FLCL: Self-Supervised Learning for Automated Cervical Cancer Brachytherapy Treatment Planning

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ABSTRACT

The standard of care for locally advanced cervical cancer includes high dose-rate brachytherapy (HDR BT). A major limitation of HDR BT is the overall procedure time, in which the longest step is treatment planning, taking 75 minutes on average.

Deep learning models using supervised learning have been proposed to automate these tasks but require large amounts of labeled ground truths, which are scarce. Self-supervised contrastive learning is an alternative approach that can leverage unlabeled data, which is far more prevalent. This method, when applied to multimodal medical image data, tasks a model with pairing images of different modalities belonging to the same patient.

This project introduces fuzzy loss contrastive learning (FLCL), which incorporates patient FIGO staging and an image similarity index. These measured identify patient images with similar disease progression and physical structure. During training, the penalty is reduced for incorrect pairs if the two patients are highly similar. FLCL pretraining was performed on a dataset of MRI and CT images for 172 patients.

Models were evaluated on an MRI segmentation task with clinical treatment plan contours. Few-shot learning was used to adapt a pretrained model for image segmentation with few labeled samples (N=15, 18 images). The model pretrained with FLCL significantly improved segmentations for the high-risk clinical target volume and some organs at risk, compared to a baseline model without pretraining on the test set (N=13, 19 images).

These results suggest that incorporating clinical information into contrastive learning is beneficial for identifying clinical targets in treatment planning.

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INTRODUCTION

37% of cervical cancer cases globally are considered locally advanced cervical cancer (LACC).[1] The standard treatment for LACC includes high dose-rate brachytherapy (HDR BT). A major **barrier to implementation** in high-income countries is overall procedure time.[2] Higher procedure time is also associated with **increased acute side effects**.[3] The most time-consuming step is treatment planning.

75 min on average[4]

Deep learning models can automate HDR BT treatment planning tasks to reduce procedure time. Previous studies have looked at supervised learning approaches, which requires labeled ground truths.
Issue: Labeled data is scarce and time-consuming to generate.
Solution: Self-supervised learning + few-shot learning, which requires much less labeled data.

Contrastive learning is a method for self-supervised learning that can be applied to multimodal medical image datasets. Patients undergoing treatment for LACC receive both CT and MRI scans, but most are not labeled.

Objective:
Group together images of the same patient — Pat. A MRI, Pat. A CT

Distance images from different patients — Pat. A MRI, Pat. B CT

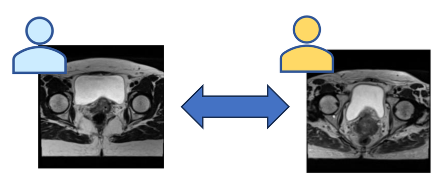
METHODS

Fuzzy Loss Contrastive Learning (FLCL)

Contrastive learning methods in natural image processing assume **large semantic differences** between subjects (i.e. dog vs cat). However, LACC patients may be similar in disease progression or physical structure. To address this, this project introduces a **similarity metric**.

Between patients:
5-year survival based on FIGO staging[5]

Between images:
structural similarity index measure (SSIM)



The **InfoNCE contrastive loss** function penalizes the model for grouping together different subjects.[6] This similarity metric was used to create a fuzzy InfoNCE loss, where the **penalty is reduced** for subjects that are highly similar.

Experiment Design

Pretraining using FLCL → Few-shot learning for segmentation

N=172, 172 MRI, 172 CT

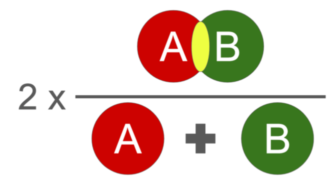
N=15, 18 MRI

RESULTS

Segmentation models were trained using **clinical contours** from MR-guided HDR BT treatment planning

5 segmentation targets:
4 organs at risk (OARs): bladder, rectum, sigmoid, bowel + High-Risk Clinical Target Volume (CTV_{HR})

Metrics:
Volumetric Dice Score (vDSC):
Measure of overlap between prediction and ground truth, (higher is better).



Added Path Length (APL):[7]
Measure of total distance needed to be manually corrected for the prediction to match the ground truth (lower is better).

An FLCL pretrained segmentation model was compared to a baseline model with identical architecture but no pretraining. The models were evaluated on a separate test set with patients not seen during pretraining or few-shot learning.

