STSR 2025 CHALLENGE

U-Mamba2-SSL for Semi-Supervised Tooth and Pulp Segmentation in CBCT

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Background & Motivation

- CBCT: an important imaging tool in dentistry.
- Precise segmentation of tooth and pulp is vital for various applications.
- Extremely time-consuming:
    - High resolution 3D nature
    - High variability across scans

- Underscore the importance of utilizing unlabeled data

Challenges

- Large CBCT volumes (up to 440x643x643) after resizing.

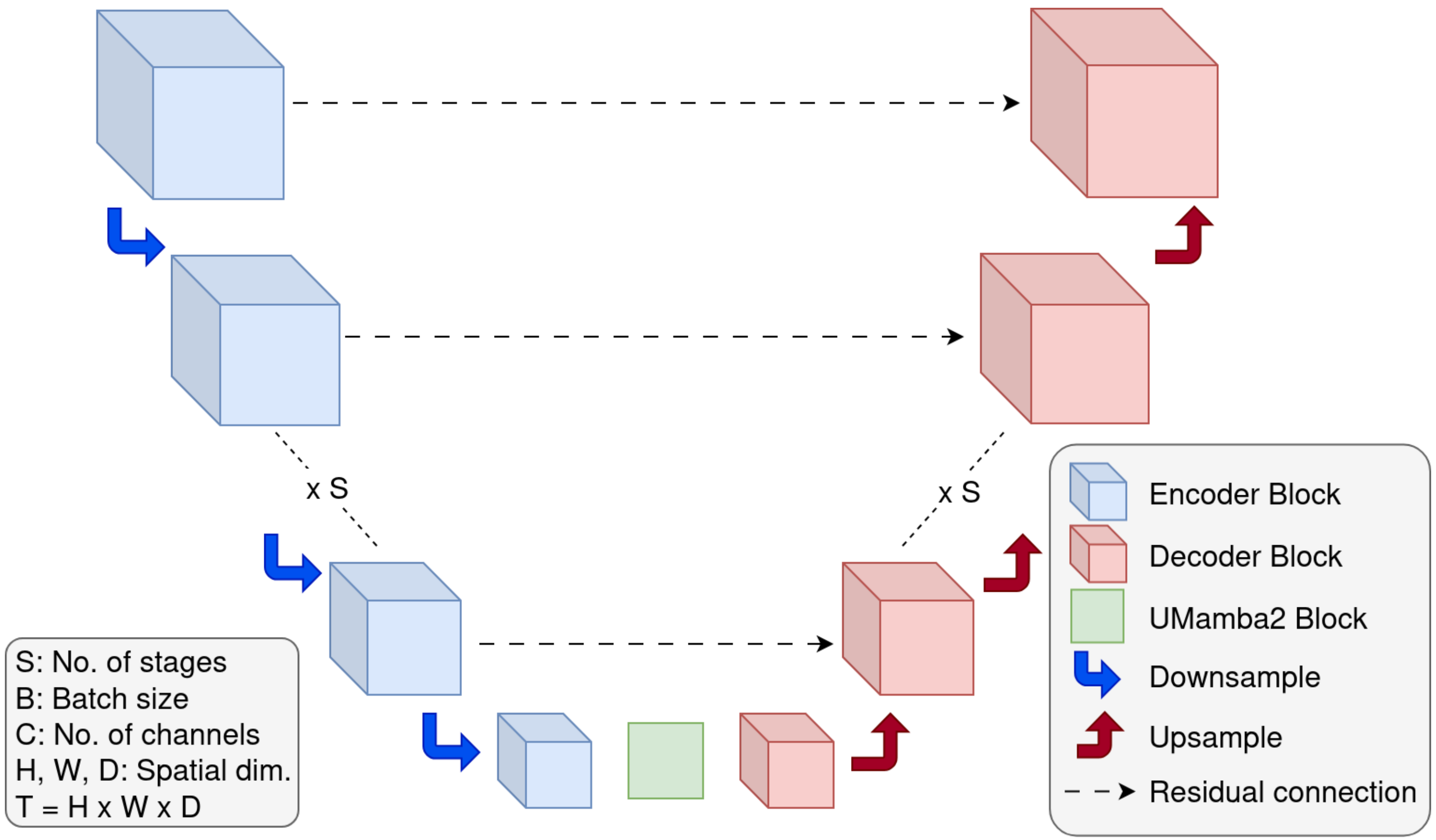
- Limited amount (30) of labeled data with a vast amount (300) of unlabeled data.

