Medical Vision Seminar

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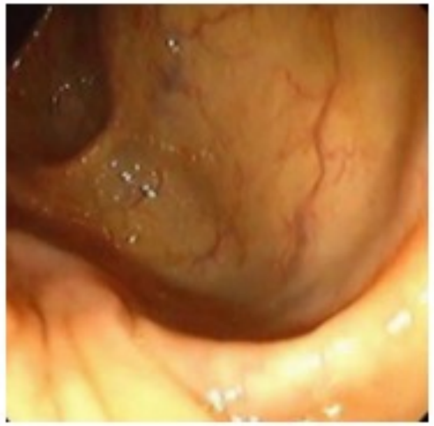
日期：2021.06.30

Mathew, S., Nadeem, S., Kumari, S., & Kaufman, A. (2020).
Augmenting colonoscopy using extended and directional CycleGAN for lossy image translation.

In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 4696-4705).

Background

- 光学结肠镜检查（OC）：几何结构 + 颜色 + 纹理 + 镜面高光信息
- 虚拟结肠镜检查（VC）：几何结构信息

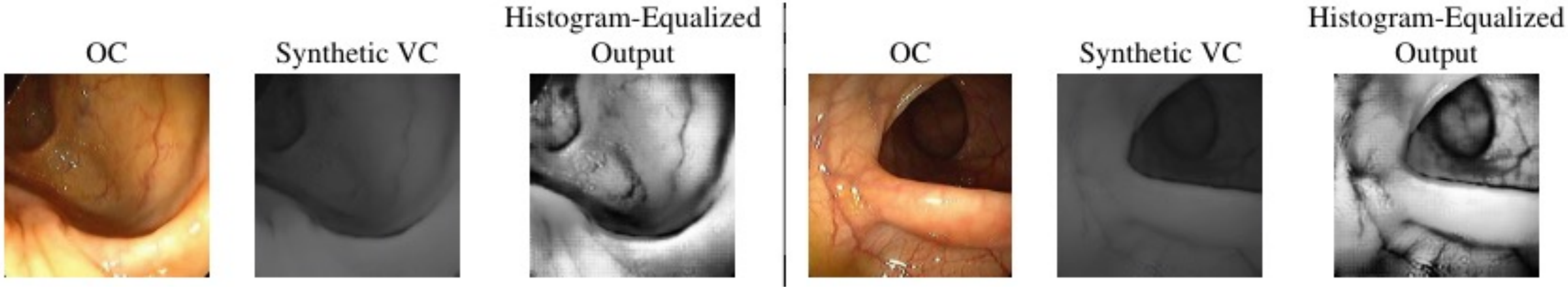


OC

VC

Background

