



Toward Next-generation Medical Vision Backbones: Modeling Finer-grained Long-range Visual Dependency

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Background

Medical images depict standardized anatomical regions across patients, resulting in high structural similarity with subtle anatomical and pathological characteristics discernible only in high resolutions containing tissue-level image textural details.

Research Gap

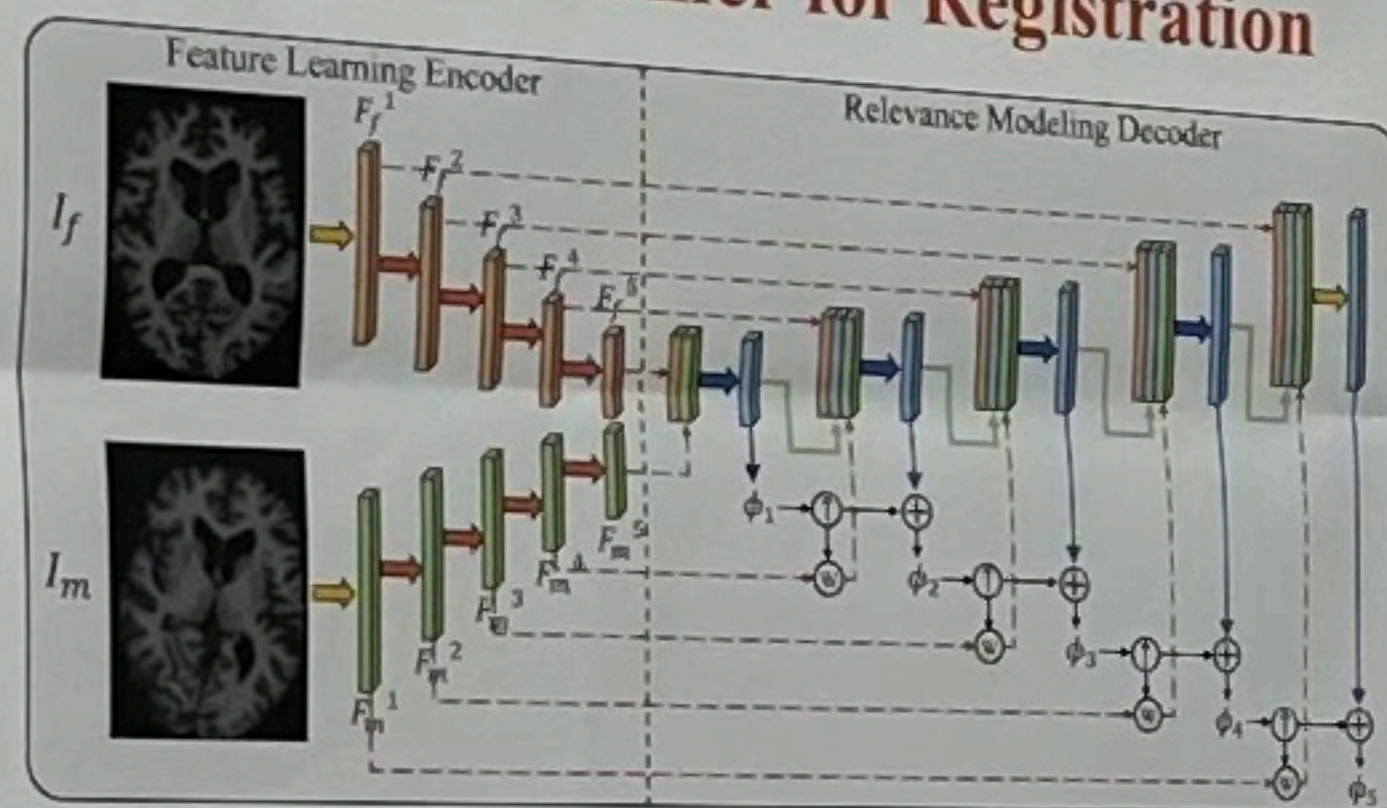
- ❖ CNN limited by intrinsic locality, while modeling long-range visual dependency is crucial for global comprehension of image contexts.
- ❖ Transformer cannot process high-resolution image features with enriched medical image details.
- ❖ MLP is a potential alternative to transformer - yet to be recognized in medical imaging community.

