Semi-supervised Learning with Contrastive and Topology Losses for Catheter Segmentation and Misplacement Prediction

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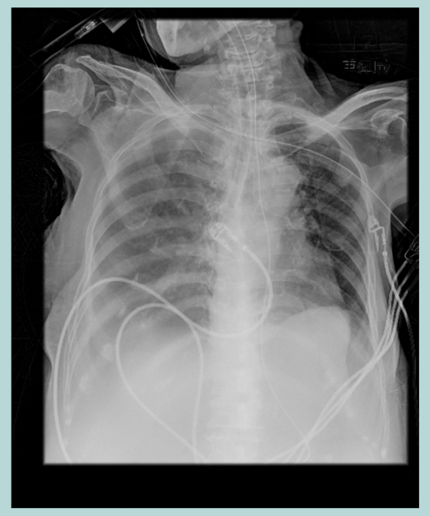
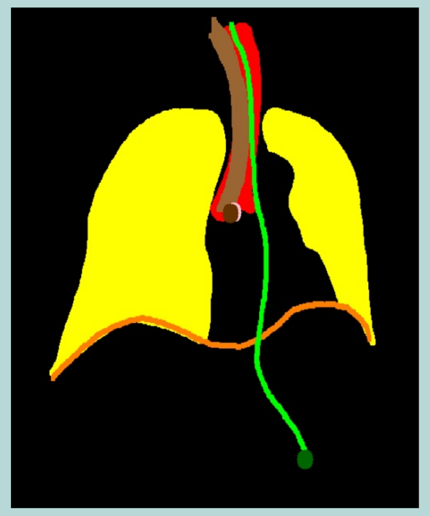
Introduction

- Incorrect placement can lead to severe complications
- Deep learning methods are developed to assist radiologists in identifying catheter misplacement
- Obtaining large, pixel-wise labeled datasets can be challenging
- We proposed a semi-supervised learning method that combines contrastive loss and topology loss



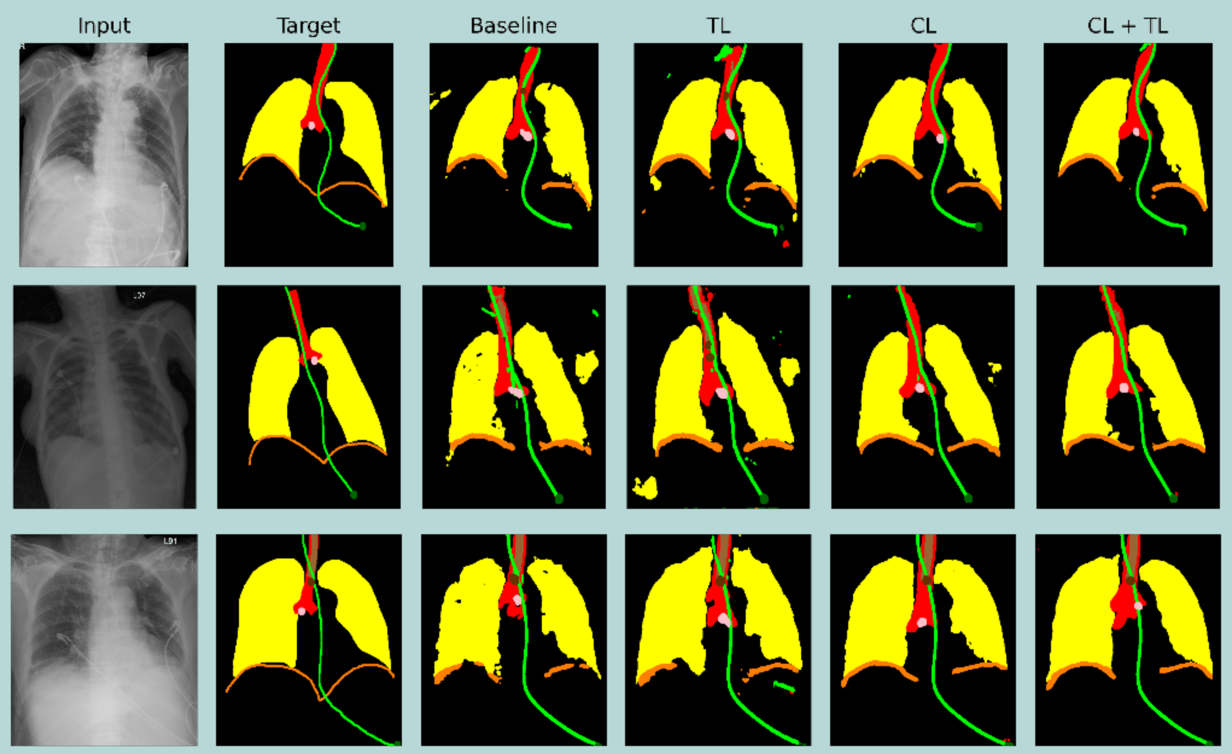


Results

Table 1: Segmentation Dice score and classification AUC of each method.

