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Improving robustness of large structures segmentation using partial annotations

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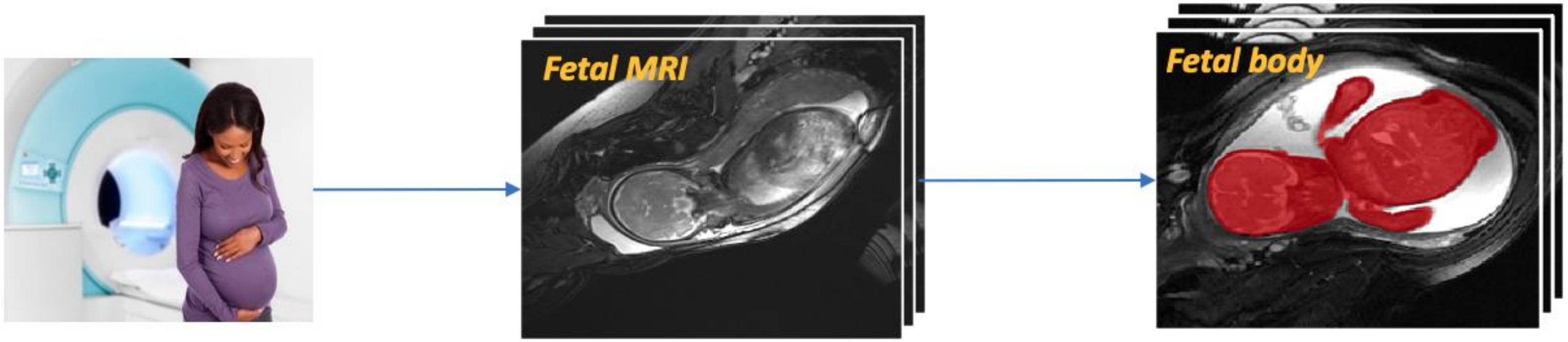
Partial annotations for segmentation of large structures Introduction

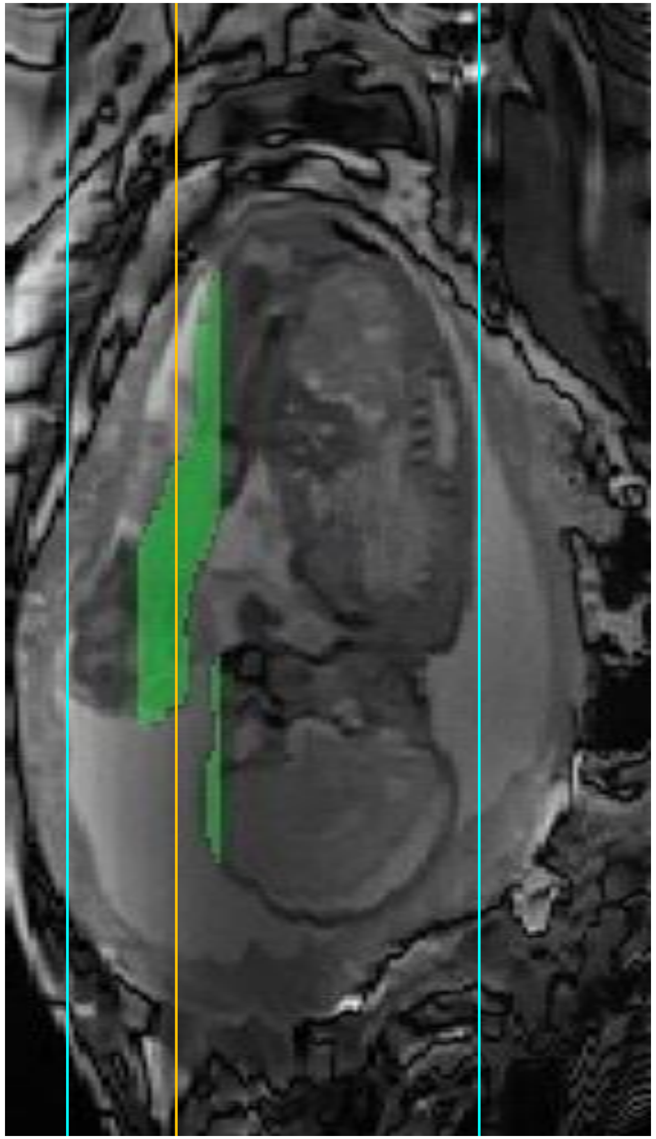
- Deep learning segmentation methods require large annotated datasets, whose manual segmentation is time-consuming and can take more than an hour for large structures
- Under low data regime, one can create more partialy annotated cases compared to fully annotated cases