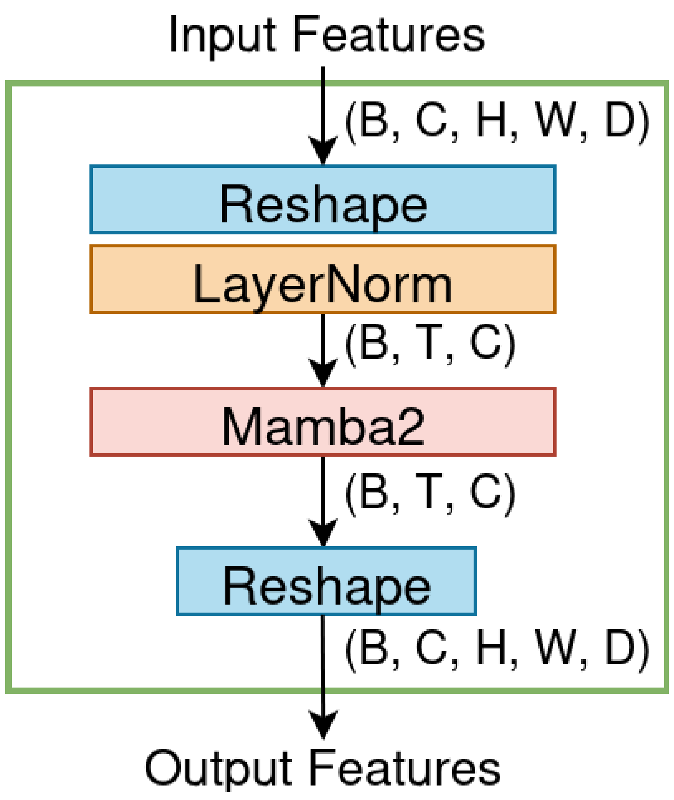
Solutions

- Utilize an effective and efficient model – U-Mamba2
  - With a large input patch size (128x256x256).
  - Mamba2 [1] learns global dependencies without significantly deteriorating speed.
- Propose a multi-stage semi-supervised learning (SSL) framework:
  - First stage: Pre-training (self-supervised)
  - Second stage: Consistency regularization training
  - Third stage: Pseudo labeling