Overview of Doctoral Thesis (Too Long? Just Look at Here!)

Research Problem & Motivation:			
Innovate transformer/MLP-based vision models to effectively capture long-range visual dependency among medical imaging characteristics to enhance diverse medical image computing tasks.			
Study I: Transformer for Registration	Study II: Transformer for Seg & Prognosis	Study III: MLP for Registration	Study IV: Empirical Investigation of MLP
Research Aim: (i) Innovate transformer-based methods for medical image registration. (ii) Explore insights into long-range visual dependency modeling in the scenario of registration.	Research Aim: (i) Innovate transformer-based methods for multi-modal imaging analysis. (ii) Explore insights into the modeling of complementary cross-modal visual dependency.	Research Aim: (i) Introduce MLP-based coarse-to-fine network for medical registration. (ii) Uncover the potential of MLPs in modeling finer-grained long-range visual dependency.	Research Aim: (i) Investigate the employment of MLP in a variety of medical vision tasks. (ii) Validate the superiority of MLPs over CNNs and transformers in modeling medical dependency.
Related Publication: MICCAI 2022, MICCAI 2023, Pattern Recognition 2024	Related Publication: IEEE JBHI 2022, MICCAI 2023, npj Precision Oncology 2024	Related Publication: CVPR 2024 (Best Paper Candidate/Finalist, Top 24)	Related Publication: MICCAI 2024 (Media Under Review)

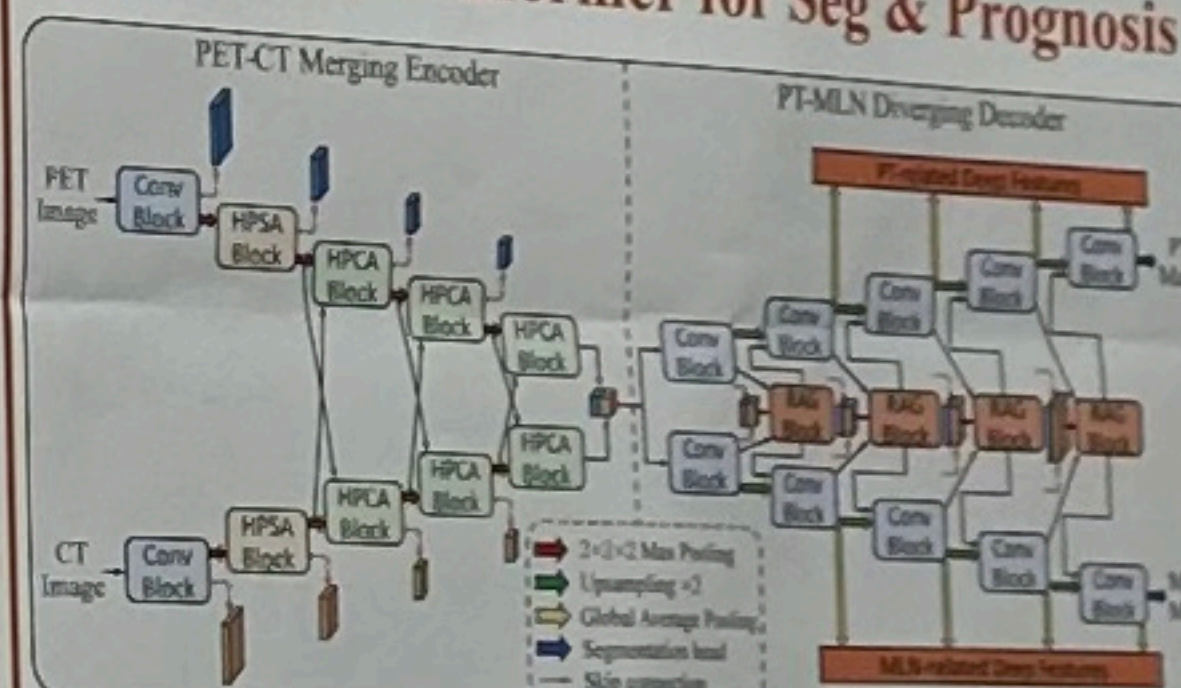
Key Finding & Conclusion:
MLP-based models provide feasibility in modeling finer-grained long-range dependency among subtle medical visual details, establishing it as a superior paradigm over transformers/CNNs for medical vision.