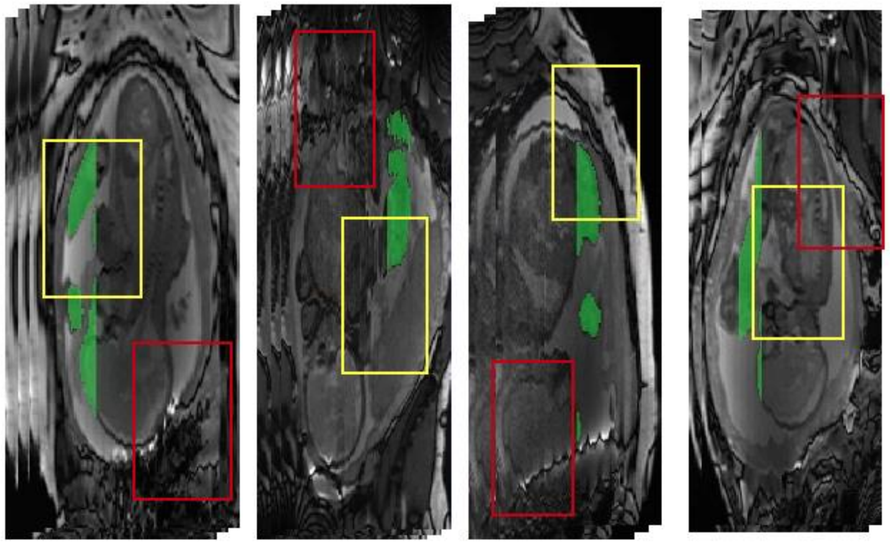
Method: Manual Partial Delineations

The user partially annotates scans with the algorithm guidance:

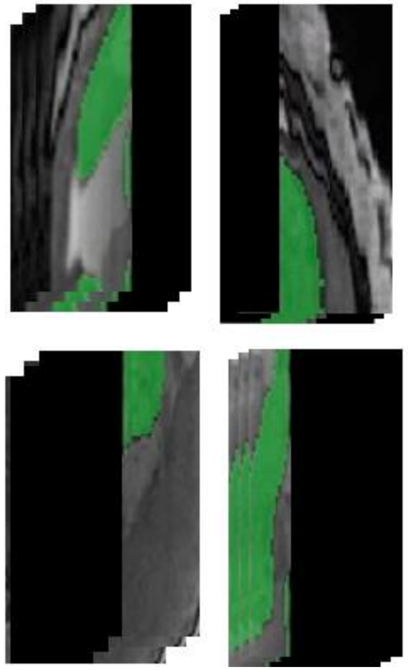
1. The uppermost and lowermost slices of the organ are manually selected by the annotator (turquoise line).
2. The algorithm randomly chooses a slice within the structure of interest (yellow line).
3. Consecutive slices are selected. The number of slices is determined by the chosen annotation percentage (green annotations).



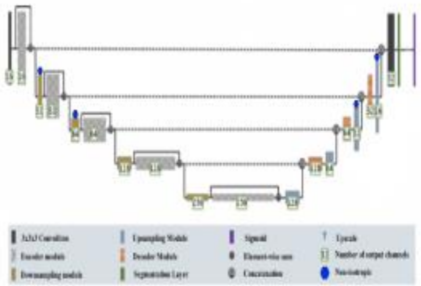
Method: Training with partial annotations



