OPTIMIZING SEGMENTATION OF NEONATAL BRAIN MRI WITH PARTIALLY ANNOTATED MULTI-LABEL DATA

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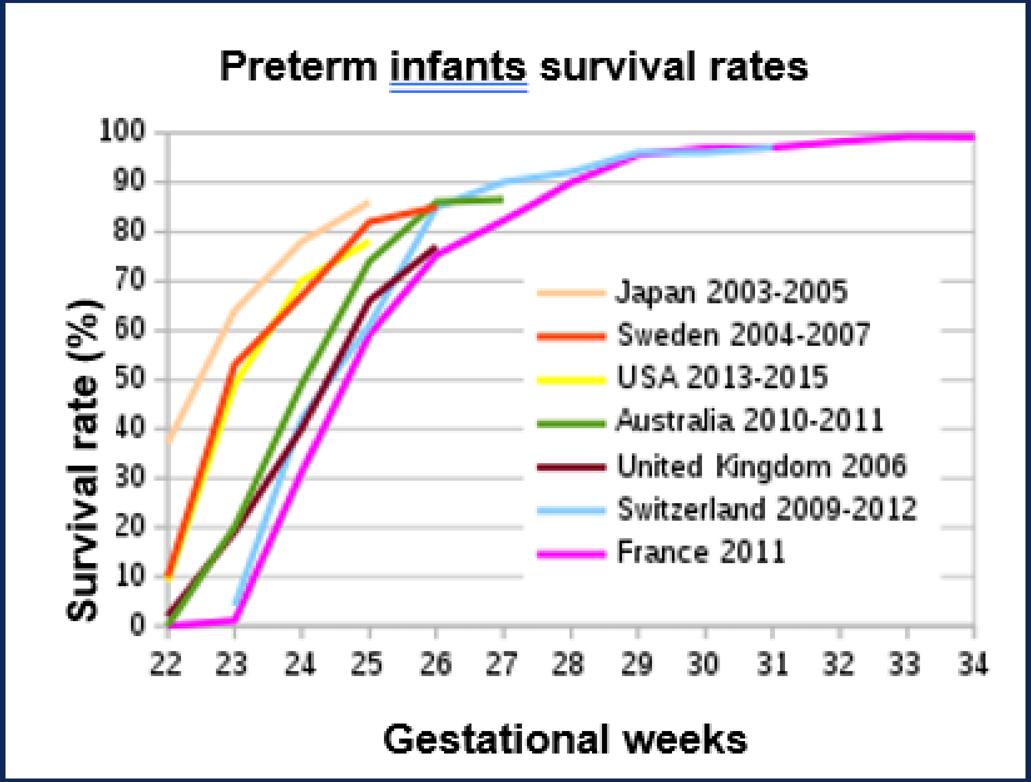
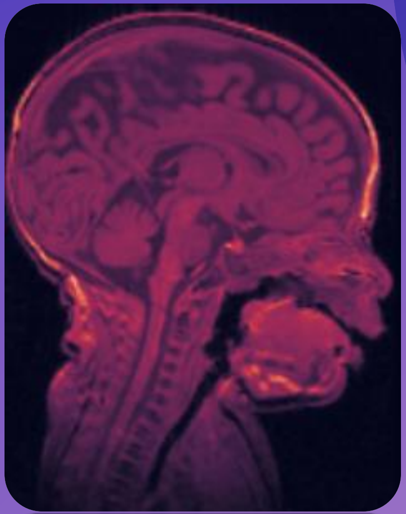
PREMATURE BIRTH



- In Canada approximately 25,000 babies are born prematurely (<37 weeks) every year.
- Preterm delivery is a traumatic process both for the mother and the baby.
- Over half of very preterm births lead to adverse neurodevelopmental outcomes and brain injuries.
- Brain injuries evolve over time.