Study I - Transformer for Registration



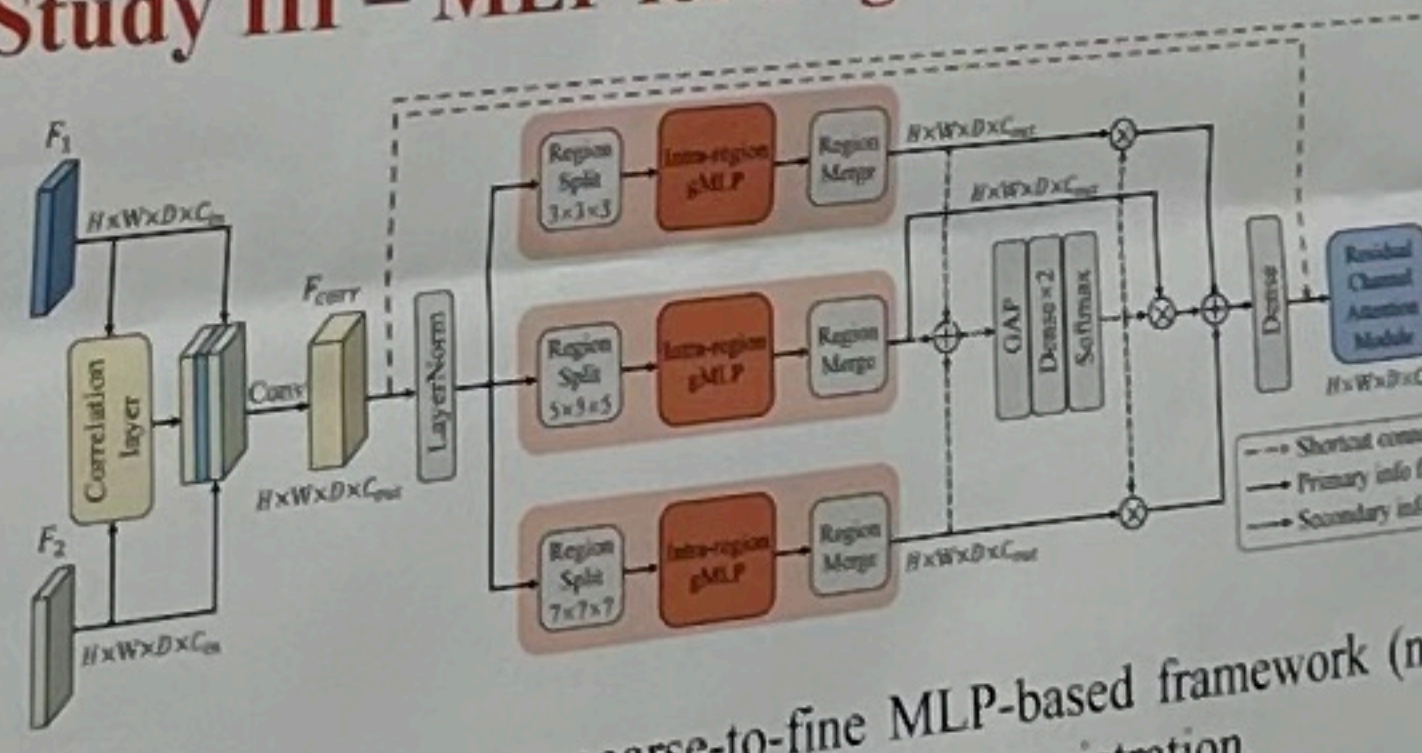
- ❖ A transformer-based model (named NICE-Trans) for medical image registration enhanced by long-range spatial dependency modeling.
- ❖ Embed transformers into a non-iterative coarse-to-fine architecture to progressively model coarse-to-fine spatial dependency in a single iteration, marking the first adopt of transformers into non-iterative coarse-to-fine registration.
- ❖ Joint affine and deformable image registration in a single network.
- ❖ Reveal key insights into how long-range dependency modeling enhances medical image registration.

