Semi-Supervised Learning for Fetal Brain MRI Quality Assessment with ROI consistency

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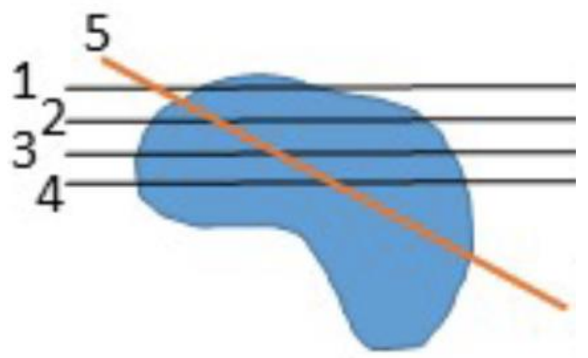
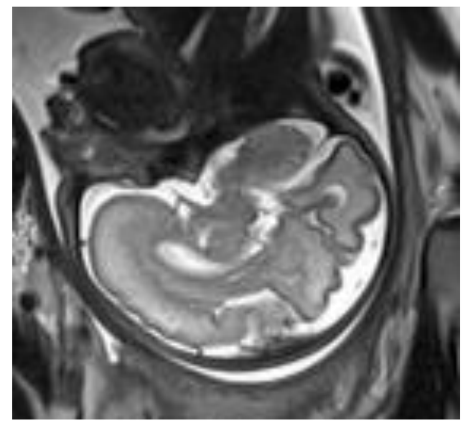
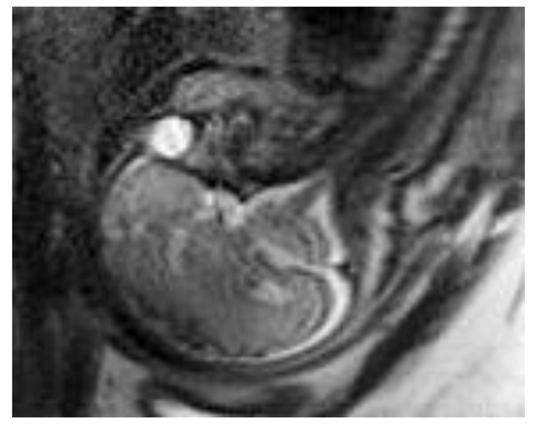
Motivation

Fetal MRI and fetal motion in MRI

- Fetal motion is unpredictable and rapid
- Motion artifacts
  - Intra-slice
  - Inter-slice







Final goal:

Building a prospective motion correction in fetal MRI that can:
- Detect intra-slice motion artifact and re-acquire those slices
- Track fetal motion [1] for inter-slice motion correction

This work:

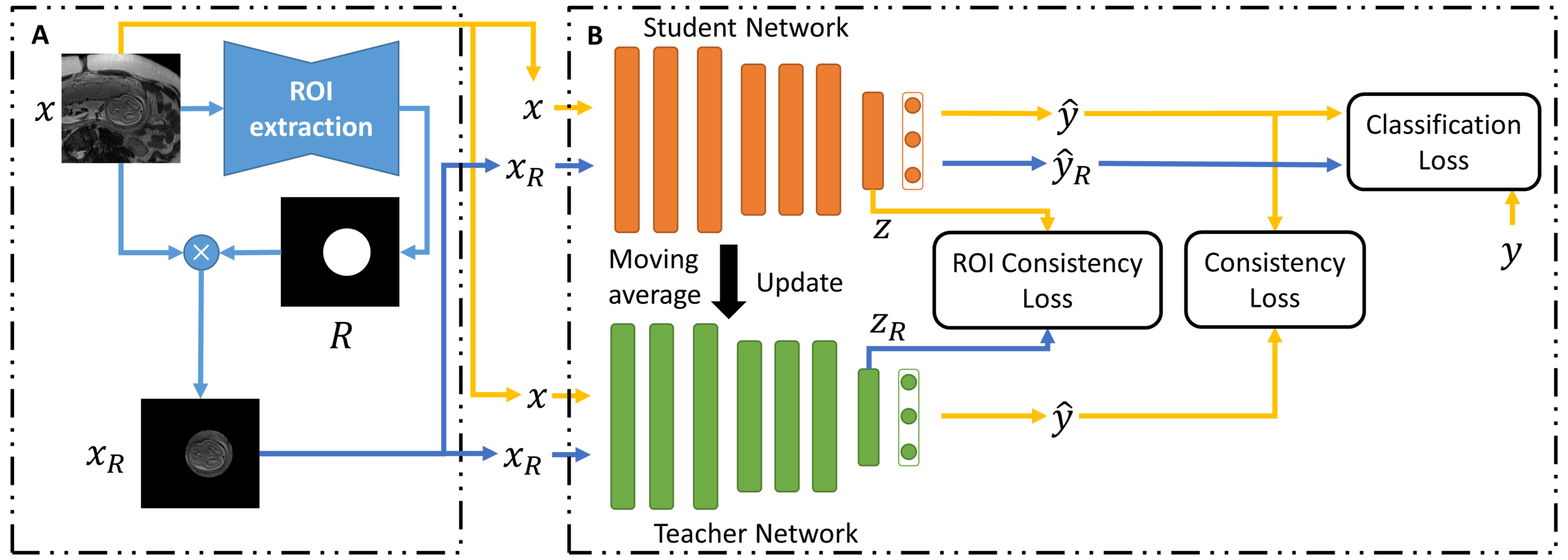
- Image quality assessment for fetal MRI with CNN
- Online reacquisition for low-quality slices