Raw MRI scan



Manual Segmentation

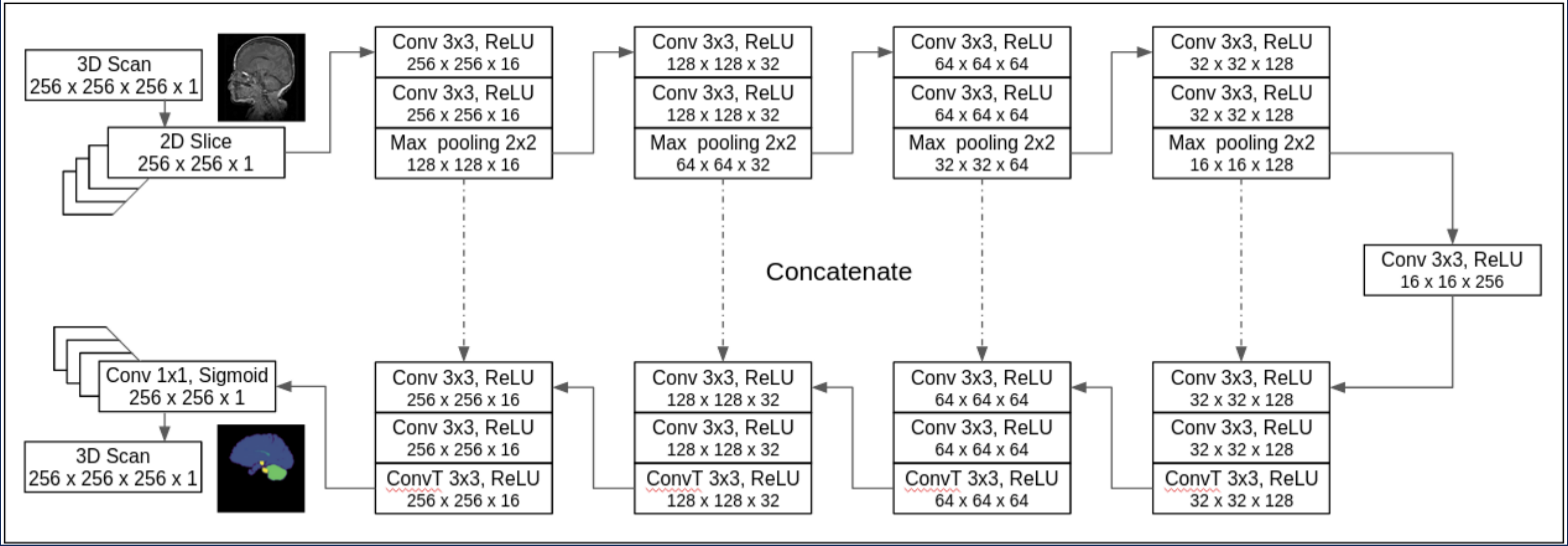
THE PROBLEM

Manual brain MRI segmentation is :
- a time-consuming process
- a labor-intensive process

THE GOAL

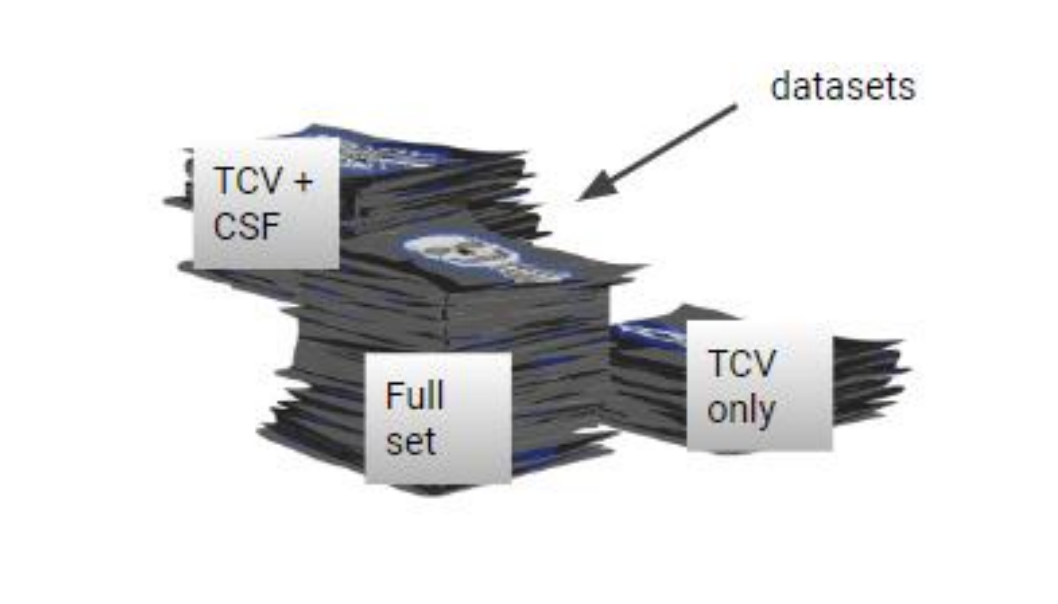
- Build a robust automatic segmentation solution, which could segment brain MRIs for neonates.
- Improve the existing model so that it could generalize well across different datasets and settings.

