Adaptive Biomedical Segmentation: Enhancing Explainability through Domain Shift Analysis

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Background & Summary

This project focuses on analyzing domain shifts in biomedical image segmentation models, with a particular emphasis on model explainability. The research addresses both binary and multiclass semantic segmentation tasks in the context of pathological modalities. The study utilizes well-known deep learning architectures such as U-Net[1] and DeepLabV3[2], fine-tuning them on various datasets, including GlaS from MICCAI (2015), CRAG, and CPM15. The primary goal is to investigate how these models' performance depends on the specific dataset they are trained on and how this affects their generalization capabilities. A key hypothesis of the project is that models like U-Net exhibit bias when trained on a specific dataset (e.g., CRAG), leading to reduced accuracy when tested on similar but distinct datasets (e.g., GlaS). This phenomenon is explored across different combinations of binary and multi-class segmentation datasets. The research also delves into the activation and filter layers of the models to understand the underlying reasons for domain shift loss and to explain the nature of the models' behavior. This approach, combining custom U-Net models with elements from DeepLabV3 and analyzing activation layers and filters, represents a novel contribution to the field of model explainability in the context of domain shift. Performance metrics such as mean Intersection over Union (mIOU)[3], Pixel Accuracy[4], Jaccard Loss[5], and Dice Score[6] are used to evaluate the models. The achieved results are comparable to previous field experiments, with mIOU scores of 0.96 for CRAG and 0.89 for GlaS datasets. This study aims to provide insights into the challenges of domain generalization in biomedical image segmentation and contribute to the broader understanding of model explainability in this domain.

Methods

- The hypothesis revolves around the fact that models like U-Net[1] get biased when trained on a specific dataset like CRAG. Then it loses its accuracy when tested on a similar dataset like GLAS.[7] Also true for other combinations of binary and multi-class segmentation datasets.

- These differences were also found in the activation and filter layers of the model for the datasets. This model analysis would help determine the real reason behind the domain shift loss and explain the nature of the model, like U-Net and DeepLabV3.[1,2,8]

- We trained and fine-tuned the U-Net, DeepLabV3 model on GlaS[7] Dataset MICCAI 2015, CRAG, CPM15, CPM17 to observe domain dependency of models on the dataset, created a pipeline to improve Image masks mIOU[3] and Dice Score[6].

- The work with a custom U-Net[1] model with different adjustments from DeepLabV3[2] and working with activation layers and filters to figure out the problem of explaining the working of the model in the field of Domain Shift was a novel idea.

- The results generated concerning mIOU Loss and Dice Score[6] were up to the standards of previous experiments conducted in this field, like **0.96** mIOU for CRAG. *(Pathological Modality)*