(1) Training input: saggital view of partially annotated scanns



(2) A batch of non-empty patches



(3) Training with a selective batch loss

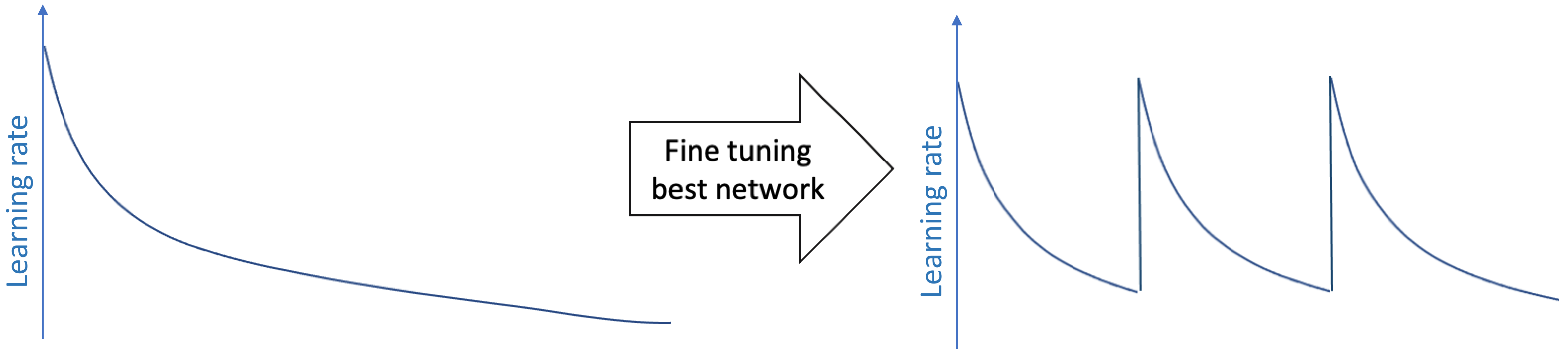
Method: Selective Dice loss

Let $\mathrm{T}' \subset \mathrm{T}$ and $\mathrm{R}' \subset \mathrm{R}$ be the ground truth in the annotated slices and the network result in the annotated slices, with minibatch voxels $t_i{}' \in T'$ and $r_i{}' \in R'$ respectively.

Selective batch Dice Loss ($\mathrm{L_{CD}}$) = $-\frac{2\sum_{N'} t_i{}' r_i{}'}{\sum_{N'} t_i{}' + \sum_{N'} r_i{}'}$

- Border slices are used by the loss function – considered "annotated slices"
- Large batch size of 8.
- Adding a binary mask specifying the locations of the annotated slices