Study II - Transformer for Seg & Prognosis



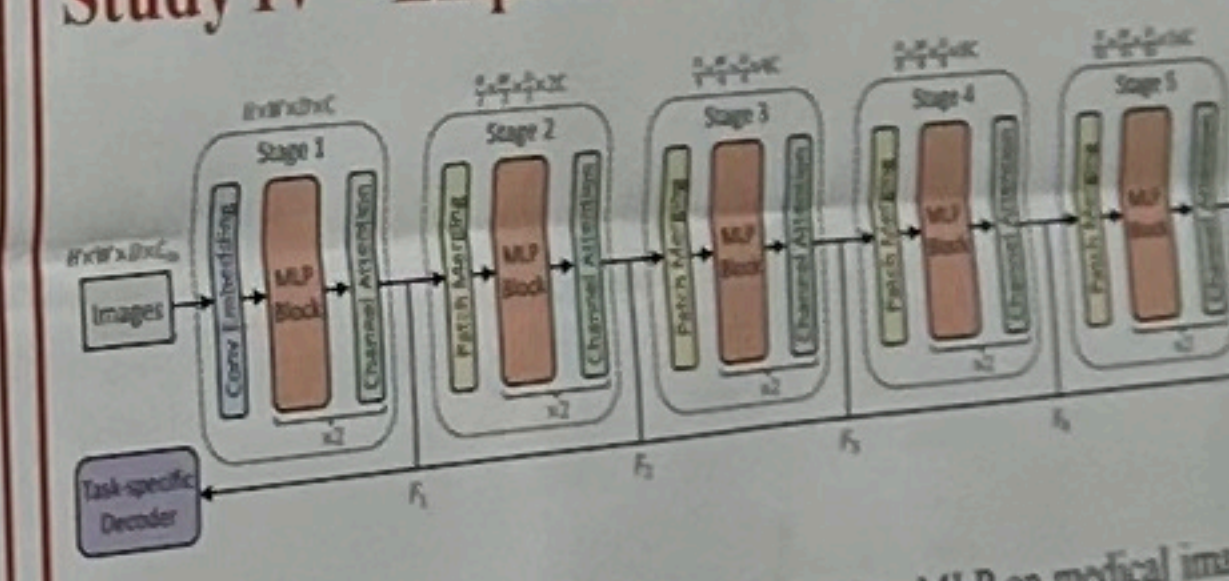
- ❖ A transformer-based model (name XSurv) for joint survival prediction and tumor segmentation from multi-modality PET-CT images.
- ❖ A new paradigm for multi-modal survival modeling with cross-modal feature interaction enhanced by long-range dependency modeling.
- ❖ A Hybrid Parallel Cross-Attention (HPCA) block was introduced to explicitly model complementary cross-modal dependency via cross-attention transformers.
- ❖ Simultaneously extract modality-specific prognostic features while sharing contextual knowledge across modalities.