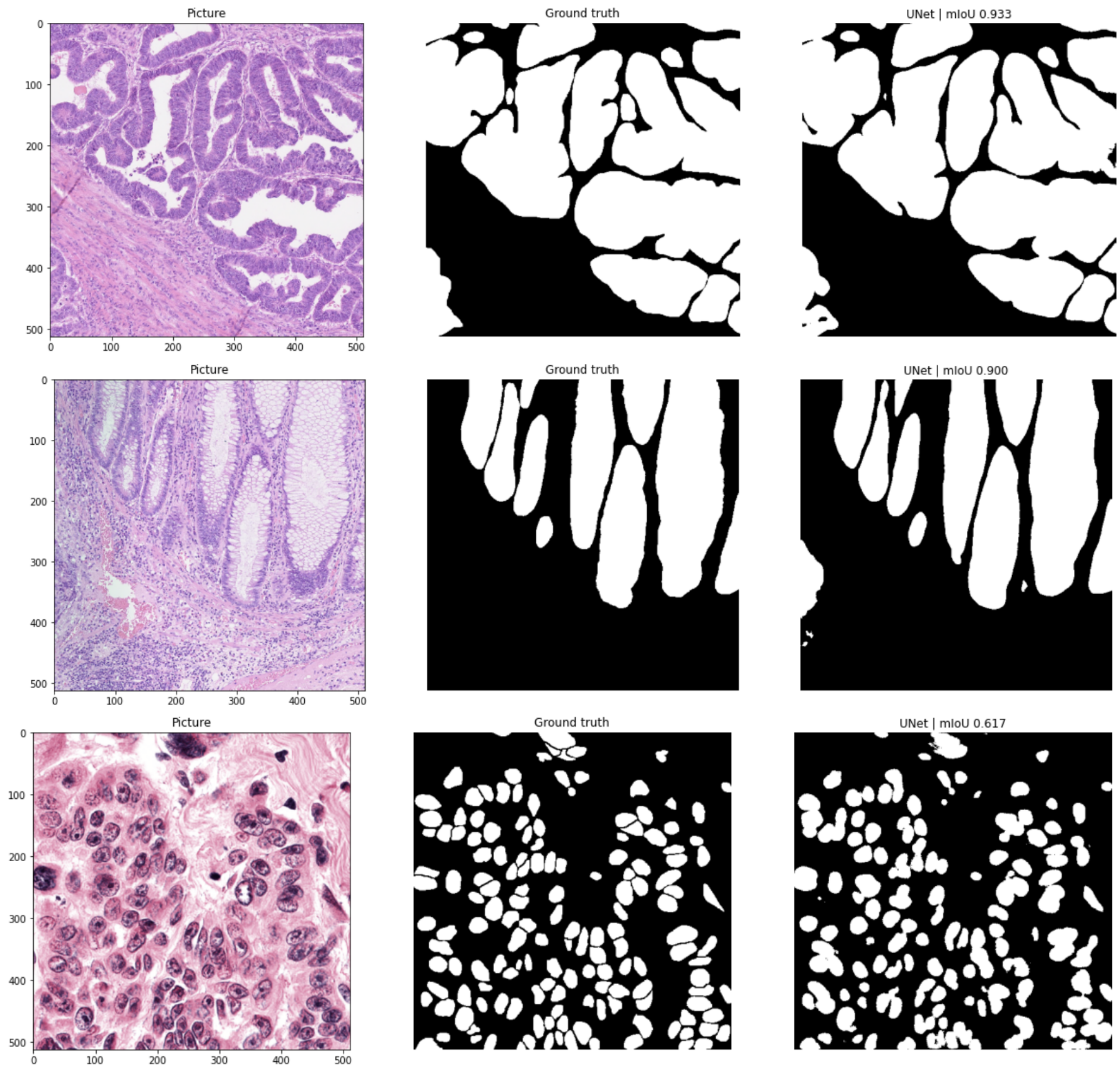


Figure 1. Example Results of segmentation on pathological datasets. The left column is Original Picture. The middle column is the Ground Truth of the Mask, and the right column is the Predictions