Previous Studies	Dataset (n=size)	Dice (95% CI)	AUC (95% CI)
FS (Sullivan et al., 2020)	Custom pediatric CXR (n=1,390)	0.74	-
FS (Elaanba et al., 2021)	CLiP (n=30,083)	-	0.80
FS (Lakhani, 2017)	Custom CXR with ETT (n=300)	-	0.81
FS (Singh et al., 2019)	Custom CXR with NGT (n=5,754)	-	0.87 (0.80, 0.94)
SD (Gherardini et al., 2020)	Custom fluoroscopy (n=12,207)	0.55	-
SD (Aryal and Yahyasoltani, 2021)	CLiP (n=30,083)	-	0.96
Ours			
FS (baseline)	NTUH (n=7,378)	0.517 (0.512, 0.522)	**0.979** (0.970, 0.987)
TL	NTUH + CLiP (n=37,461)	0.385 (0.379, 0.390)	0.974 (0.964, 0.983)
CL	NTUH + CLiP (n=37,461)	0.584* (0.579, 0.590)	0.968 (0.955, 0.979)
CL + TL	NTUH + CLiP (n=37,461)	**0.614*** (0.609, 0.619)	0.977 (0.968, 0.986)

FS = Fully-supervised, SD = Synthetic data
TL = Semi-supervised with topology loss, CL = Semi-supervised with contrastive loss
Asterisk (*) denotes statistical significance over baseline with p-value < 0.05
Bold denotes the best performance results



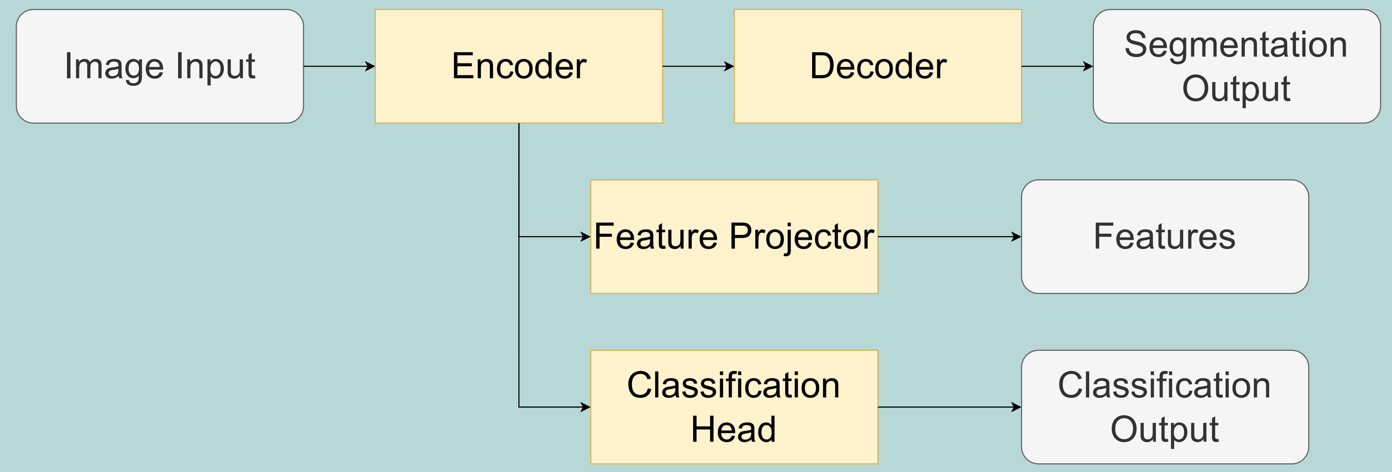
Conclusion

- This study proposes a semi-supervised learning method using contrastive and topology losses
- This method improves segmentation performance while maintaining accuracy
- This method can be extended to enhance segmentation in other tasks with known topological prior

Methods

1. Model

In addition to the U-Net architecture for segmentation, we add a feature projector and a classification head after the encoder.