Method: Two-step Training



1. Reduce on plateau scheme

2. Reduce on plateau with learning rate restarts scheme

Data and Experimental Design

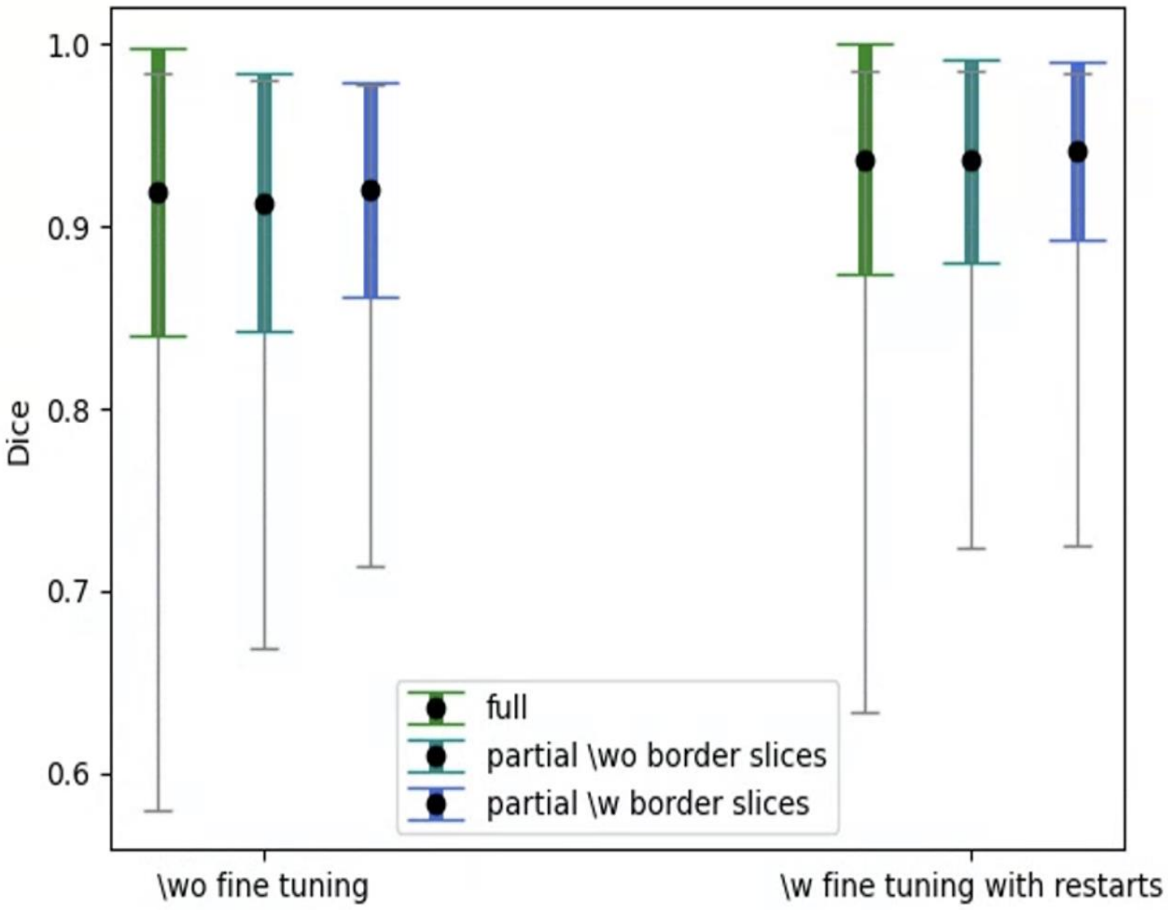
Data

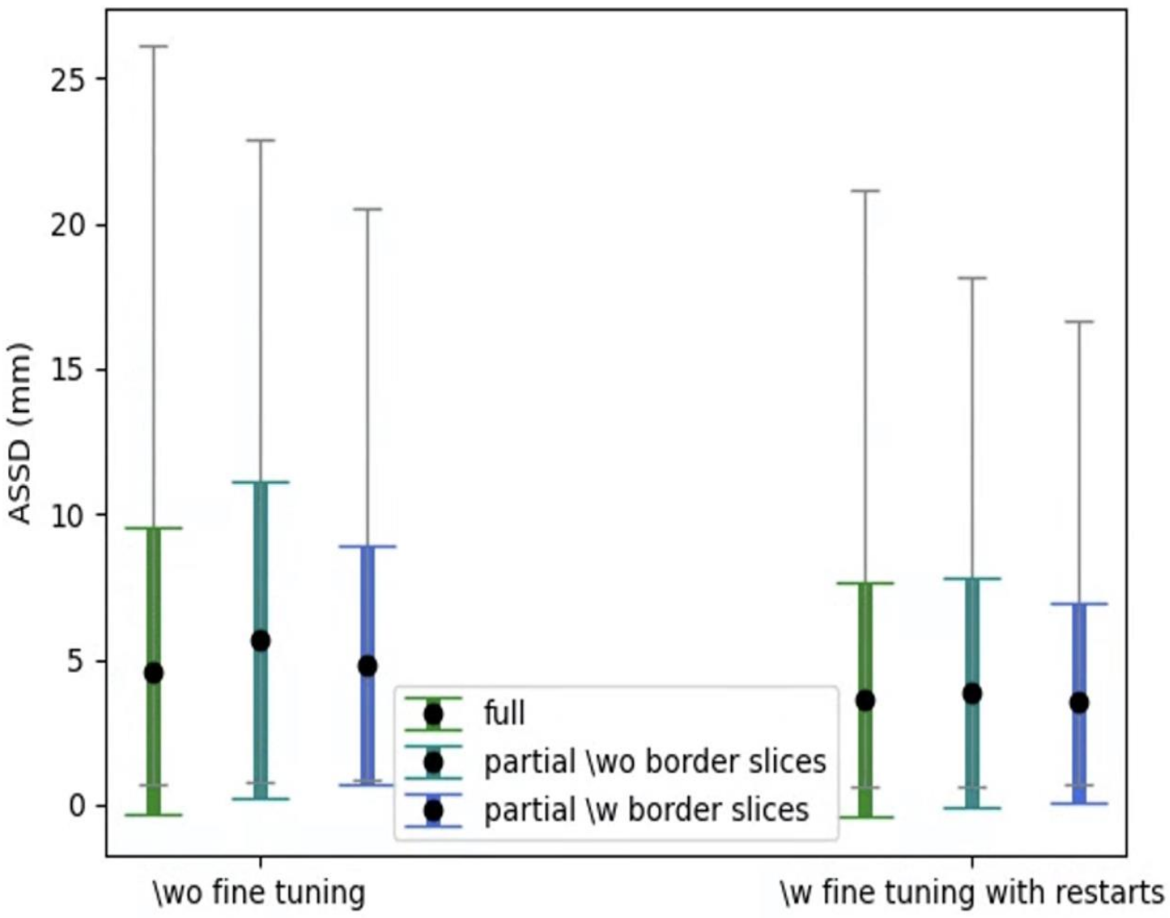
1. TRUFI body: 101 cases in total with gestational Age (GA) 28-39, 58 in-distribution (ID) test cases
2. FIESTA body: 137 cases in total. ID cases with GA 28-39 similar to training set (68 test cases) and most Out of Distribution (OOD) cases with GA 16-24 (33 test cases)