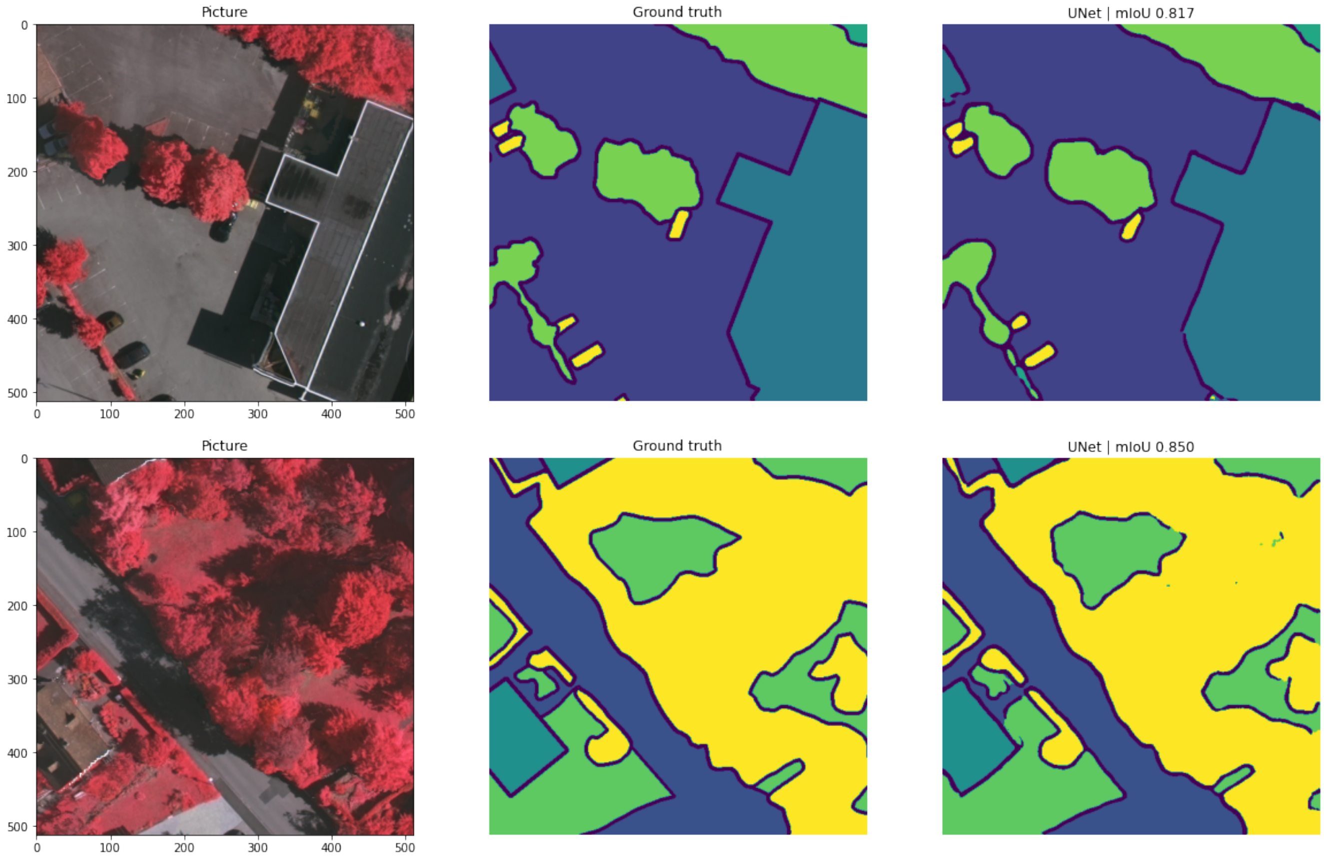


Figure 2. Performance of Unet on the Vaihingen dataset. (IRPRS) The left column is Original Picture. The middle column is the Ground Truth of the Mask, and the right column is the Predictions. This is a representation of multiclass segmentation analysis. The activation layers and filters are observed in contrast to the Postdom dataset. (IRPRS)[9, 10]

