Effective Disjoint Representational Learning for Anatomical Segmentation

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Motivation and Methodology

Motivation: Effective multi-organ anatomical segmentation and mitigation of representation bias due to disparities in relative organ proportions.

Approach: Investigation of organ-specific feature learning through dedicated organs-specific decoders and anatomical knowledge sharing through in-domain transfer learning strategies [1-3].

Data:

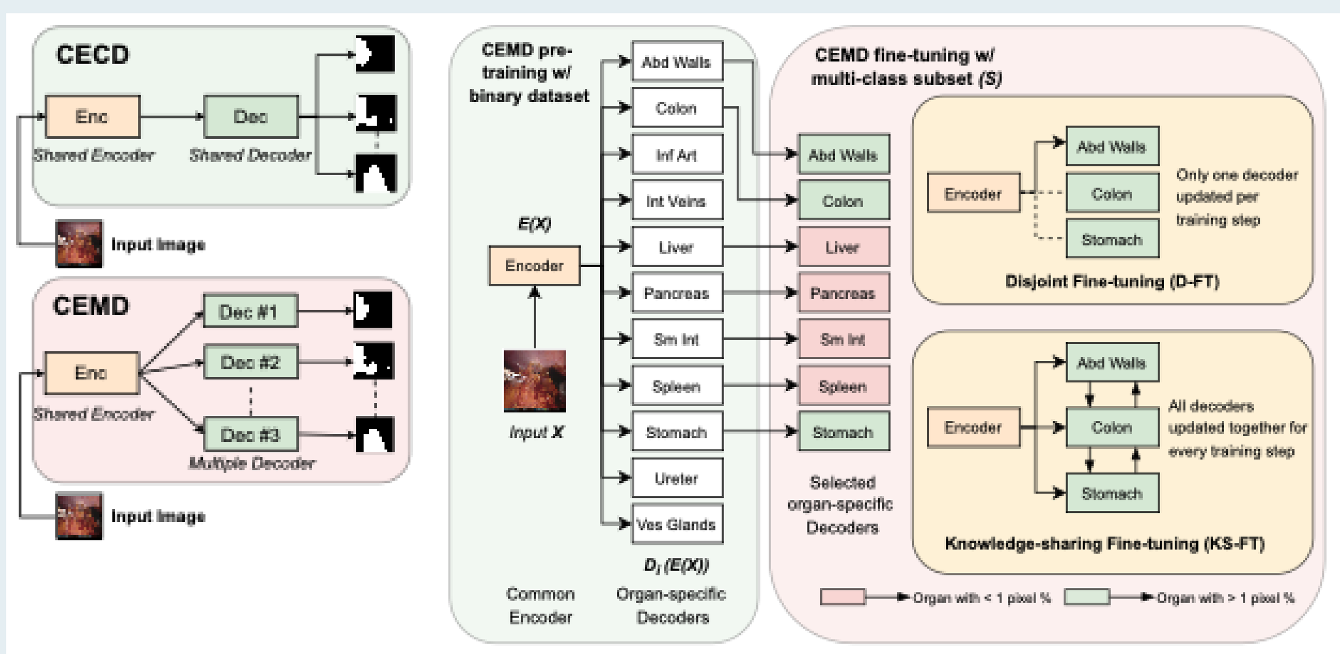
- Dresden Surgical Anatomy (DSA) Dataset [4] containing 13,195 high-resolution laparoscopic images from 32 surgeries, with 1000 images per organ.
- Provides binary segmentation masks for 11 abdominal organs and a multi-class subset of 1,430 images covering 7 organs.

Training Framework: Common Encoder-Multiple Decoder (CEMD), Common Encoder-Common Decoder (CECD), and Extended Common Encoder-Common Decoder (E-CECD).

Models: Four different segmentation architectures, DeepLab, SegFormer, AU-Net, and PVT U-Net.

Parameter Sharing Strategies: Knowledge Sharing Fine-Tuning (KS-FT) and Disjoint Fine-Tuning (D-FT)