Semi-supervised learning

- Difficult to get large labeled dataset
- Utilize large scale unlabeled dataset
- Mean teacher model [2]
- ROI consistency for fetal brain MRI

Method

Semi-supervised IQA with mean teacher model and ROI consistency



$$L = L_{\text{cls}} + L_{\text{cls-roi}} + \lambda L_{\text{con}} + \beta L_{\text{con-roi}} + \gamma L_{\text{ent}}$$

$$L_{\text{cls}} = \sum_{i=1}^{N_l} H(y_i, f_\theta(x_i, \eta))$$

$$L_{\text{con}} = \sum_{i=1}^{N} D_{KL}(f_{\theta'}(x_i, \eta'), f_\theta(x_i, \eta))$$

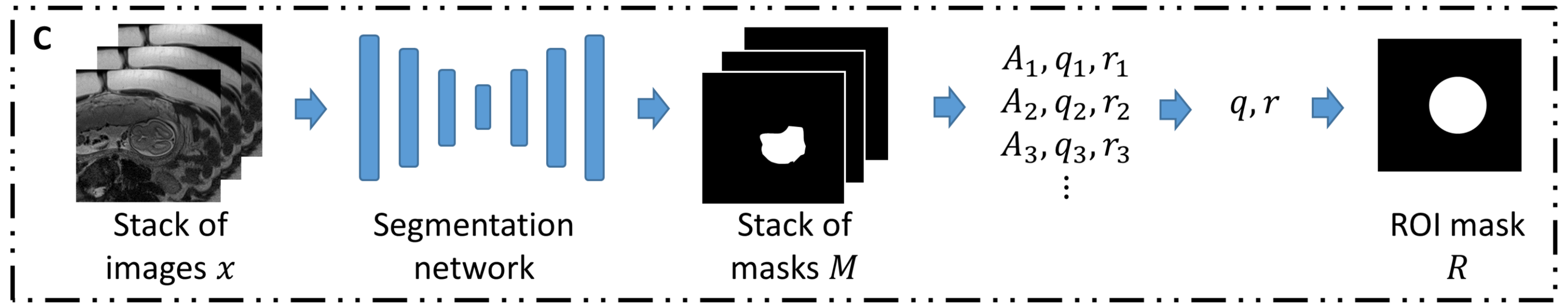
$$L_{\text{con-roi}} = \sum_{i=1}^{N} \|z_{\theta'}(x_i \odot R_i, \eta) - z_\theta(x_i, \eta)\|_2^2$$

$$L_{\text{cls-roi}} = \sum_{i=1}^{N_l} H(y_i, f_\theta(x_i \odot R_i, \eta))$$

$$L_{\text{ent}} = \sum_{i=1}^{N} H(f_\theta(x_i, \eta), f_\theta(x_i, \eta))$$

x	Input MR image
y	IQA label
f	Neural network
θ	Parameters of neural network
z	Output feature before classifier
H	Cross entropy
D_{KL}	KL divergence
η	Input noise
N	Number of samples
N_l	Number of labeled samples
A	Area of segmentation mask
q	Center of bounding circle
r	Radius of bounding circle
R	ROI mask