Study III - MLP for Registration

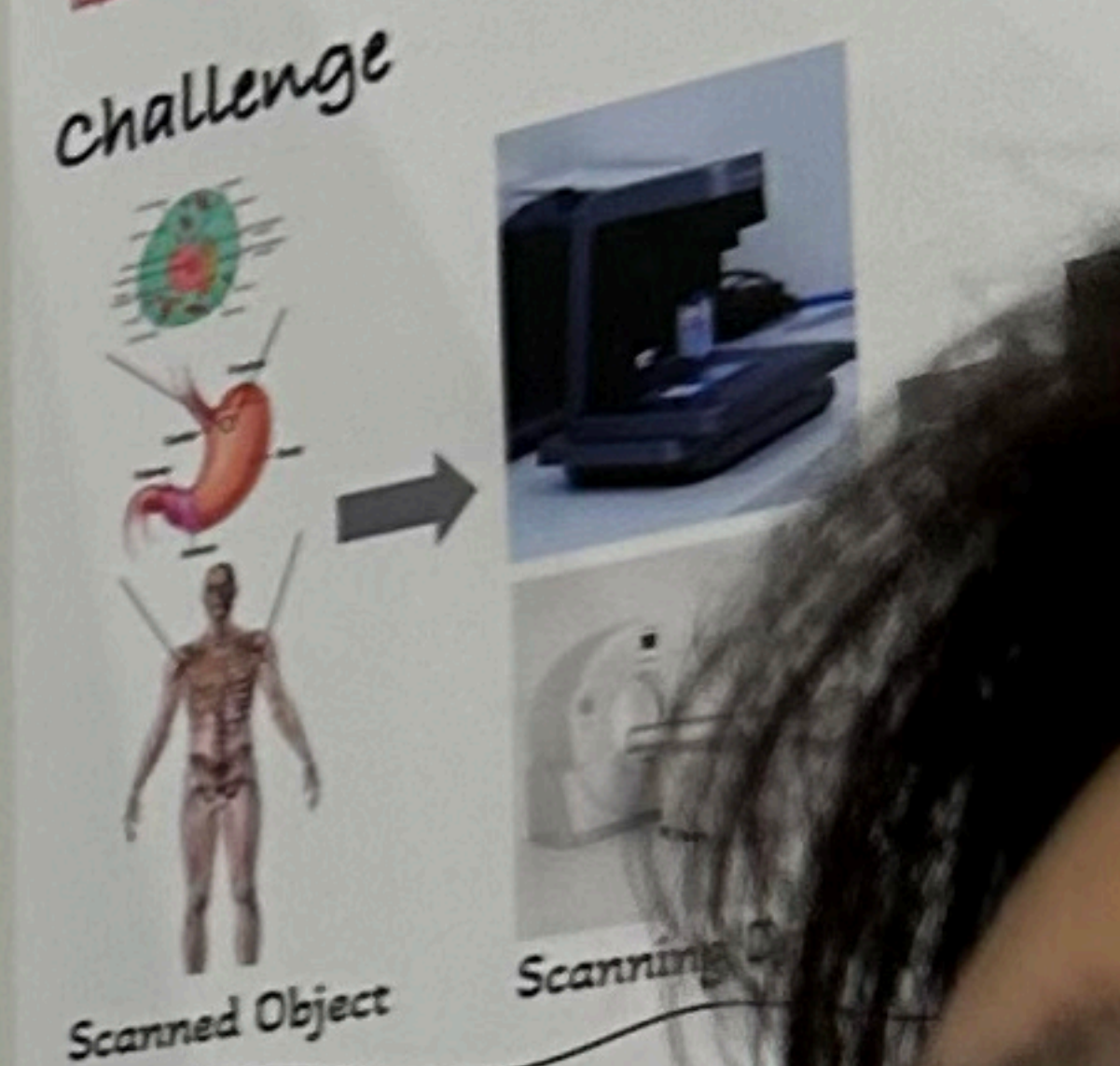


- ❖ A correlation-aware coarse-to-fine MLP-based framework (named CorrMLP) for deformable medical image registration.
- ❖ First MLP-based coarse-to-fine registration network unlocking the potential of MLPs for capturing pixel-wise spatial dependency.
- ❖ First MLP block designed to model correlation-aware multi-range visual dependency for medical image registration.
- ❖ A novel correlation-aware registration architecture leveraging both image-level and step-level correlations.
- ❖ Preliminarily establish MLP as promising backbones for medical vision tasks due to its capability to capture fine-grained pixel-wise long-range dependency.