THE FIRST STEP: A U-NET-BASED SEGMENTATION MODEL



THE NEXT STEP: GENERALIZE WELL ACROSS DIFFERENT DATASETS

Partially labeled data



APPROACHES TO DEAL WITH *PARTIALLY LABELED DATA*

Separate models for each label

+ Can use all the data we have

- Overlap between predicted labels

- Cannot be used for Hierarchical Multi-Label Classification (HMLC)

Pseudo-labeling (Semi-supervised learning)

+ No overlapping

+ Can be used as a base for HMLC

- Not using the actual labels we have

- Needs help from experts with thresholds

Multi-Label Learning from Single Positive Labels

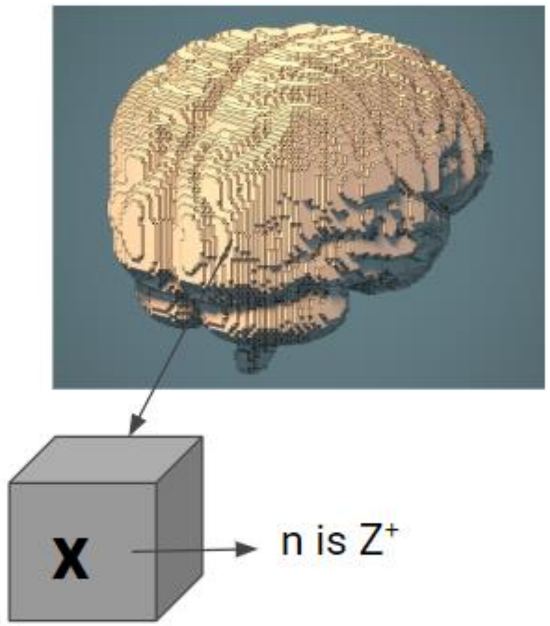
+ Use all of the datasets

+ No overlap

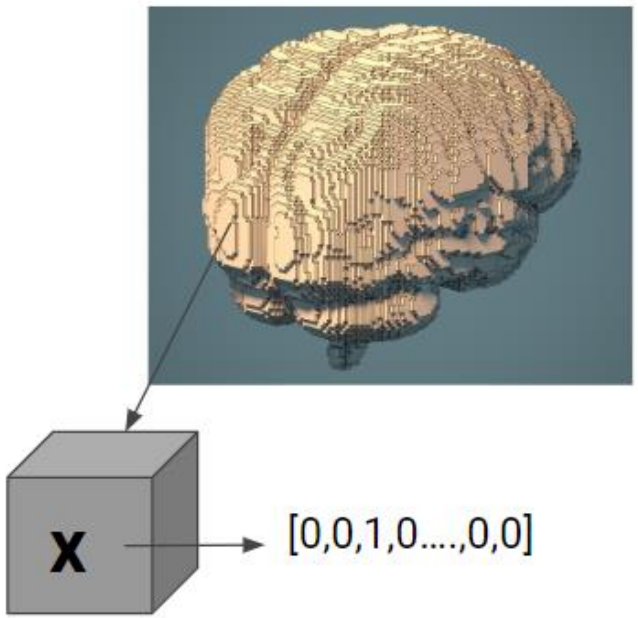
+ Can be used for Hierarchical Multi-Label Classification (HMLC)