Fetal brain ROI extraction



- Generate coarse brain mask using a pre-trained U-Net [3] for a stack of images
- Compute area of each brain mask and find the bounding circle
- Aggregate the stack of bounding circle to generate ROI mask

$$q = \frac{1}{|B|}\sum_{i\in B} A_i q_i, \quad \sigma^2 = \frac{1}{|B|}\sum_{i\in B} A_i \|q_i - q\|_2^2, \quad r = \sigma + \max_{i\in B} r_i$$

$$B = \{i \mid A_i \geq A_{\min}\}$$

Experiments and Results

Dataset

T2-weighted fetal brain MRI

Three categories
- Diagnostic
- Non-diagnostic
- Without brain ROI

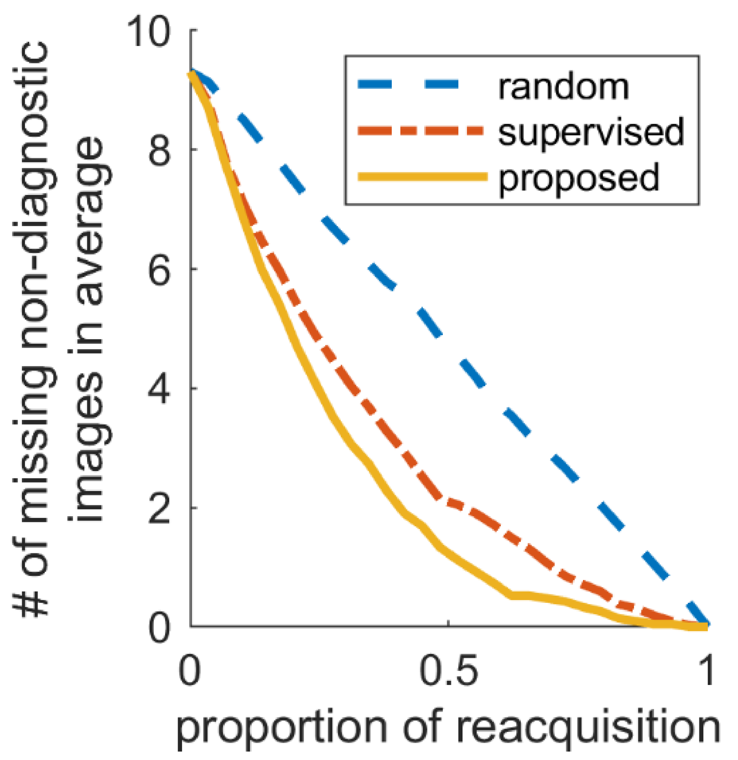
Labeled data: 11223
- Train: 7717
- Validation: 1782
- Test: 1724