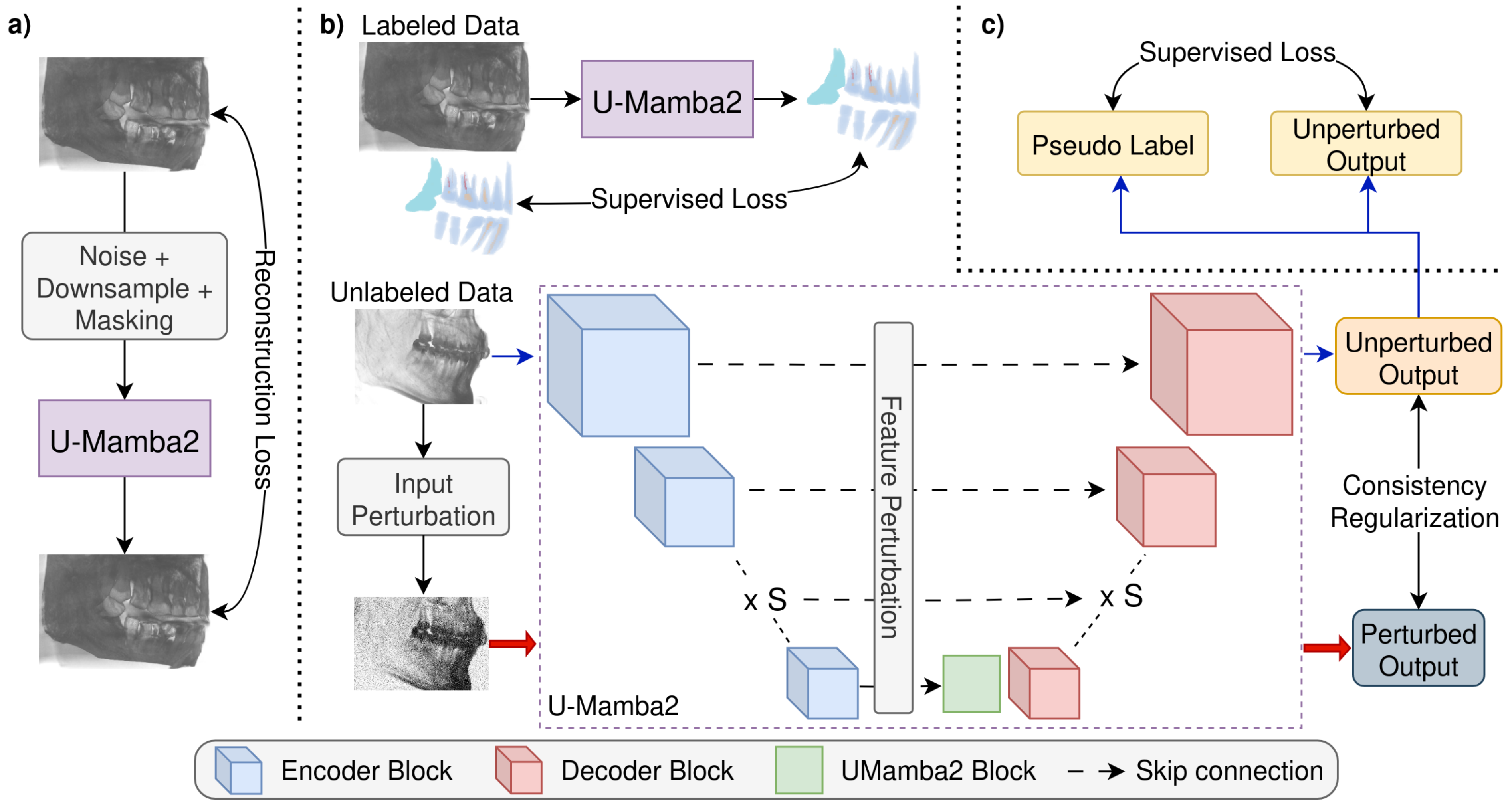
1. Dao, T., Gu, A.: Transformers are SSMs: Generalized models and efficient algorithms through structured state space duality. ICML 2024.

Methodology





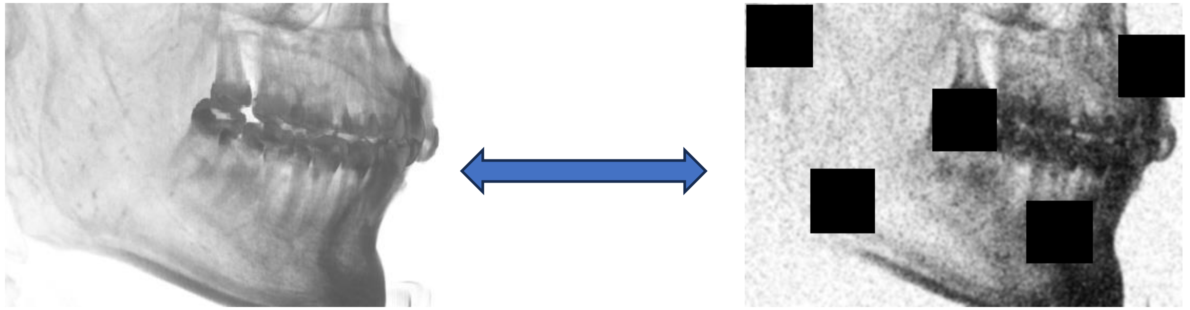
Methodology



Methodology

First stage: Pre-training

- Based on disruptive autoencoders [2] with the reconstruction objectives:
  - Denoising
  - Super-resolution
  - Masked Reconstruction