GO FROM

MULTI-CLASS TO MULTI-LABEL

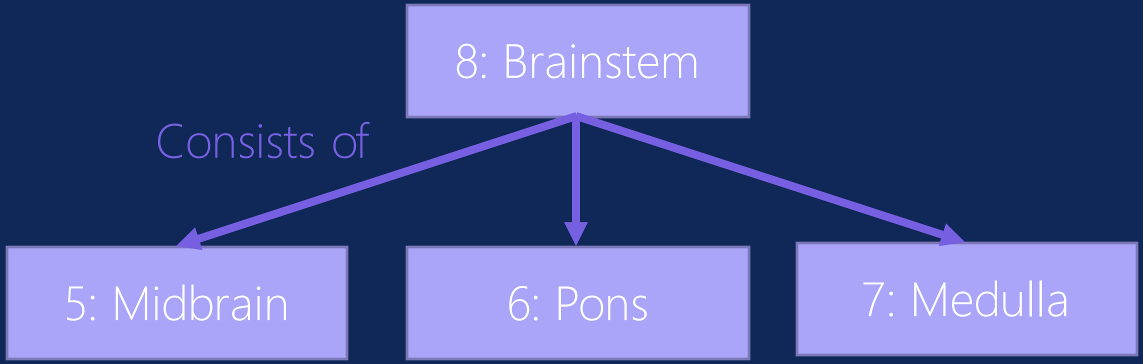


X is assigned a single label from {1, . . . , L}, where L is the number of classes



x is associated with a vector of labels y from the label space $Y = \{0, 1\}^L$

REPRESENTATION OF WEAK LABELS



FULL ANNOTATION

0	1	2	3	4	5	6	7	8
0	0	0	0	0	1	0	0	1

WEAK ANNOTATION

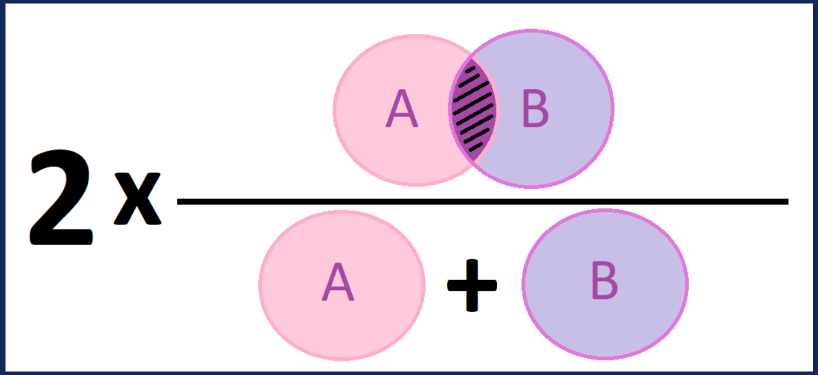
0	1	2	3	4	5	6	7	8
0	0	0	0	0	2	2	2	1

LEARN FROM PARTIALLY LABELED DATA

$$\mathcal{L}_{IU}(x,y) = -\frac{1}{L}\sum_{i=1}^{L}(1_A(x_i)\log(y_i) + 1_B(x_i)\log(1-y_i))$$

- L stands for the number of classes;
- x is a vector of original labels for the current pixel; $x \in \{0, 1, 2\}^L$,y is a vector of class probabilities predicted by the model for some input pixel.
- 1_A and 1_B are indicator functions, where A={1} and B = {0}