Experimental Design

- Training regime with 30 partially annotated cases and 20% annotated slices are compared to training with 6 fully annotated cases.
- The 6 cases are randomly chosen from the 30 partially annotated cases.
- Results are an average of 4 different randomizations.

Results on TRUFI body





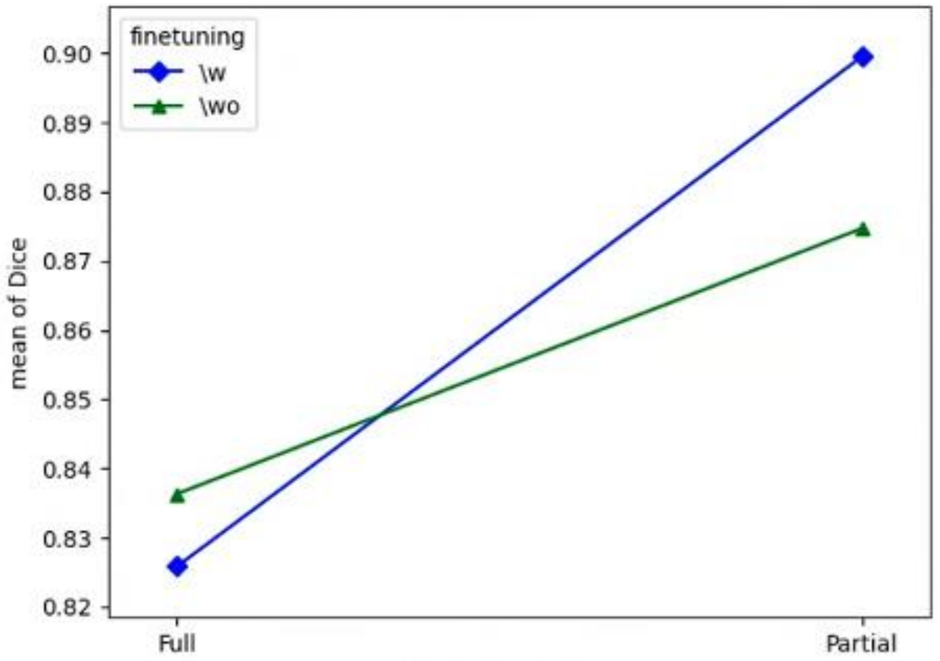
Results on FIESTA Body

Data distribution	Network training	Dice	Hausdorff (mm)	2D ASSD (mm)
In-Distribution (ID)	Full	0.959±0.044	34.51±37.26	2.15±2.33
	Full fine-tuned	0.964±0.040	32.98±36.86	1.88±2.07
	Partial	0.959±0.034	34.15±35.96	2.21±1.67
	Partial fine-tuned	0.965±**0.029**	31.89±35.82	1.90±**1.39**
Out-of-Distribution (OOD)	Full	0.836±0.178	39.34±29.26	7.46±10.61
	Full fine-tuned	*0.826±0.214*	*39.61±32.66*	*8.86±16.54*
	Partial	0.875±0.091	36.19±21.44	5.47±3.92
	Partial fine-tuned	**0.899±0.067**	**30.37±18.86**	**4.00±2.26**