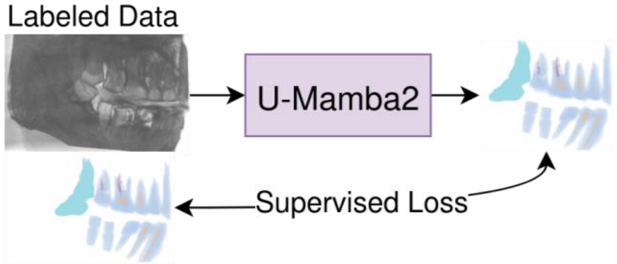
2. Valanarasu, J.M.J., et al.: Disruptive autoencoders: Leveraging low-level features for 3d medical image pre-training. MIDL 2024.

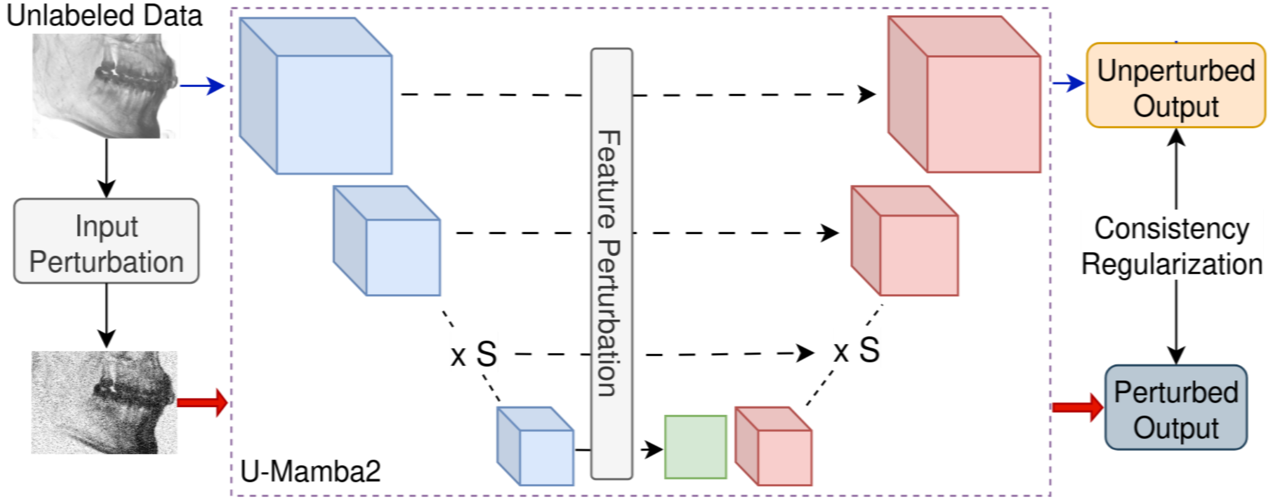
Methodology

Second stage: Consistency regularization training

- Supervised learning of labeled data (Dice + CE loss)
- Unsupervised learning of unlabeled data (L1 loss)
  - o Non-spatial input perturbations
  - o Feature perturbations
    - Random spatial dropout
    - Random activation dropout
    - Noise injection