- 光学结肠镜检查（OC）：几何结构 + 颜色 + 纹理 + 镜面高光信息
- 虚拟结肠镜检查（VC）：几何结构信息
- OC → VC: lossy



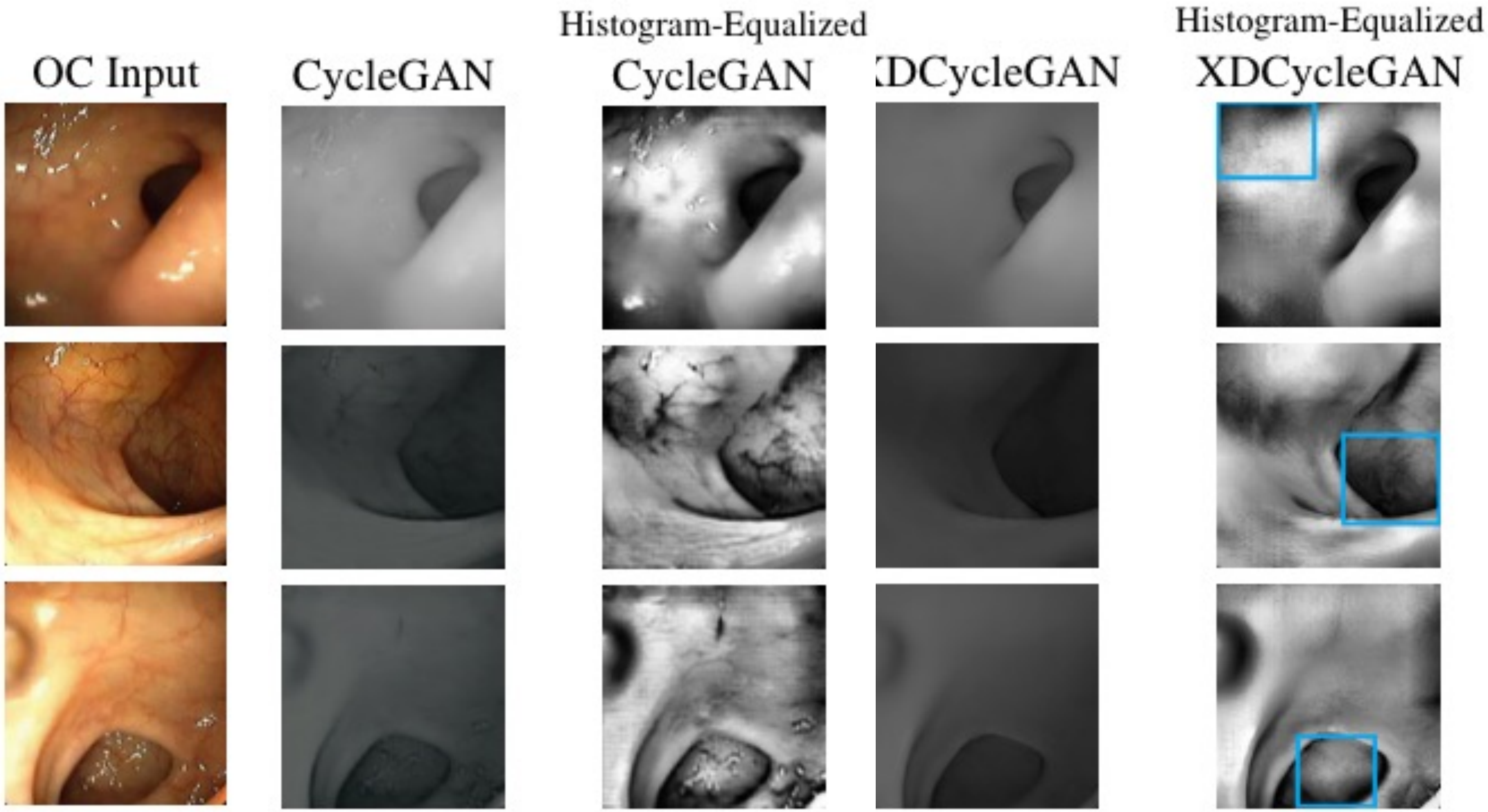
Contributions

- **Lossy** image-to-image translation to **remove** texture, color and specular highlights from VC.
- The same framework can synthesize realistic OC.

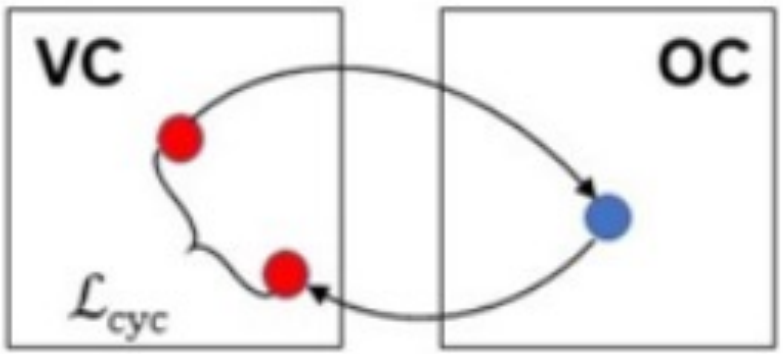
OC $\rightarrow$ VC (**remove** texture, color and specular highlights)

VC $\rightarrow$ OC (augmneted textures, colors, and specular reflections)