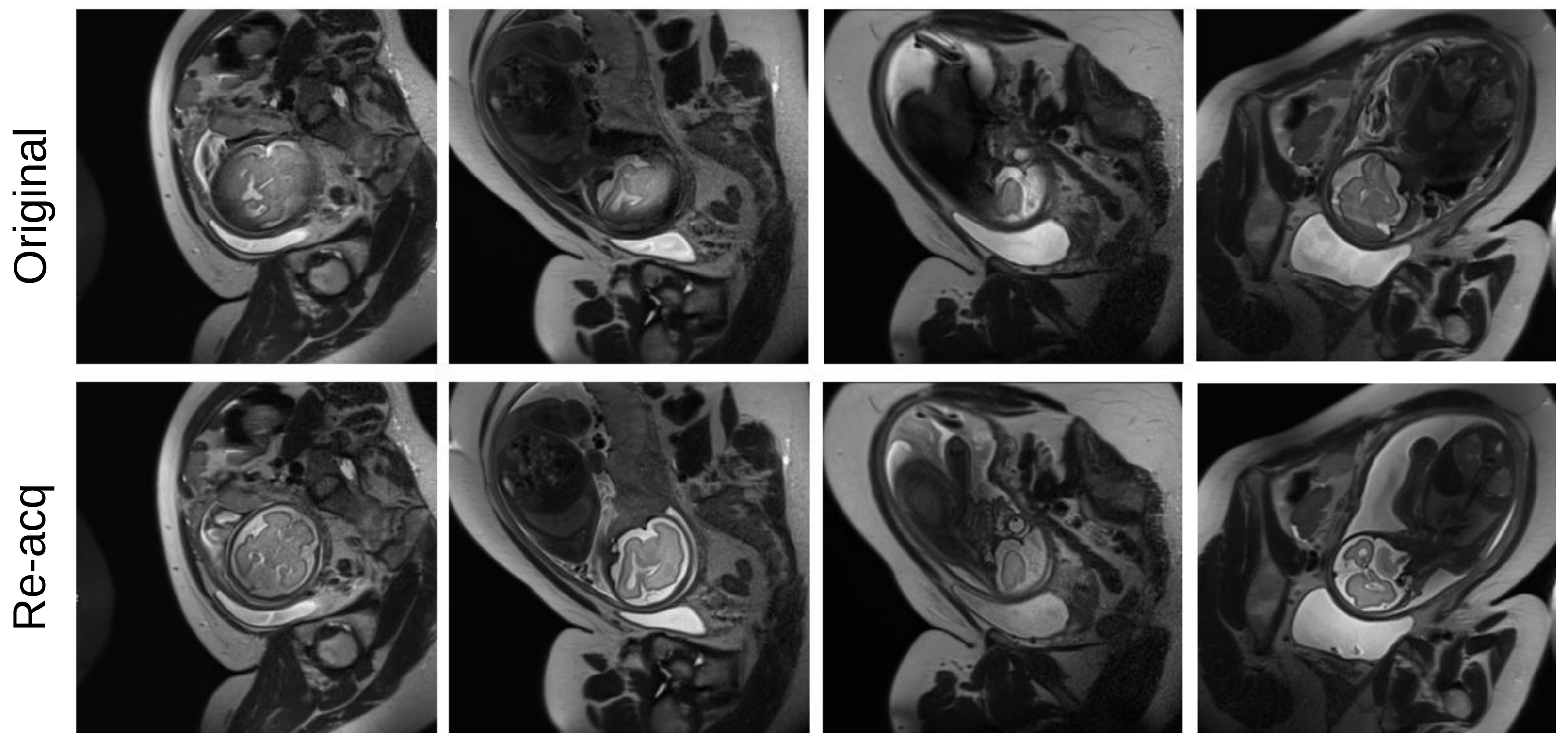
Unlabeled data: 205906

Metric	Method	1000 labels	2000 labels	4000 labels	All labels
Acc.	Supervised	75.58 ± 0.93	77.40 ± 0.68	79.33 ± 0.94	79.37 ± 0.38
	VAT [4]	76.06 ± 2.18	77.51 ± 1.90	80.45 ± 2.35	81.25 ± 1.21
	MT [2]	79.27 ± 0.85	80.35 ± 0.56	81.21 ± 0.81	81.89 ± 0.63
	Proposed	82.87 ± 0.92	83.73 ± 0.86	84.37 ± 0.37	85.19 ± 0.19
	$\lambda = 0$	80.88 ± 1.07	81.38 ± 0.70	82.47 ± 0.42	82.88 ± 0.31
	$\beta = 0$	80.78 ± 0.66	82.01 ± 1.03	83.27 ± 0.34	83.81 ± 0.52
	$\gamma = 0$	80.61 ± 0.26	80.92 ± 0.61	82.68 ± 0.53	83.77 ± 0.40
AUC	Supervised	0.788 ± 0.016	0.818 ± 0.012	0.826 ± 0.008	0.815 ± 0.012
	VAT [4]	0.815 ± 0.021	0.822 ± 0.014	0.833 ± 0.017	0.844 ± 0.044
	MT [2]	0.831 ± 0.008	0.851 ± 0.005	0.856 ± 0.011	0.864 ± 0.006
	Proposed	0.869 ± 0.008	0.881 ± 0.003	0.889 ± 0.007	0.899 ± 0.006
	$\lambda = 0$	0.829 ± 0.007	0.822 ± 0.001	0.841 ± 0.011	0.854 ± 0.008
	$\beta = 0$	0.854 ± 0.006	0.872 ± 0.005	0.875 ± 0.004	0.887 ± 0.006
	$\gamma = 0$	0.855 ± 0.009	0.860 ± 0.003	0.878 ± 0.006	0.882 ± 0.005

Online implementation

- Setup: The trained CNN is deployed on a GPU equipped computer which is connected to the MRI scanner's internal network.
- In each scan, N_{acq} slices were acquired and the IQA scores are computed, $s = 1 - P_N$
- Then the N_{re} slices with lowest IQA scores were reacquired.





Reference

[1] Xu, Junshen, et al. "Fetal Pose Estimation in Volumetric MRI using a 3D Convolution Neural Network." *MICCAI 2019*
[2] Tarvainen, Antti, and Harri Valpola. "Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results." *Advances in neural information processing systems*. 2017.
[3] Salehi, Seyed Sadegh Mohseni, et al. "Real-time automatic fetal brain extraction in fetal MRI by deep learning." *ISBI 2018*
[4] Miyato, Takeru, et al. "Virtual adversarial training: a regularization method for supervised and semi-supervised learning." *IEEE transactions on pattern analysis and machine intelligence* 41.8 (2018): 1979-1993.