$$\mathcal{L} = \mathcal{L}_S + \omega_{CR}\mathcal{L}_{CR}$$



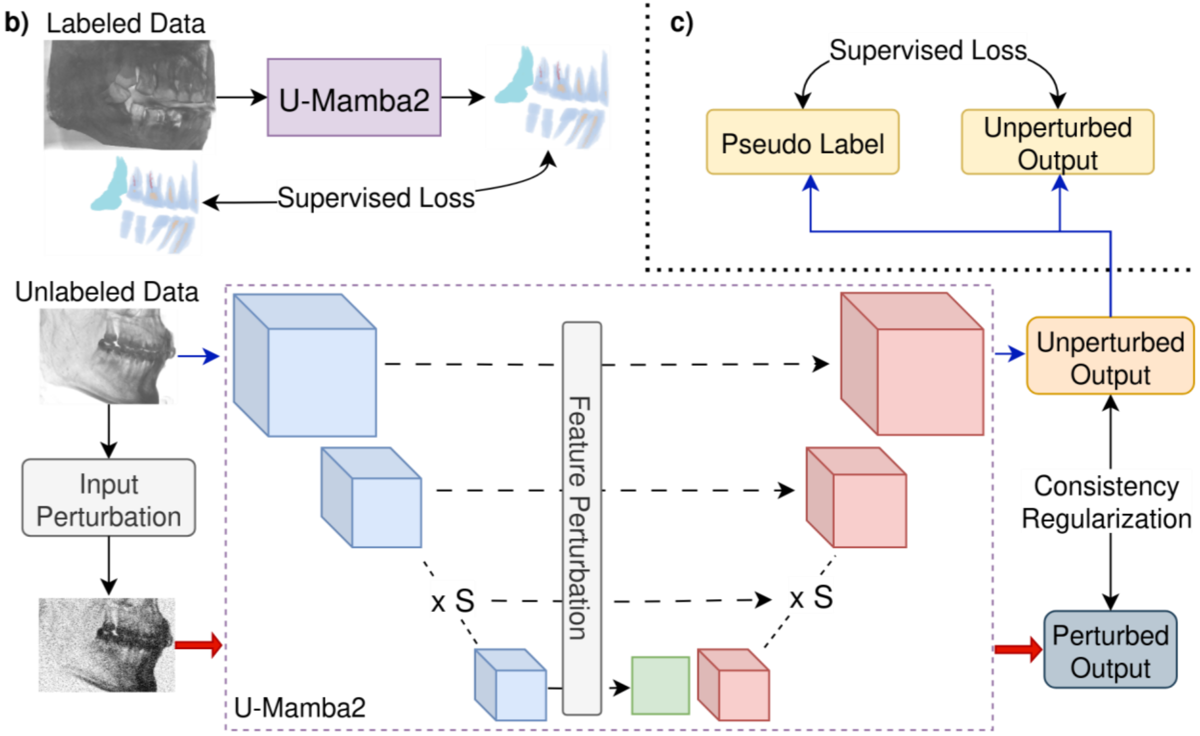


Methodology

Third stage: Pseudo labeling

- Use high confidence voxel as pseudo label
- Ignore loss value from other regions

$$\mathcal{L} = \underbrace{\mathcal{L}_S + \omega_{CR}\mathcal{L}_{CR}}_{\text{Second Stage}} + W_{PL}\mathcal{L}_{PL}$$