Test dataset size: N=13, 19 MRI

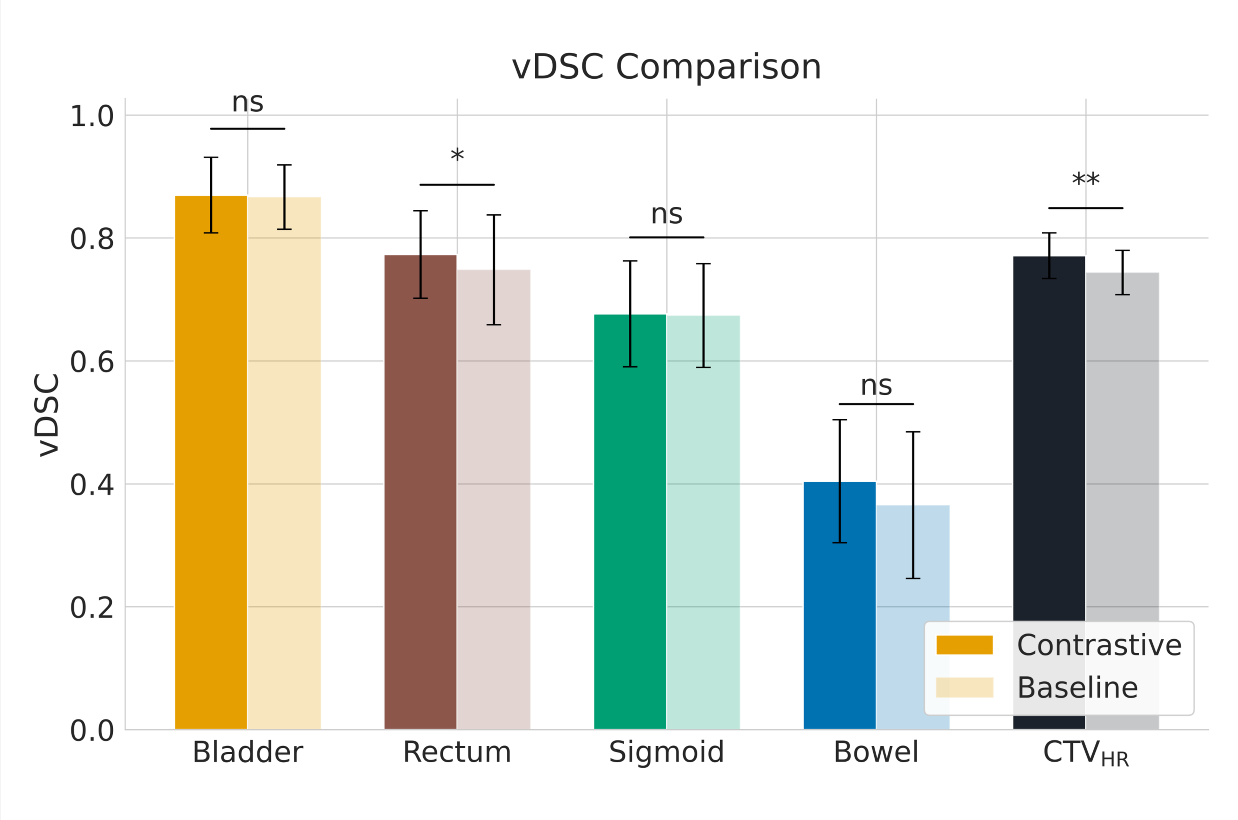


Figure 1. Comparison of vDSC metric for pretrained and baseline segmentation models