Scores

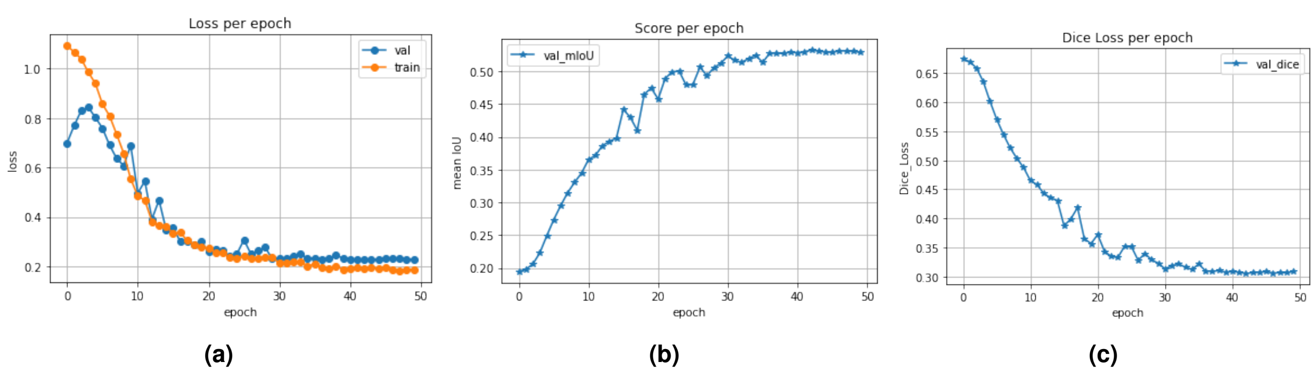
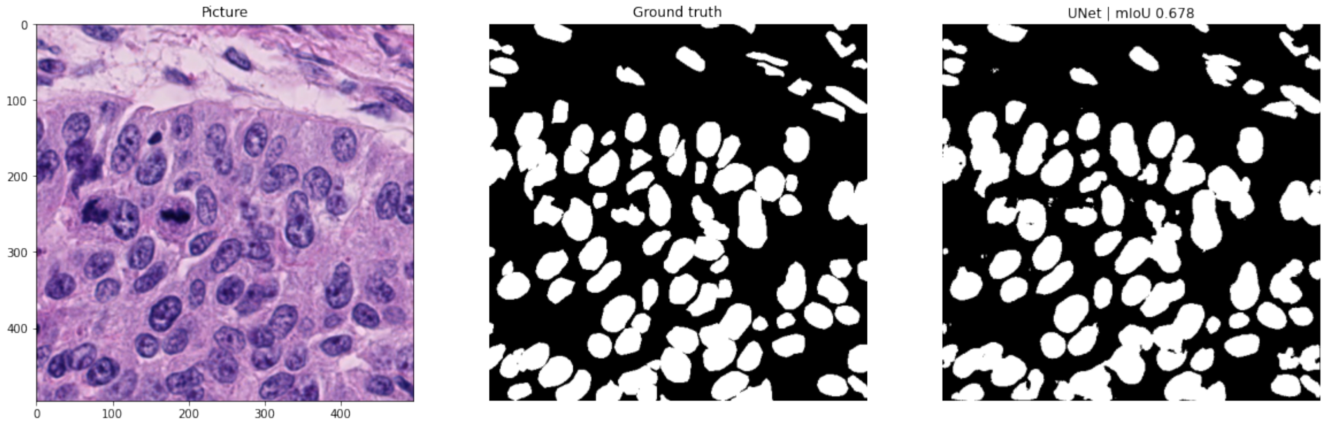
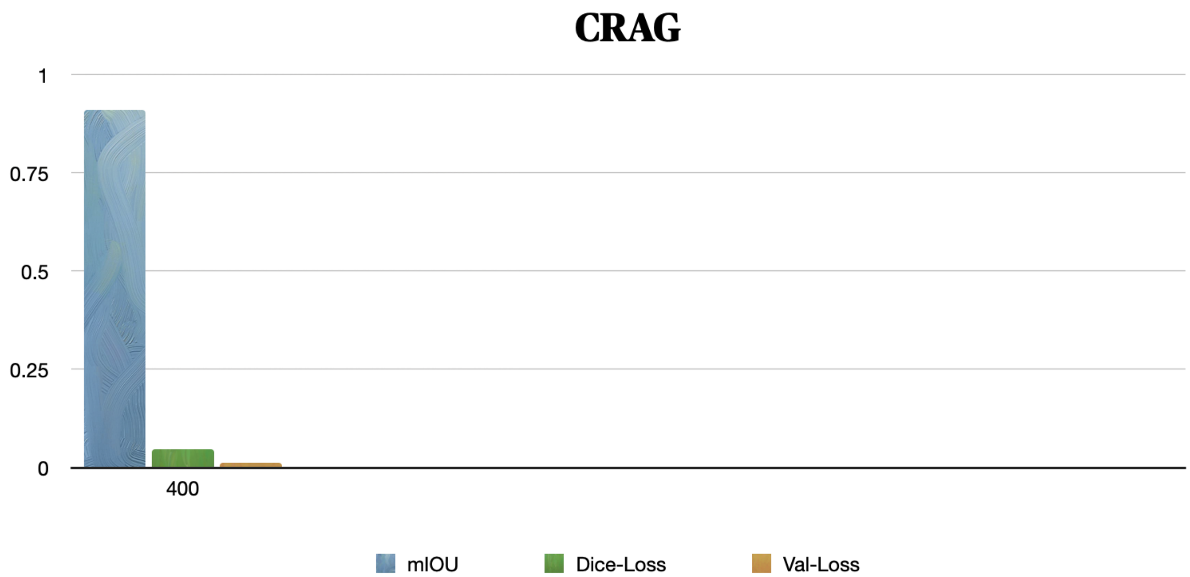


Figure 3. The Above results are of the trained-Unet Model over the CPM15 dataset. The Scores represent the training performance with Jaccard Loss (a), Mean IOU (b), and Dice Loss (c).[1, 3, 5, 6]



(a)



CRAG

Epoch	mIOU	Dice-Loss	Val-Loss	
400	0.91	0.0464	0.013	

(b)

Figure 4. (a) The above figure represents training or fine-tuning of the model that provides this kind of result over the CPM15 dataset. The left column is Original Picture. The middle column is the Ground Truth of the Mask, and the right column is the Predictions. (b), The sample scores of the CRAG dataset, when tested with a cross-trained model on GLAS, show evidence of domain shift.[1,6,9,10]

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