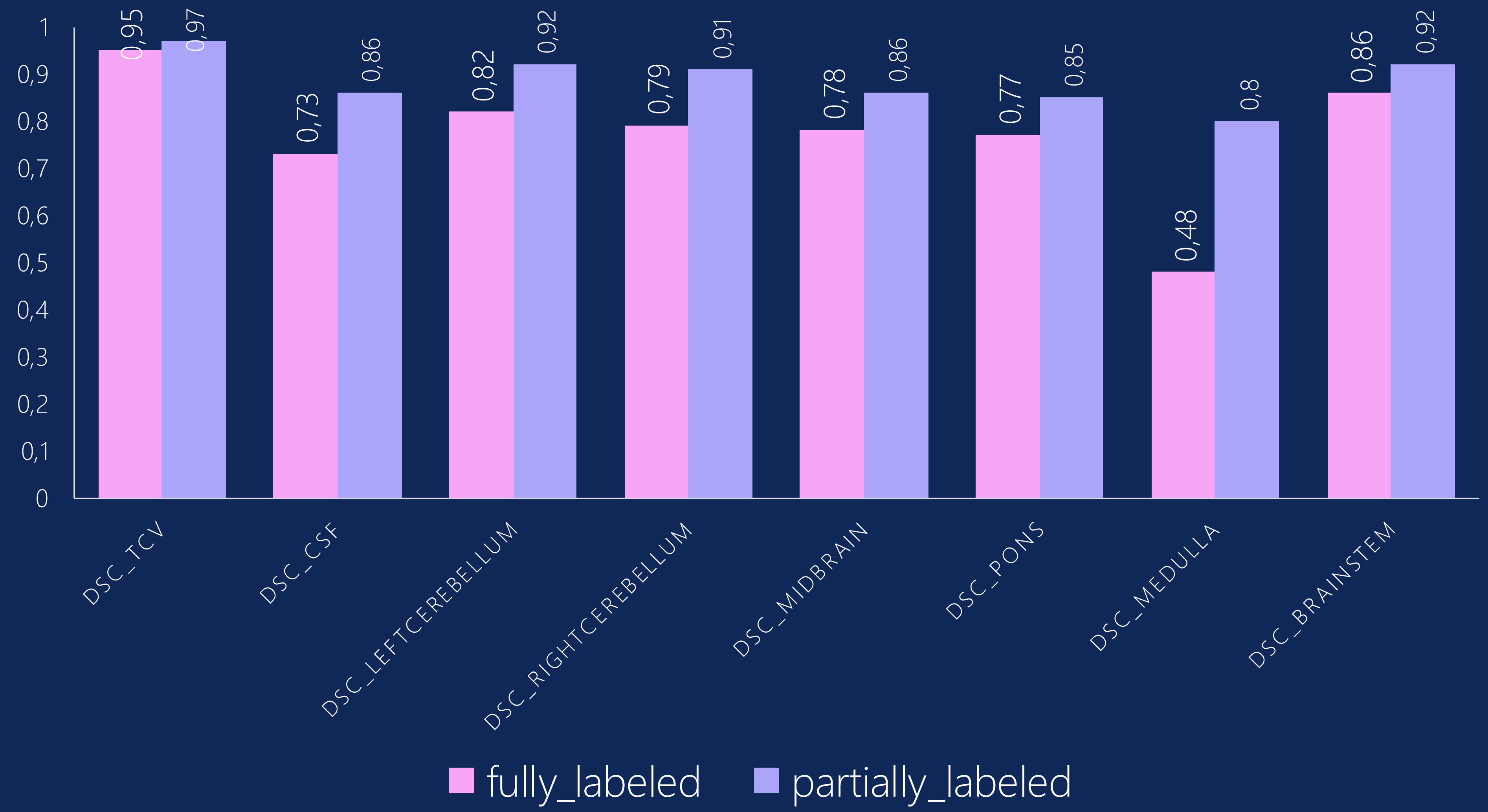
RESULTS:
EVALUATION METRIC AND EXPERIMENTS