2. Contrastive Loss

Contrastive loss is a loss function used in self-supervised contrastive learning, which aims to learn visual representations from unlabeled images.

$$\mathrm{Contr}(B') = -\frac{1}{2b}\sum_{i=1}^{2b}\log\frac{\exp(\mathrm{sim}(z_i, z_{\sigma(i)})/\tau)}{\sum_{k=1}^{2b}\mathbb{1}_{[k\neq i]}\exp(\mathrm{sim}(z_i, z_k)/\tau)}$$

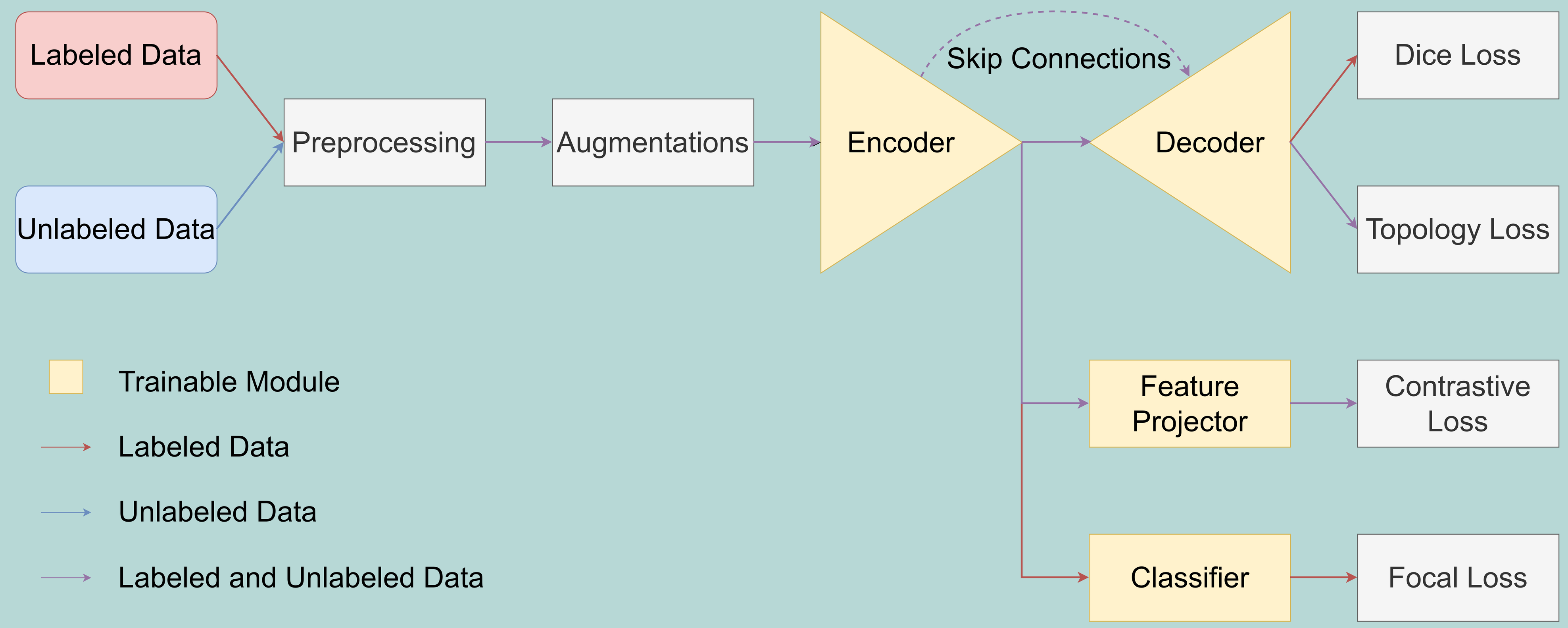
3. Topology Loss

Topology loss is a segmentation loss that is based on persistent homology, which does not require segmentation labels but instead uses topology priors. We modified the loss such that the target can be applied on a range of acceptable Betti numbers, instead of an exact value.

$$\mathrm{Topo}(\hat{y}) = \sum_k \left(\sum_{l=1}^{\beta_{k,a}}(1-|B_{l,k}(\hat{y})|)^2 + \sum_{l=\beta_{k,b}+1}^{\infty}|B_{l,k}(\hat{y})|^2\right)$$

4. Semi-supervised Learning

The semi-supervised training pipeline that we proposed, where the contrastive loss and the topology loss are computed on unlabeled data.



To effectively train a diverse task that requires aggregating multiple loss functions, a dynamic weighting mechanism is implemented during training.

$$\text{Total Loss} = \omega_D \mathrm{Dice}_l + \omega_F \mathrm{Focal}_l + \omega_T \mathrm{Topo}_l + \alpha_u \omega_T \mathrm{Topo}_u + \omega_C \mathrm{Contr}_{l,u}$$