Results

20 training and 10 internal validation split

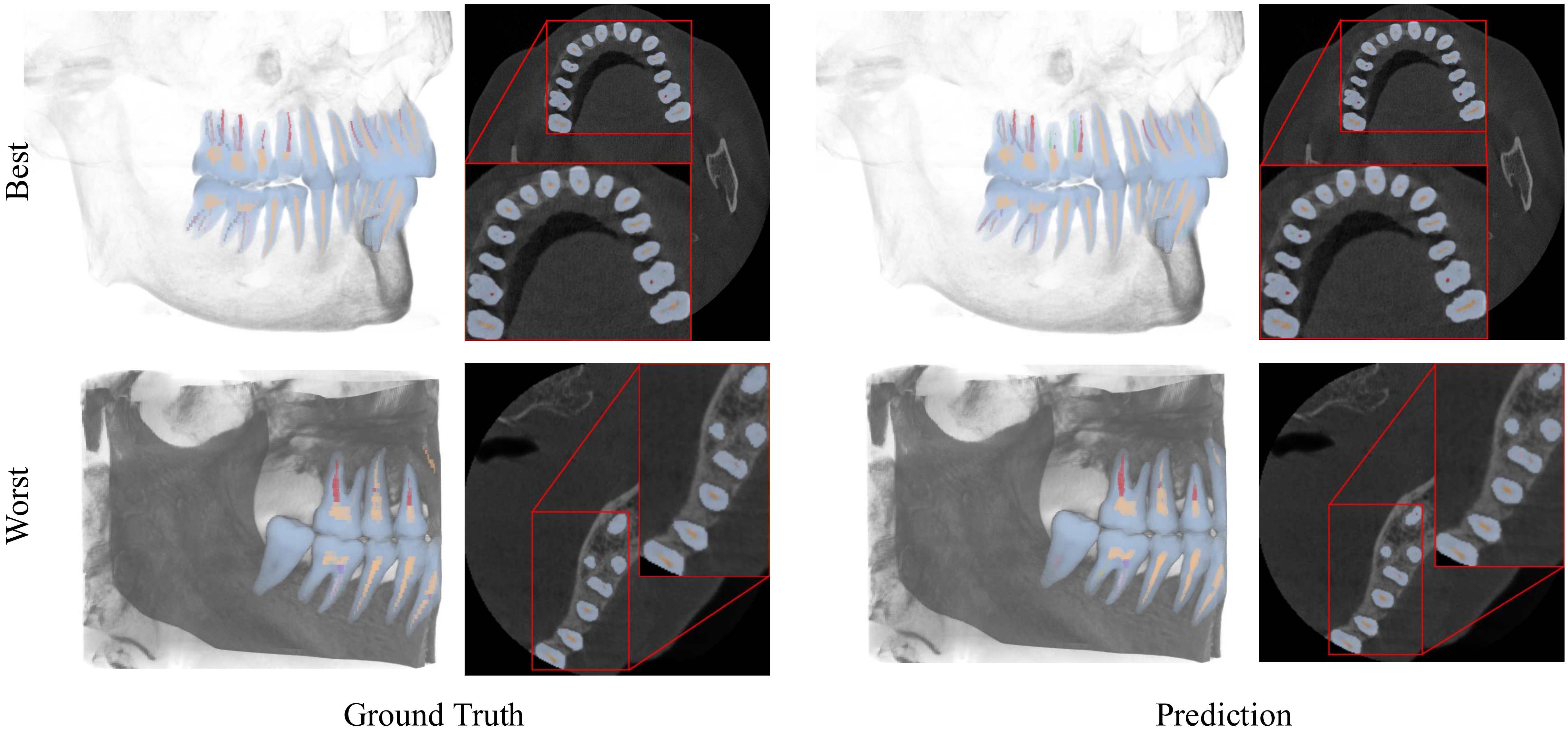
Methods	Pre-train	CR	PL	DSC	NSD	mIoU	IA	Average
nnU-Net	-	-	-	0.963	0.997	0.928	0.286	0.794
U-Mamba2	-	-	-	0.965	0.998	0.930	0.464	0.839
U-Mamba2-SSL	✓	✗	✗	0.967	0.998	0.937	0.731	0.908
	✓	✓	✗	0.967	0.999	0.935	0.736	0.910
	✓	✓	✓	0.967	0.999	0.935	0.738	0.910

Final submission:

- Using all training data
- Longer training schedule (1000 epoch)
- Increased patch size to 160x256x256

DSC	NSD	mIoU	IA	Average
0.969	0.998	0.940	0.806	0.928

Visualization



Limitations & Conclusion

Our method did not consider the following:

- Limited field of view CBCTs present different properties than full view CBCTs.
- Only small region in full view CBCTs contains tooth and pulp.

In summary:

- We proposed U-Mamba2-SSL, a novel multi-stage SSL framework.
- Our multi-stage framework that progressively utilizes unlabeled data is effective than other methods.
- We achieved an average score of 0.928 on the validation set of Task 1.

Acknowledgements

We are grateful to

- the data owners for making the medical images publicly available, and
- Codabench for hosting the challenge platform.