Statistical Analysis for OOD Data

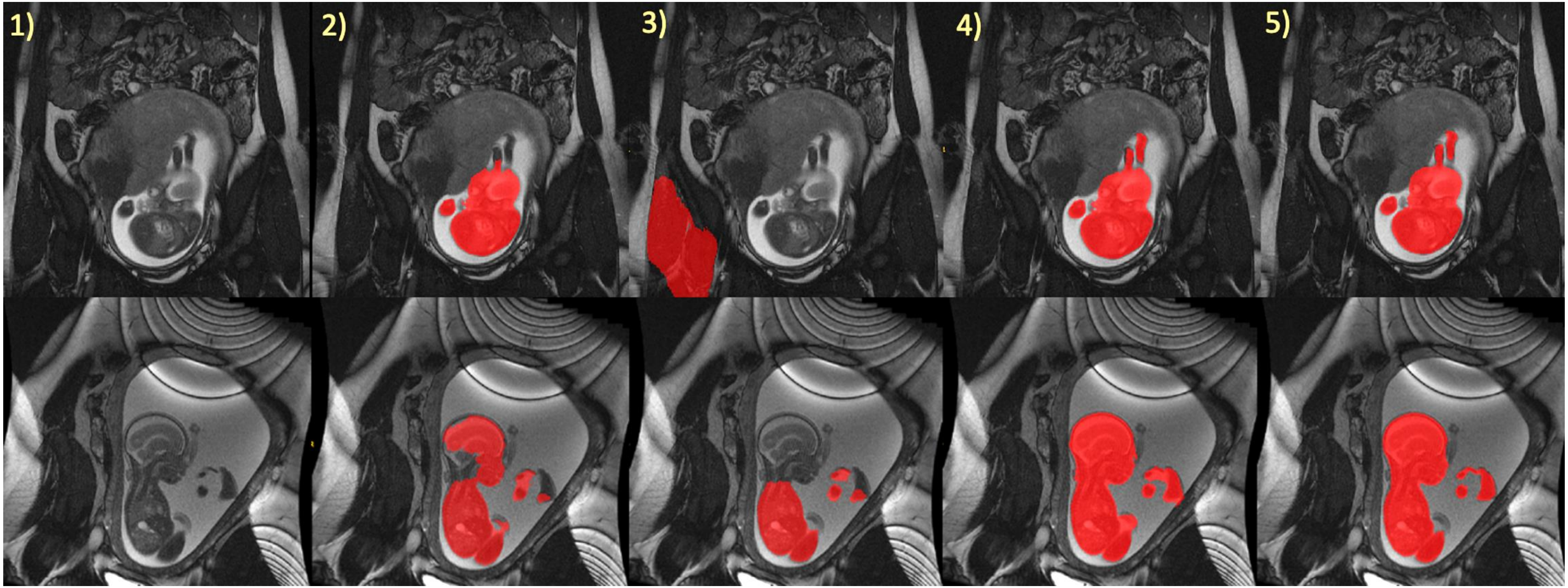
Annotation strategy	Dice	Hausdorff Distance	2D ASSD
Fine-tuning (w/wo)	F=1.69 p=0.202	F=6.15 p=0.019*	F=0.007 p=0.934
Annotation strategy (Full / Partial)	F=8.96 p=0.005**	F=5.83 p=0.022*	F=6.473 p=0.016*
Interaction	F=7.74 p=0.009**	F=9.88 p=0.004**	F=7.78 p=0.009**

Repeated measurements two-way ANOVA. Significance codes: *<0.05; **<0.01.



Interaction plot for Dice score.

Results on FIESTA Body



Full annotations no fine-tuning

Full annotations with fine-tuning

Partial annotations with fine-tuning

Ground Truth

Conclusions

- We have presented a new method for using partial annotations for large structures.
- The method demonstrated better robustness in a low data regime compared to full annotations.
- We also presented a simple two-step optimization scheme for low data regime that combines fine-tuning with learning rate restart.
- The optimization was useful for partial annotations regime on both ID and OOD data. For full annotations it decreased performance on OOD data.