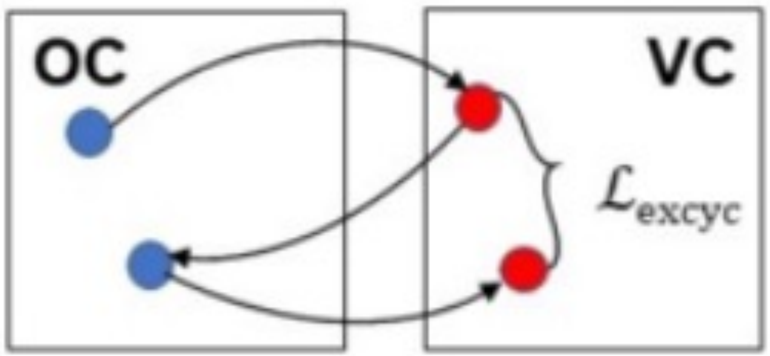
Contributions



Extended Cycle Consistent Loss



Cycle consistency loss

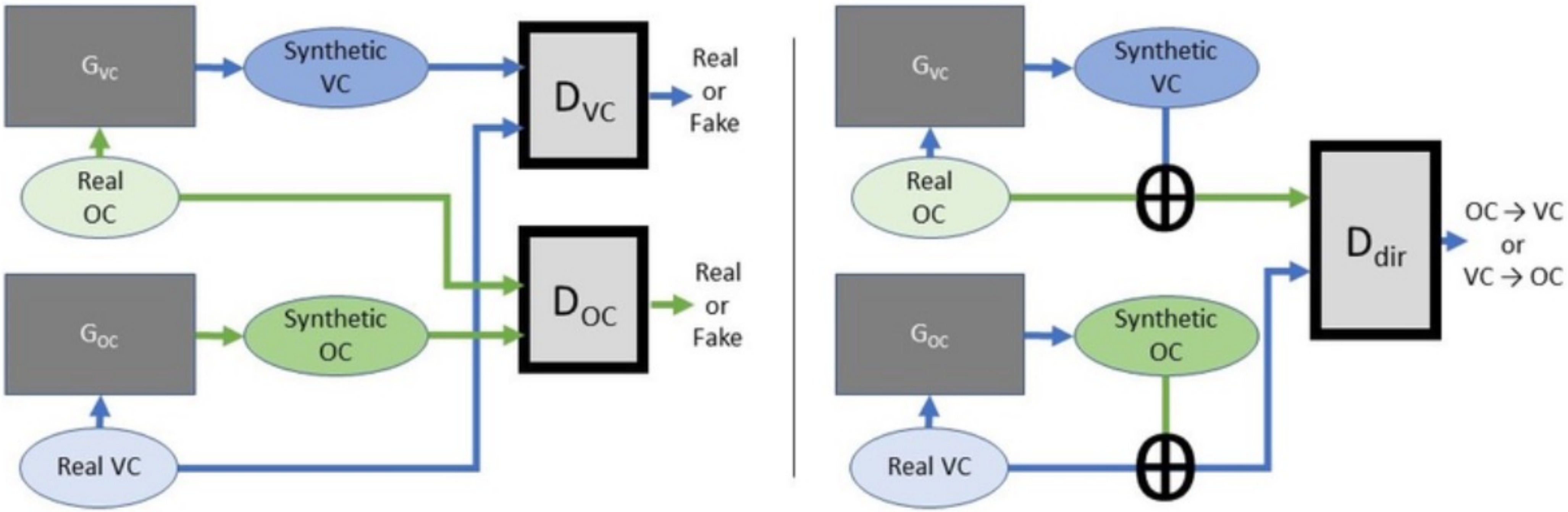


Extended Cycle Consistent Loss

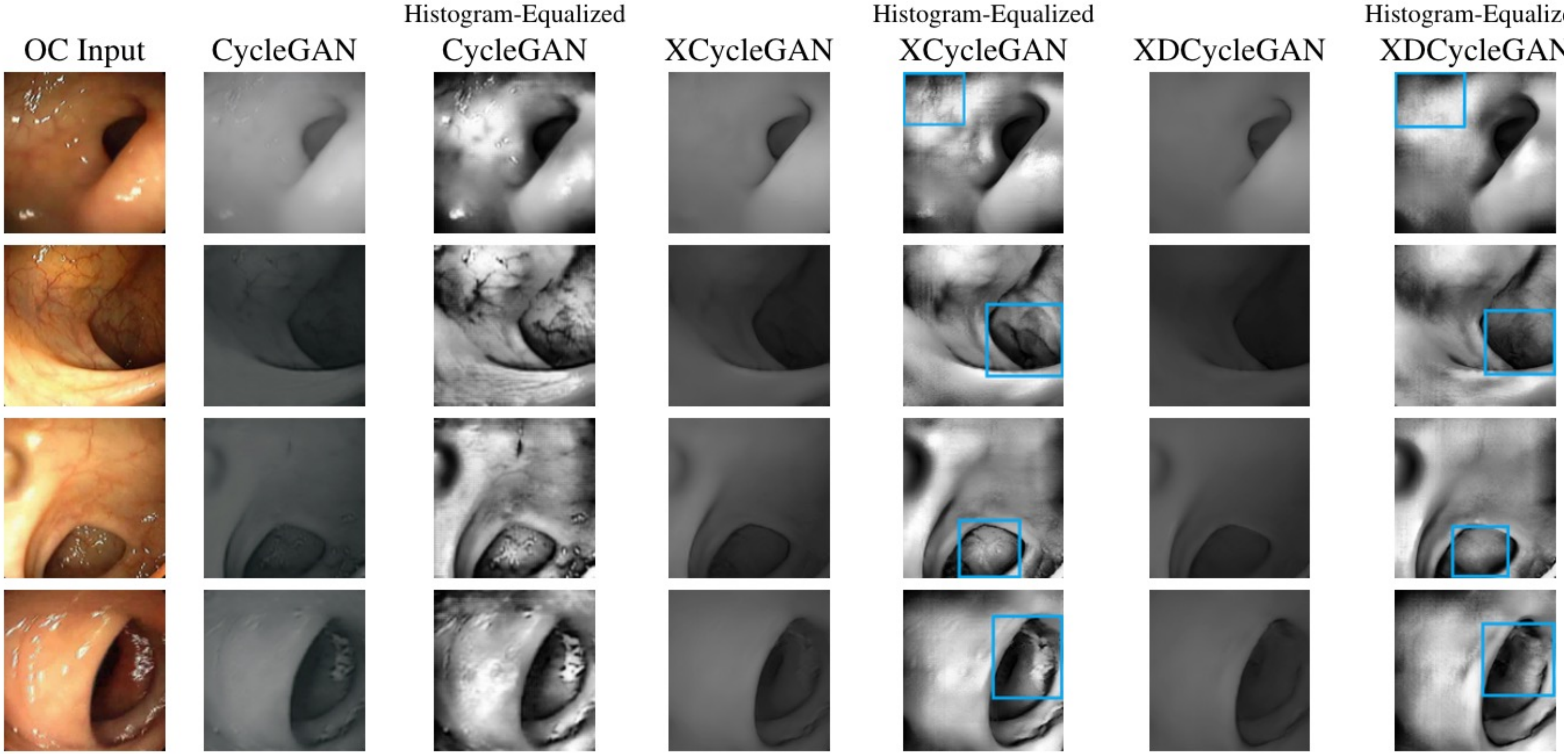
$$\mathcal{L}_{cyc}(G_a, G_b, A) = \mathbb{E}_{y \backsim p(A)} \|y - G_a(G_b(y))\|_1$$

$$\mathcal{L}_{excyc}(G_a, G_b, A) = \mathbb{E}_{y \backsim p(A)} \|G_b(y) - G_b(G_a(G_b(y)))\|_1$$

Directional Discriminator



Results



XCycleGAN : Extended CycleGAN
XDCycleGAN : Extended and Directional CycleGAN

Guo, P., Wang, P., Zhou, J., Jiang, S., & Patel, V. M. (2021).
Multi-institutional collaborations for improving deep learning-based magnetic resonance image reconstruction using federated learning.

In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 2423-2432).