(A) Training Framework (B) Parameter Sharing Strategies

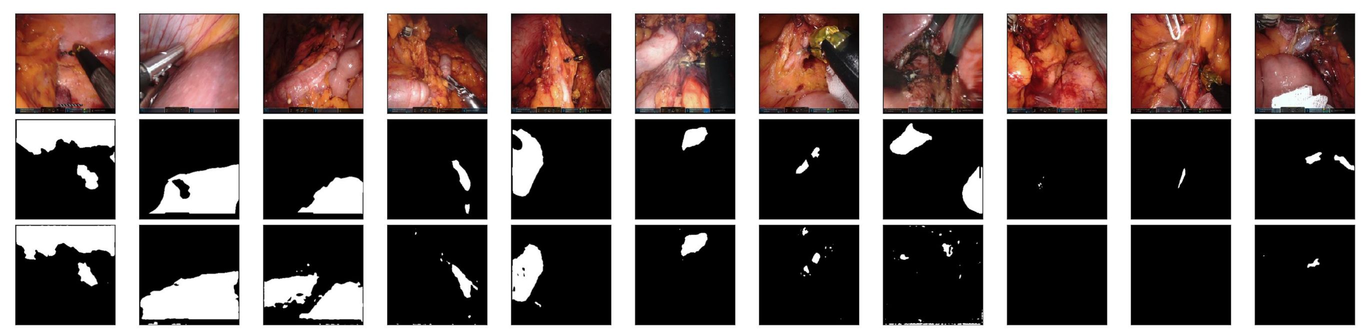


(A) **CEMD** involves a shared encoder with dedicated decoders for each of the eleven target organs. **CECD** uses a single decoder and produce multi-channel output.
(B) **KS-FT** facilitates cumulative knowledge sharing by simultaneously updating all decoders during fine-tuning. **D-FT** employs disjoint learning by updating each decoder while freezing others.

