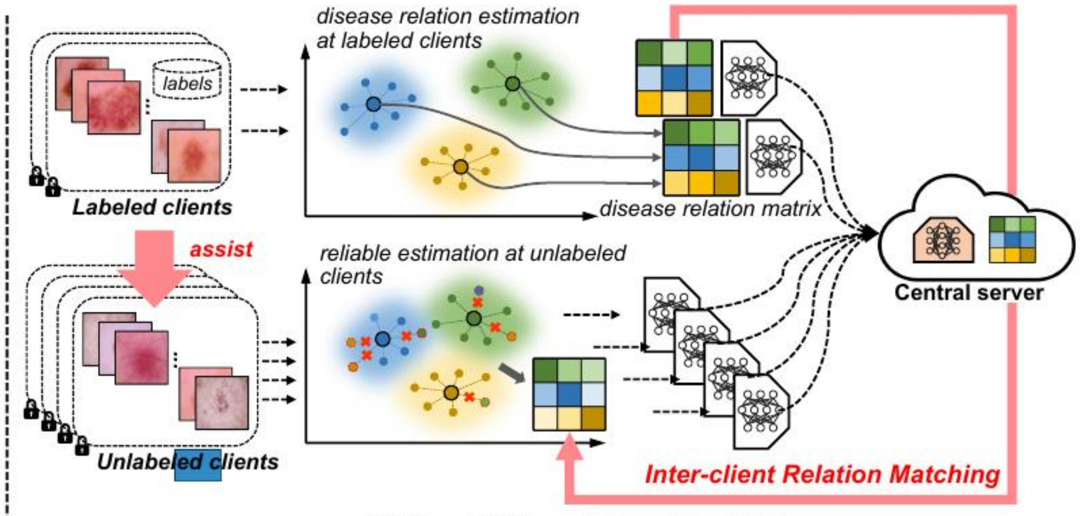
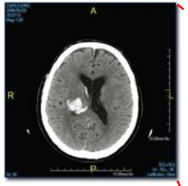
Fed-Consistency [31]	2	8	84.83 ± 0.79	57.26 ± 1.93	90.87 ± 0.62	88.35 ± 1.32	57.61 ± 1.08
FedIRM (ours)	2	8	$\mathbf{87.56 \pm 0.56}$	$\mathbf{59.57 \pm 1.57}$	$\mathbf{91.53 \pm 0.81}$	$\mathbf{88.89 \pm 1.29}$	$\mathbf{59.86 \pm 1.65}$

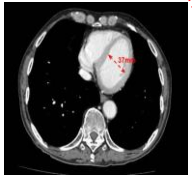
Making the use of unannotated data reduces the cost in individual annotations which can be redirected to more meaningful research.

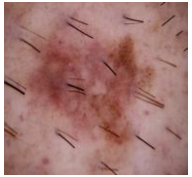


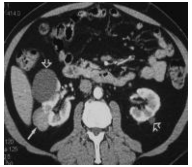
(b) Our FSSL solution (FedIRM)

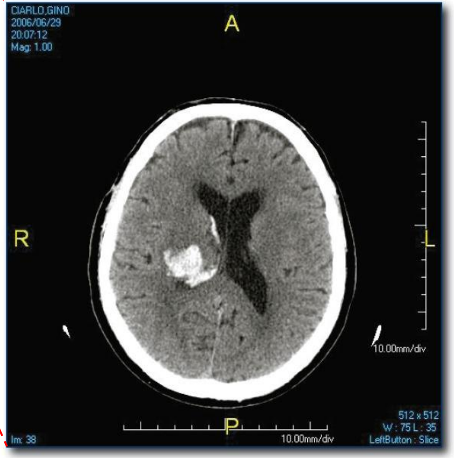
Intracranial Hemorrhage

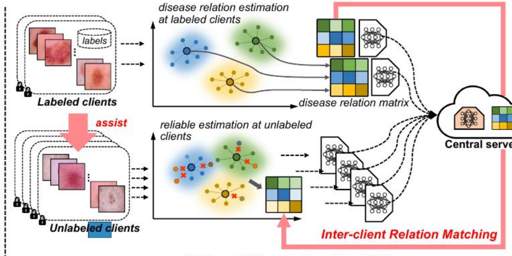












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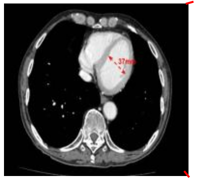
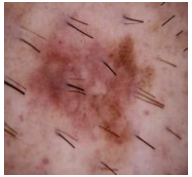
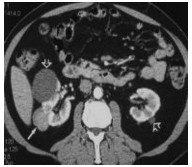
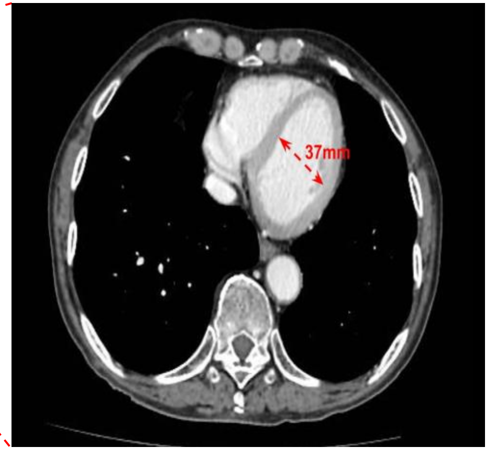
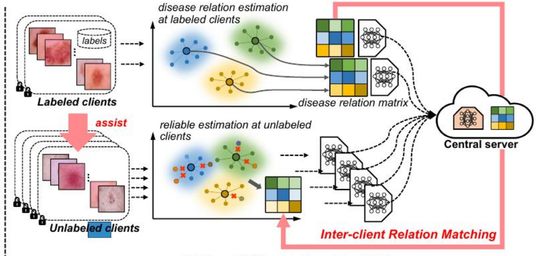
Myocardial Infarction