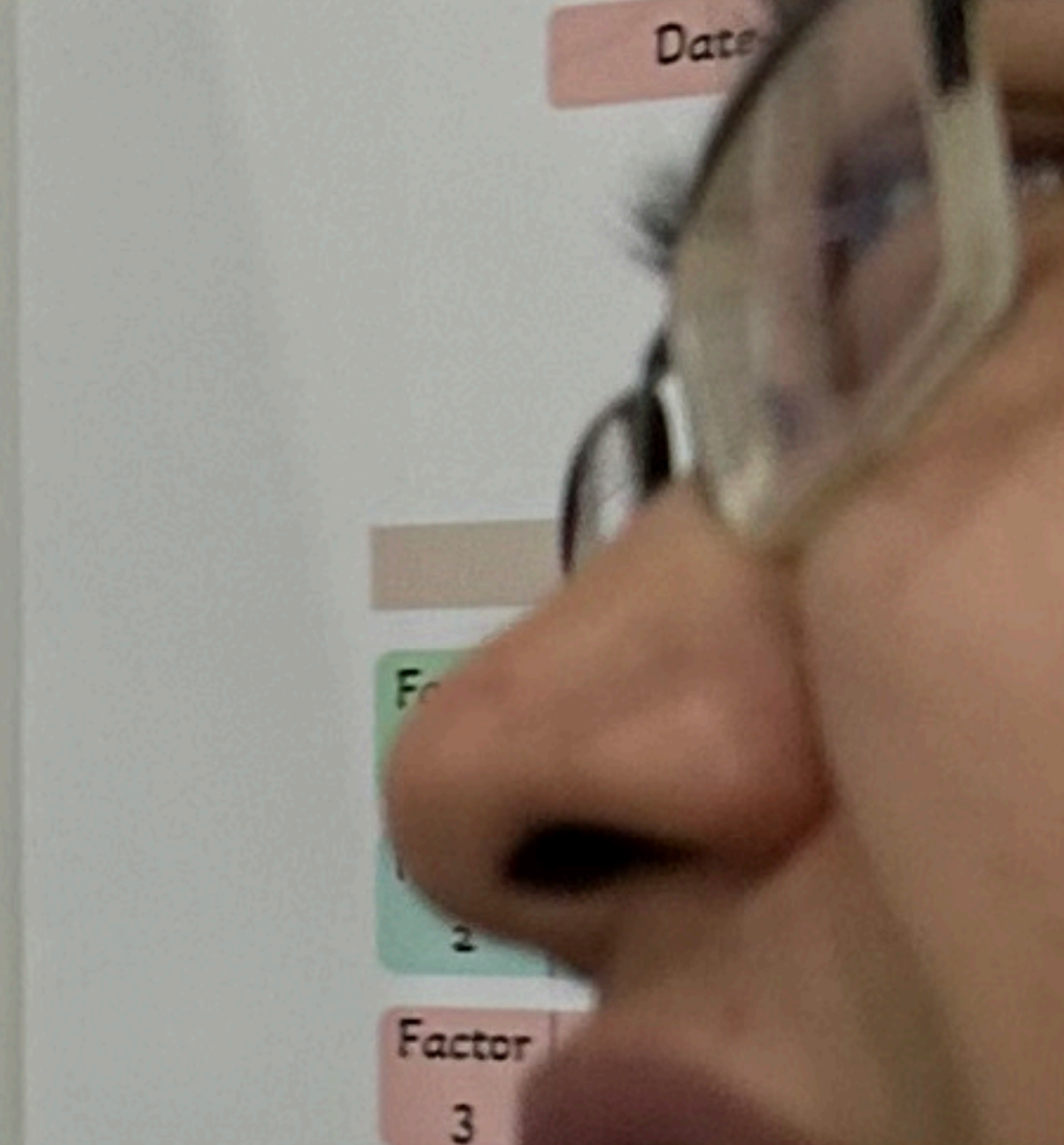
Study IV - Empirical Investigation of MLP