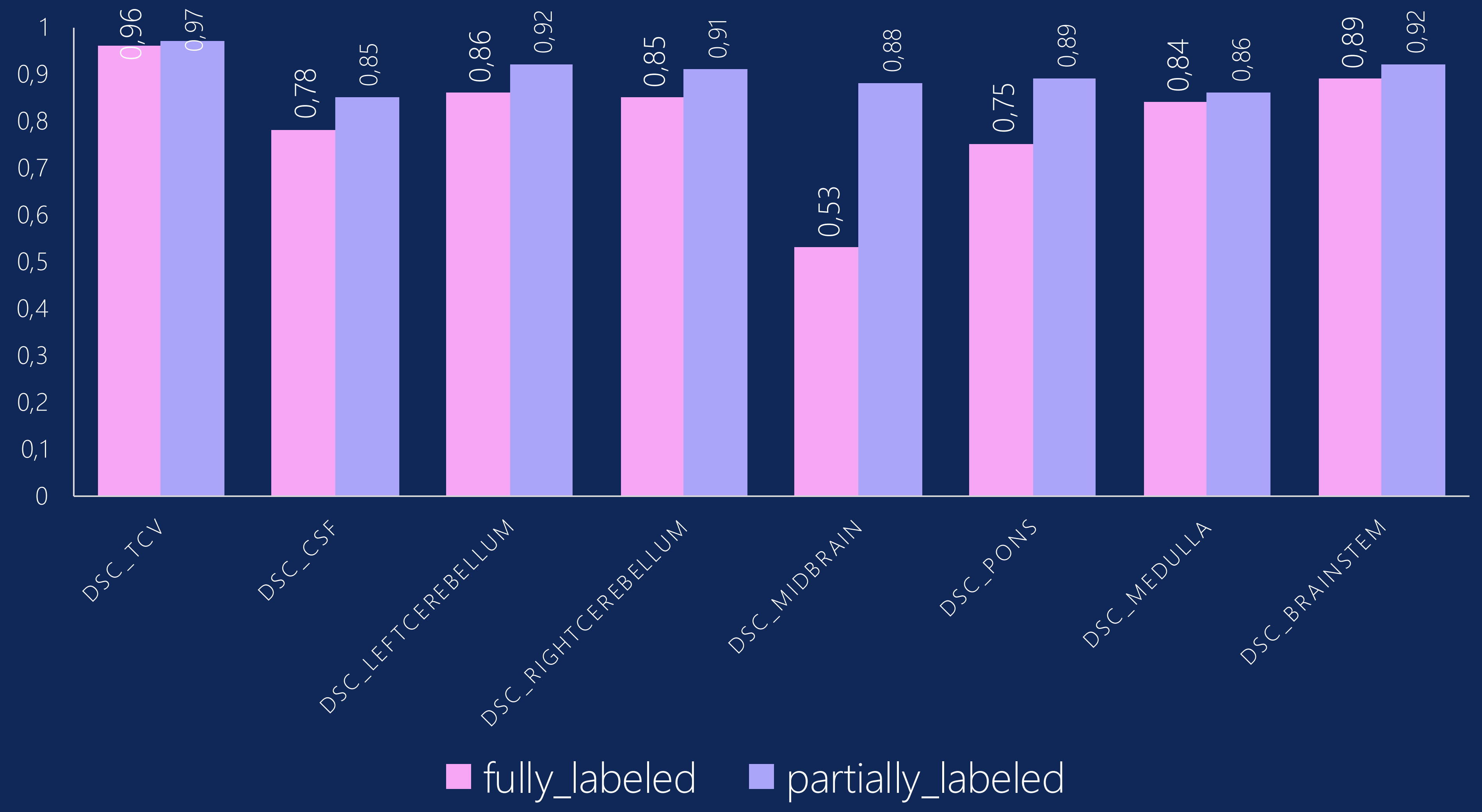
Dice Score Similarity

Model trained only on 5% of Fully-Labeled (FL) data	Model trained on 5% Fully-Labeled data and 95% of Partially-Labeled (PL) data
Model trained only on 10% of Fully-Labeled data	Model trained on 10% Fully-Labeled data and 90% of Partially-Labeled data
Model trained only on 20% of Fully-Labeled data	Model trained on 20% Fully-Labeled data and 80% of Partially-Labeled data