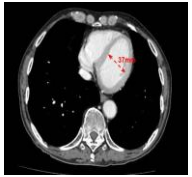
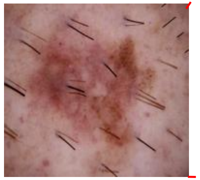
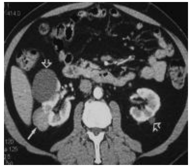
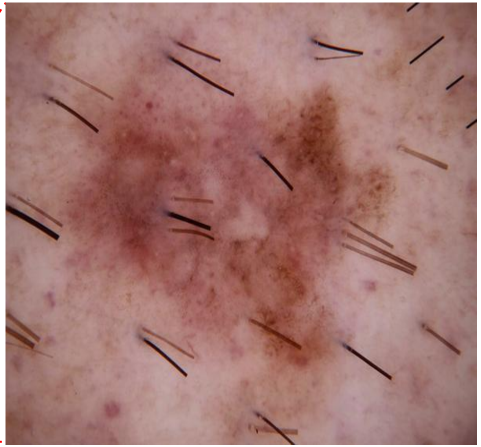
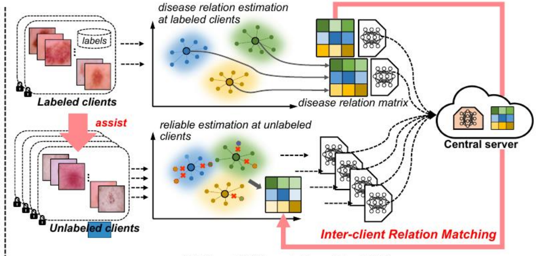






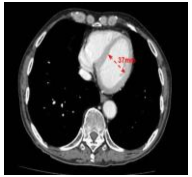
(b) Our FSSL solution (FedIRM)

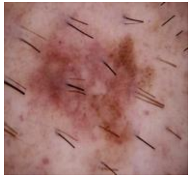
Skin Lesions

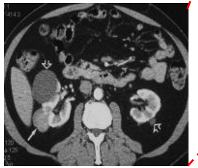







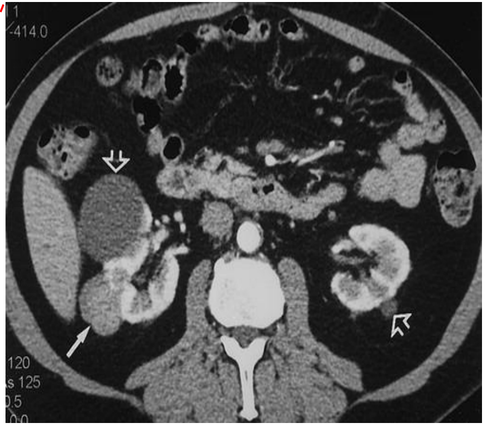
(b) Our FSSL solution (FedIRM)

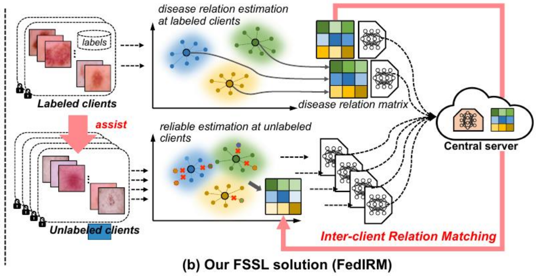
Renal Cell Carcinoma



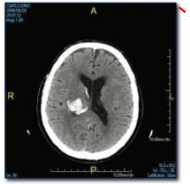


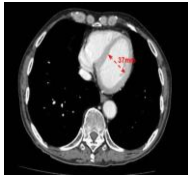


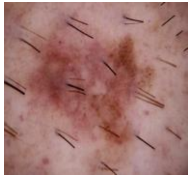


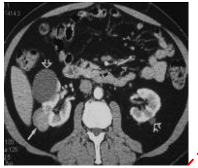


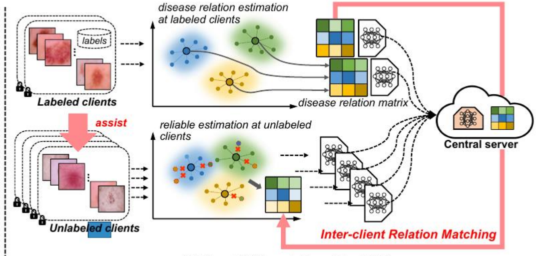
Huge number of application possibilities











(b) Our FSSL solution (FedIRM)

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Thanks!

Any *questions* ?

You can find me at

- cs21mtech16001@iith.ac.in