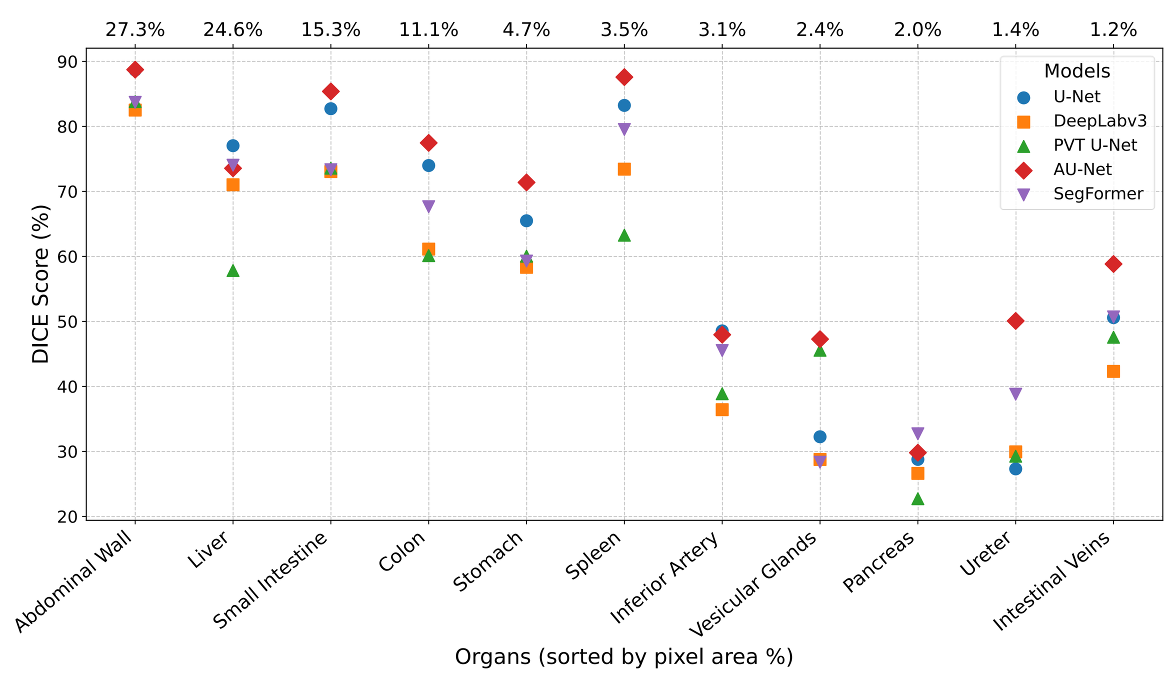
Results

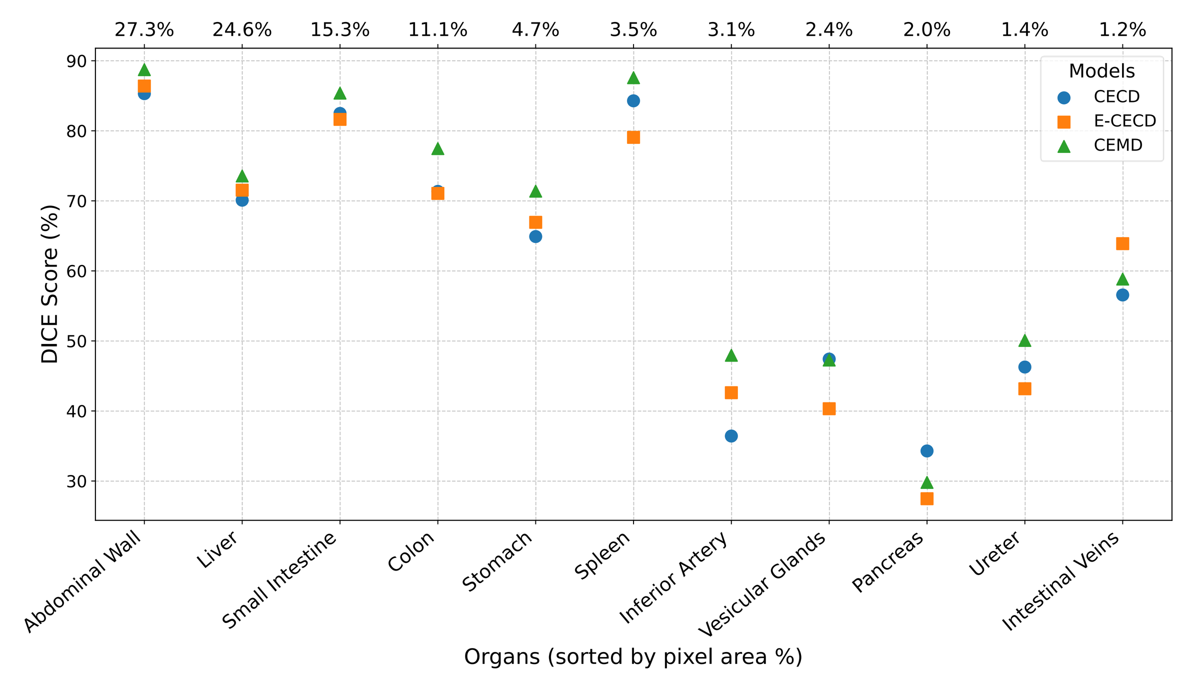
1. Comparison of Backbone Models

- AU-Net with CEMD achieves the highest DICE scores on 8 out of 11 organs.
- Segmentation performance correlates positively with organ proportions, reflecting class imbalance challenges.
- Organ attributes are influential besides their pixel proportions. Spleen > Liver and Intestinal vein > Pancreas.



AU-Net trained with CEMD architecture with rows indicating input, target mask and prediction mask.





Criterion	CECD	E-CECD	CEMD
Average Dice	61.78 ± 23.91	61.14 ± 23.93	**65.27 ± 19.85**
Parameters (M)	**31.39**	152.83	156.83
GMACs	**55.95**	482.65	443.71
Memory Footprint (MB)	**893.95**	2984.21	5442.54
Execution Time (ms)	**2.72 ± 0.15**	12.38 ± 0.11	29.04 ± 0.37

Organ	Pixel (%)	CEMD DICE	KS-FT DICE	D-FT DICE
Abdominal Wall	7.69	56.17	62.64	**63.98**
Stomach	6.97	65.21	65.52	**66.22**
Colon	5.60	33.38	21.42	**38.56**
Overall	-	51.59	49.86	**56.92**

2. CECD v/s CEMD

- CEMD outperforms CECD and E-CECD and 6 organs have increase of at least ≈ 5% Dice in CEMD than E-CECD.
- Trade-off between computational efficiency and segmentation performance.
- CEMD handles class imbalance better, excelling in smaller organs (inferior artery and ureter); pancreas remains challenging due to limited visibility.

3. DFT v/s KFT

- D-FT outperformed both baseline and KS-FT, with a +5.33% overall DICE improvement.
- KS-FT led to degraded performance on Colon.

Conclusion and Future Work

- Model architecture plays a more significant role in segmentation accuracy than capacity alone.
- Organ-specific decoders (CEMD) outperform similar-capacity models by better capturing unique anatomical features.
- Transfer learning with disjoint feature learning improves performance than cumulative feature learning.
- Future work should address class imbalance, explore advanced segmentation architectures, and optimize models using parameter-efficient fine-tuning or pruning.

1. Kolbinger et al. (2023). *Anatomy segmentation in laparoscopic surgery: Comparison of machine learning and human expertise – an experimental study. International Journal of Surgery.*
2. Maack et al. (2024). *Efficient anatomy segmentation in laparoscopic surgery using multi-teacher knowledge distillation. Medical Imaging with Deep Learning (MIDL).*
3. Jenke et al. (2024). *One model to use them all: Training a segmentation model with complementary datasets. International Journal of Computer Assisted Radiology and Surgery.*
4. Carstens et al. (2023). *The Dresden Surgical Anatomy dataset for abdominal organ segmentation in surgical data science. Scientific Data.*