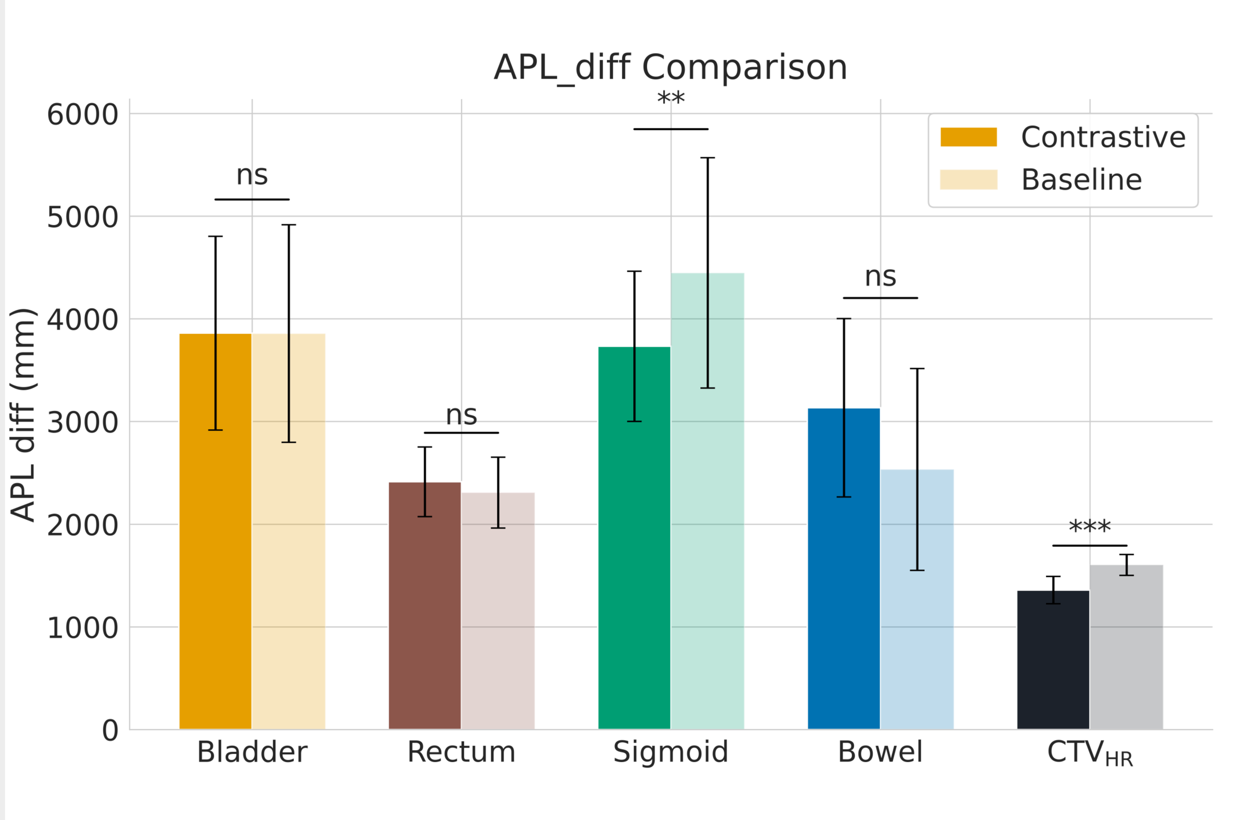


Figure 2. Comparison of APL metric for pretrained and baseline segmentation models

DISCUSSION

The FLCL pretrained model had statistically significant improvements (using 1-sided Wilcoxon signed-rank test) in:

Measure	FLCL	Baseline	P-value
Rectum vDSC	0.77 ± 0.07	0.75 ± 0.09	0.04
Sigmoid APL	3700 ± 700	4000 ± 1000	0.004
CTV_{HR} vDSC	0.77 ± 0.03	0.74 ± 0.04	0.004
CTV_{HR} APL	1400 ± 100	1600 ± 100	0.0003

These results show promise for using FLCL pretraining to improve performance in automated HDR BT treatment planning.

In practice, clinical reports are used in combination with imaging to guide CTV_{HR} contouring, highlighting the **need for clinical information**. FIGO staging provides many details on the patient's disease progression. We hypothesize that the inclusion of this information in FLCL pretraining resulted in the significant improvement in CTV_{HR} segmentation, by encouraging to model to learn **differences in disease stage** between patients.

OARs can serve as **landmarks** for identifying patients by physical structure. The use of SSIM in FLCL pretraining encourages the model to use this strategy, which may have resulted in improvements in segmentation for some OARs. However, the difference in performance between the models was inconsistent, so further experiments are needed to assess the value of SSIM in pretraining.

Future Steps

1. Source FIGO staging for more patients to expand the dataset for pretraining.
2. Implement additional patient clinical information such as histopathology or tumour descriptions in the similarity metric.
3. Perform experiments to optimize the balance of clinical information and SSIM in the similarity metric.
4. Test other model architectures such as Swin Transformer or ConvNeXt.
5. Implement few-shot learning for other HDR BT treatment planning tasks.

CONCLUSIONS

This work introduces FLCL, a contrastive learning method incorporating clinical and structural patient information. Using FLCL pretraining followed by few-shot learning for segmentation resulted in a significant improvement in performance for the CTV_{HR} and some OARs. This motivates further research into self-supervised learning methods that highlight patient differences.

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