RESULTS (PRETERM):
5% FULLY LABELED VS 5% FL + 95% PARTIALLY LABELED

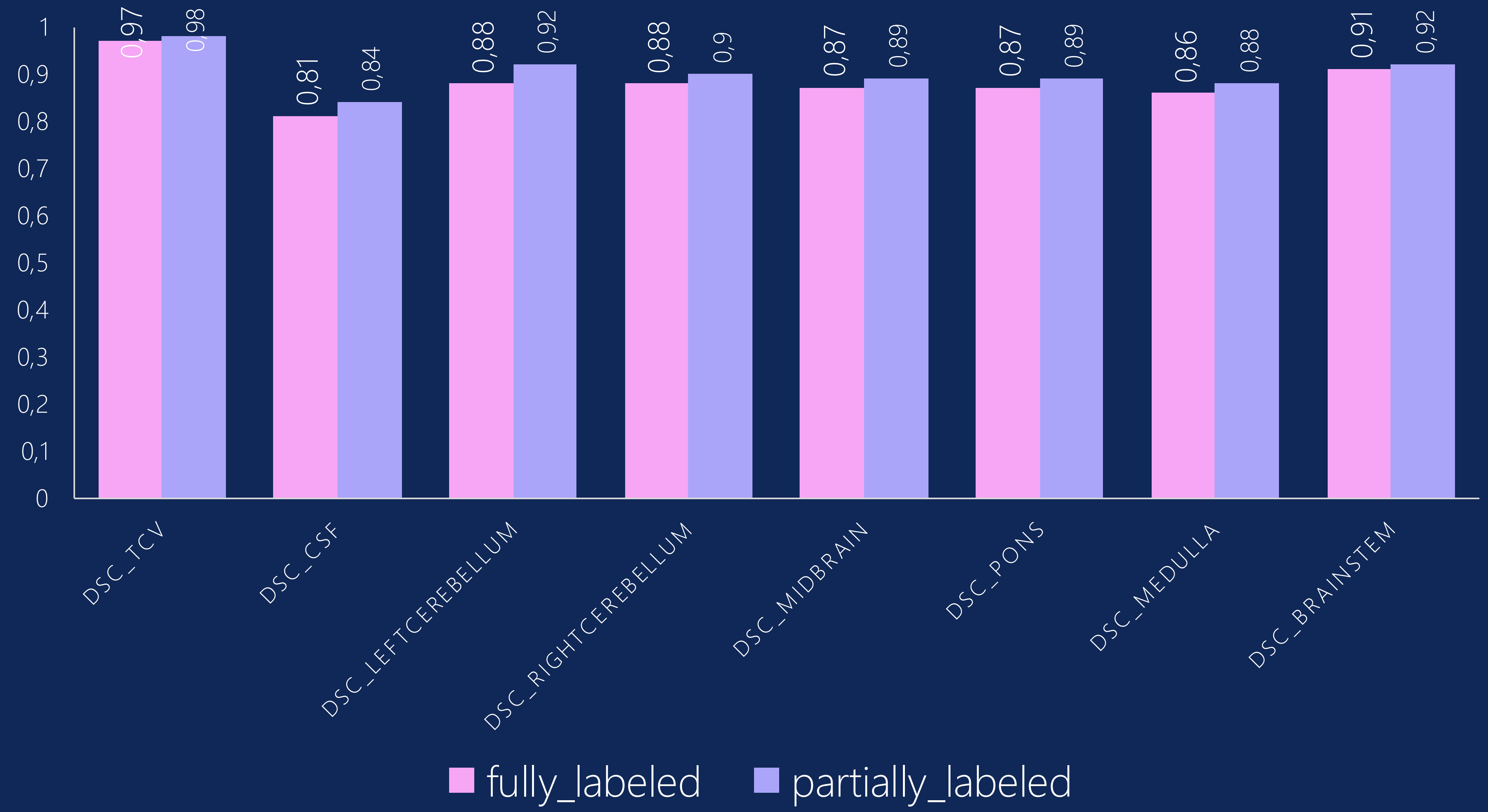


RESULTS (PRETERM):
10% FULLY LABELED VS 10% FL + 90% PARTIALLY LABELED



RESULTS (PRETERM):

20% FULLY LABELED VS 20% FL + 80% PARTIALLY LABELED



CONCLUSION

- Extensive research was conducted on cutting-edge technologies in the fields of automatic Medical Image Segmentation, Multi-Label Classification, and Learning from Partially labeled data
- A new Multi-Label Segmentation model was developed by introducing upgrades to both the preprocessing and postprocessing stages, as well as a new loss function.
- The new model also created an opportunity for further improvements in terms of generalization across datasets from various hospitals

THANK YOU FOR YOUR ATTENTION