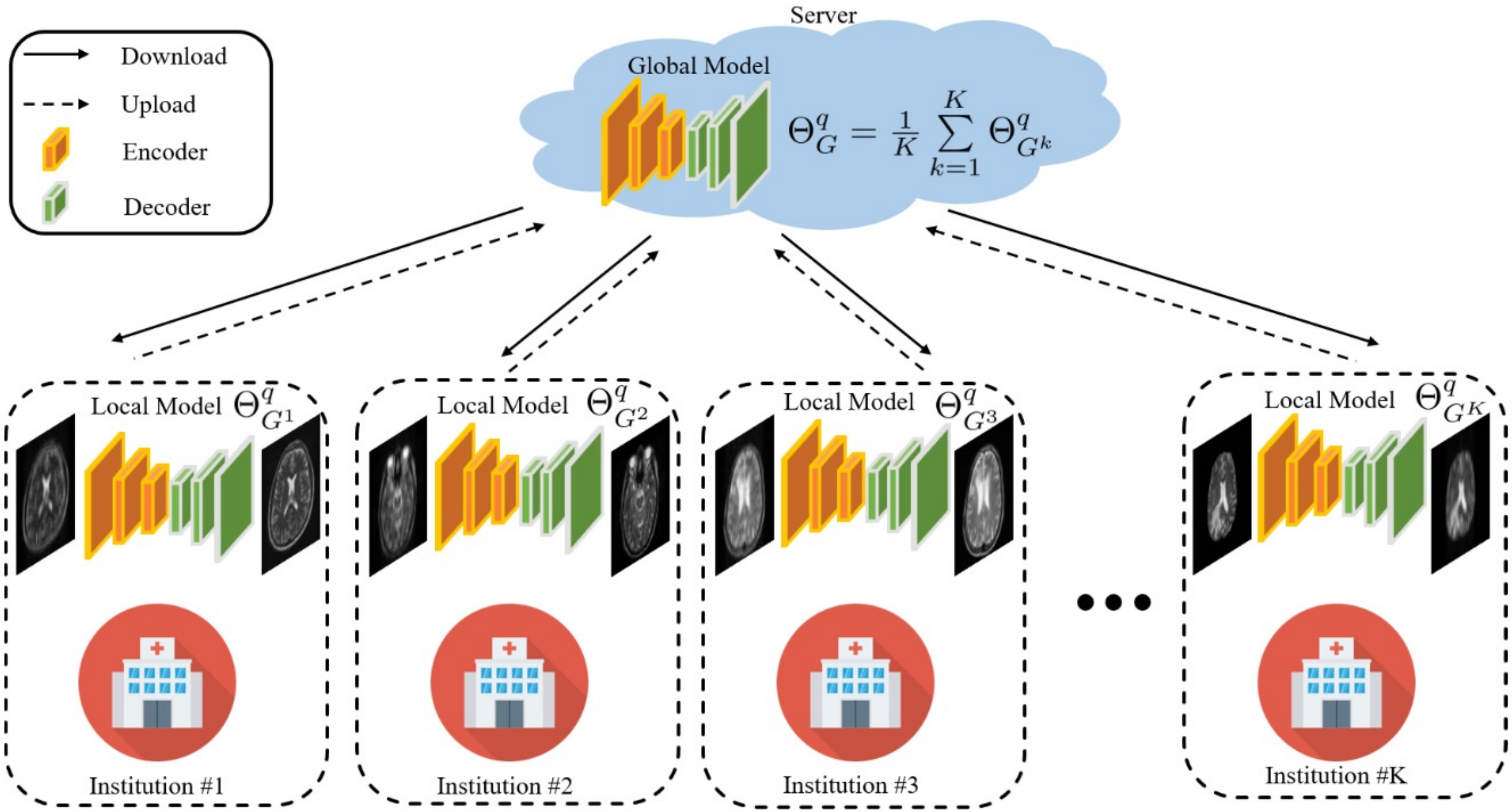
Background

- Data is difficult to collect and share due to the **high cost** of acquisition and medical data **privacy regulations**.
- The generalizability of models trained with the FL setting can still be suboptimal due to **domain shift**.