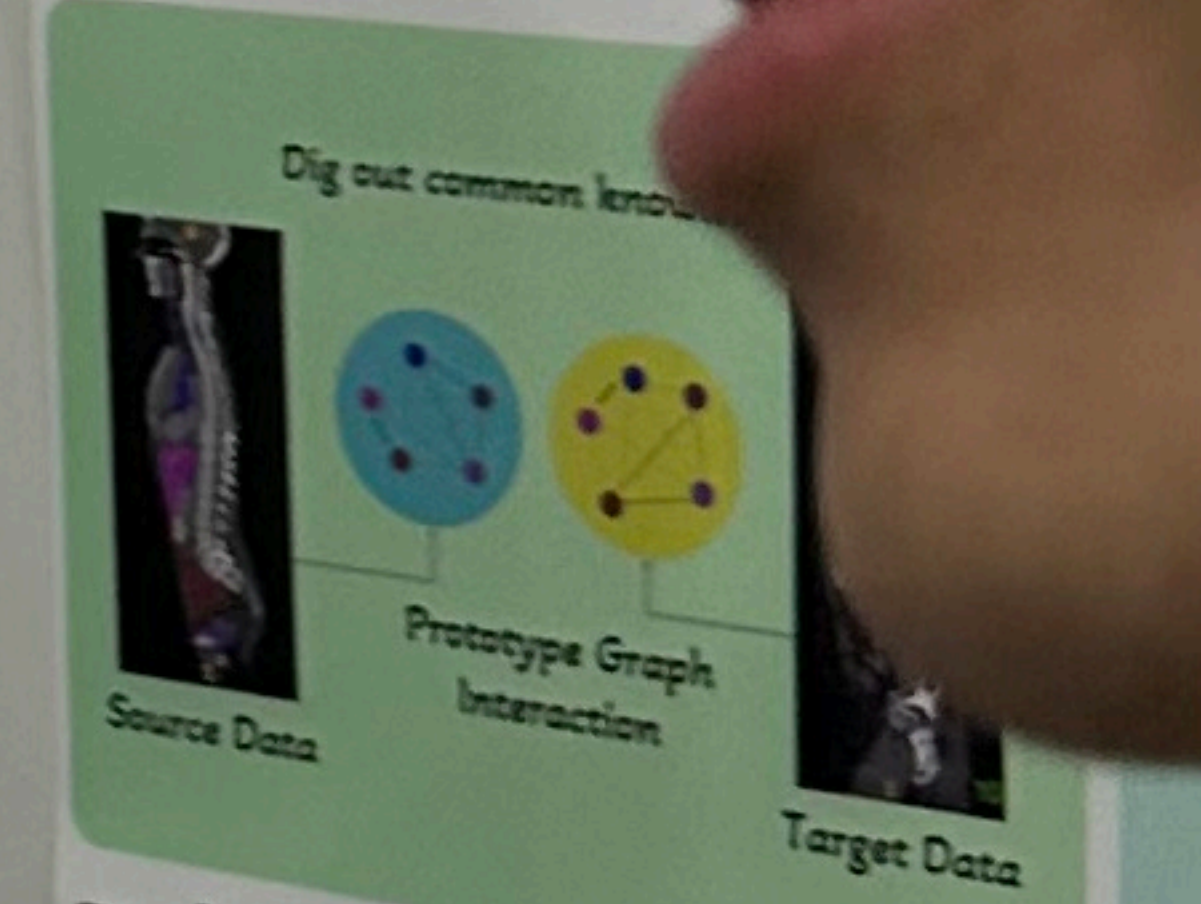
- ❖ A comprehensive empirical study evaluating MLP on medical image reconstruction, registration, and segmentation.
- ❖ Regardless of the specific MLP variants, employing MLP blocks at full resolution consistently enabled superior performance over CNN- and transformer-based methods across all evaluation tasks, even outperforming task-optimized specialist models.
- ❖ Uncover the under-explored capability of MLP to capture fine-grained long-range dependency among subtle medical visual details.
- ❖ Step toward next-generation medical vision backbones equipped with finer-grained long-range medical vision dependency modeling.



Overview



Proposed Solution



Reference

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4. Chen, W., et al. "Liu, H., et al. "Bun-4: Spatial-temporal hierarchical reinforcement learning for open set domain adaptation." IEEE Transactions on Medical Imaging 43.12 (2024): 3500-3512.