Contributions

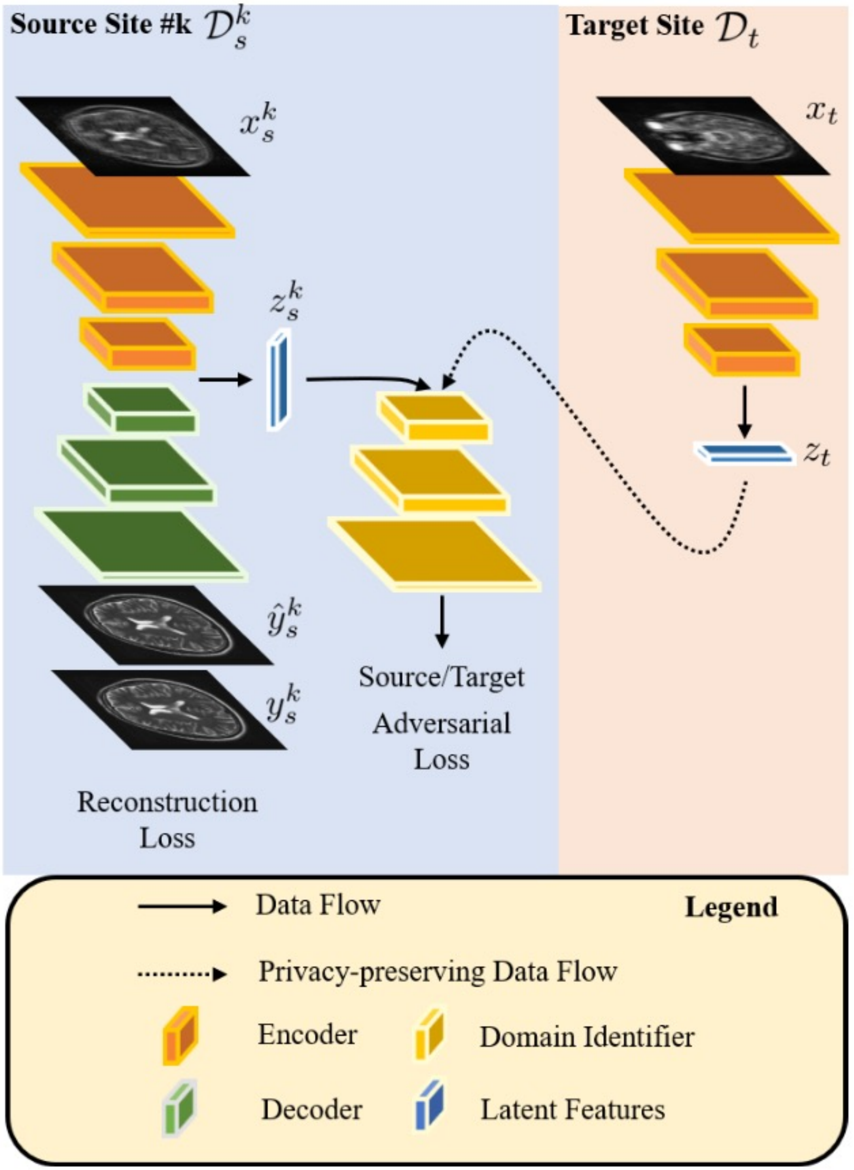
- **Federated Learning-based** Magnetic Resonance Imaging Reconstruction (FL-MR) is proposed which enables **multi-institutional** collaborations for MRI reconstruction in a **privacy-preserving** manner.
- FL-MR with Cross-site Modeling is proposed to **align the latent space distribution** between the source domain and the target domain.

Method



Server
Global Model
$\Theta_G^q = \frac{1}{K}\sum_{k=1}^{K}\Theta_{G^k}^q$
Download
Upload
Encoder
Decoder
Local Model $\Theta_{G^1}^q$
Local Model $\Theta_{G^2}^q$
Local Model $\Theta_{G^3}^q$
Local Model $\Theta_{G^K}^q$
Institution #1
Institution #2
Institution #3
Institution #K

Method



Algorithm 2: FL-MR with Cross-site Modeling

Input: $\mathcal{D}_s = \{\mathcal{D}_s^1, \mathcal{D}_s^2, \ldots, \mathcal{D}_s^K\}$, data from the K source institutions; $\mathcal{D}_t$, data from the target institution; P, the number of local epoches; Q, the number of global epoches; γ, learning rate; $\Theta_{G_s^1}$, ..., $\Theta_{G_s^K}$, parameters of the local models in the source sites; $\Theta_{\mathcal{C}^1}$, ..., $\Theta_{\mathcal{C}^K}$, domain identifiers; Θ_G, the global model; Θ_{E_t}, the encoder part of G in the target site.

▷ parameters initialization

for *q = 0 to Q* **do**

  for *k = 0 to K* ***in parallel*** **do**

    ▷ deploy weights to local model

    for *p = 0 to P* **do**

      Reconstruction:

      ▷ compute reconstruction loss $\mathcal{L}_{\text{recon}}$ using Eq. 2

      Cross-site Modeling:

      ▷ compute adverisal loss $\mathcal{L}_{\text{adv}\mathcal{C}^k}$ and $\mathcal{L}_{\text{adv}E_s^k}$ using Eq. 5 and Eq. 6

      ▷ compute the total loss using Eq. 7 and update $\Theta_{G_s^k}$, $\Theta_{\mathcal{C}^k}$, and Θ_{E_t}

    end

    ▷ upload weights to the central server

  end

  ▷ update the global model using Eq. 4

end

return Θ_G^Q

Result