

Novel Convolutional Embeddings for Domain Adaptation in Medical Segmentation

Supervisor: Erick Purwanto

Authors: Mingzirui Wu, Sitang Gong, Dongheng Lin, Qiaochu Zhao, Suqi Zhang, Doyeon Kim

Abstract

Medical Artificial Intelligence recently focuses on **annotating organs** on cell image dataset to perform clinical diagnoses and to suggest suitable treatments. While there are some progress on **single-organ dataset** [1], demands from Medical Community for a more accurate AI model capable of segmenting **multi-organ dataset** arise. Our team attempted new methods of data processing and novel models to segment Functional Tissue Units (FTU). We introduced the **Convolutional Embedding** algorithm and obtained an accuracy of 0.88 and similarity coefficient of 0.81 in **HuBMAP + HPA - Hacking the Human Body 2022 Kaggle Competition** [2]. We have **seized a GOLD prize**, and achieved **the 5th rank out of 920 competitors**.

Background & Method

Introduction

Given a dataset consists of biopsy images and their masks from five different organs: **kidney, prostate, large intestine, spleen, and lung**, we want to annotate the FTUs within them.

Original Images and Masks

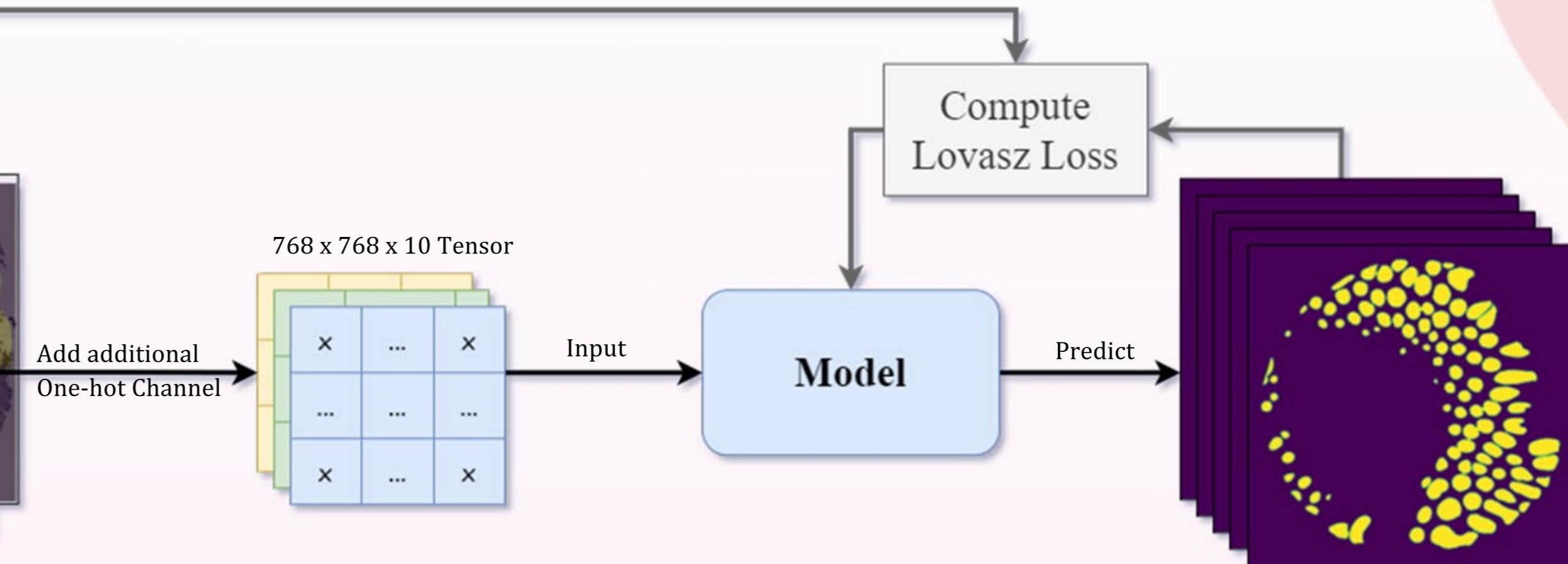


In order to cope with dataset diversity and organ type inconsistency:

- Firstly, we have applied complicated **Data Augmentation and Color Stain Normalization** combinations to cover all the features that may appear in the diverse testing set.
- Secondly, we implemented **Multimodal Mechanism** by adding one-hot organ channels to each sample which will then be converted to **Organ Embeddings** by the model.

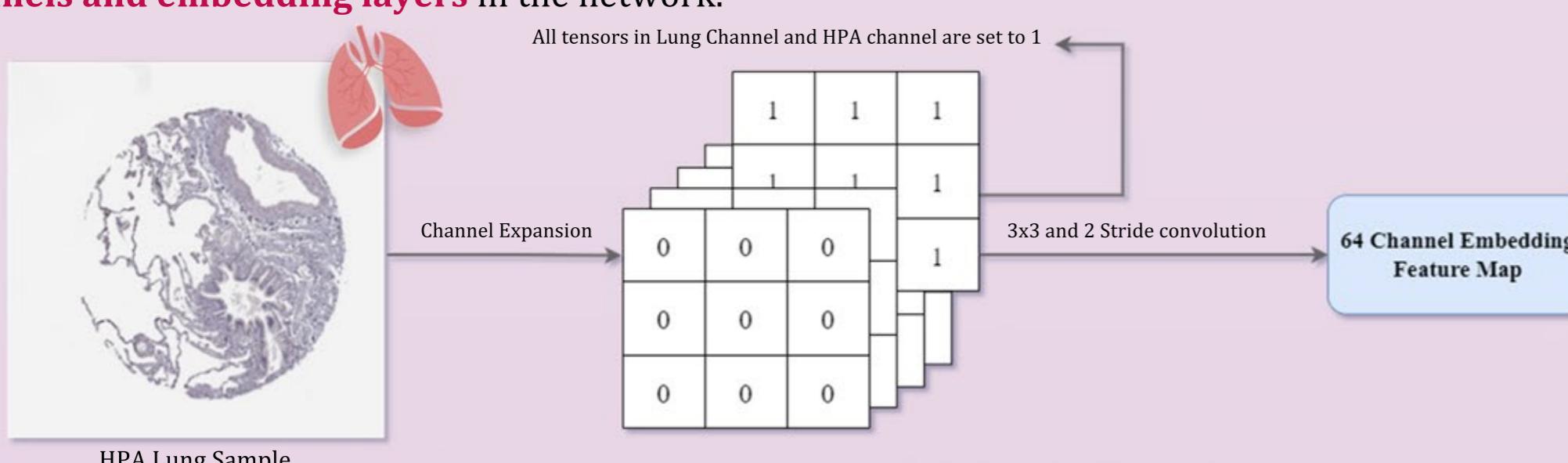
General Process

Provide Groundtruth Masks



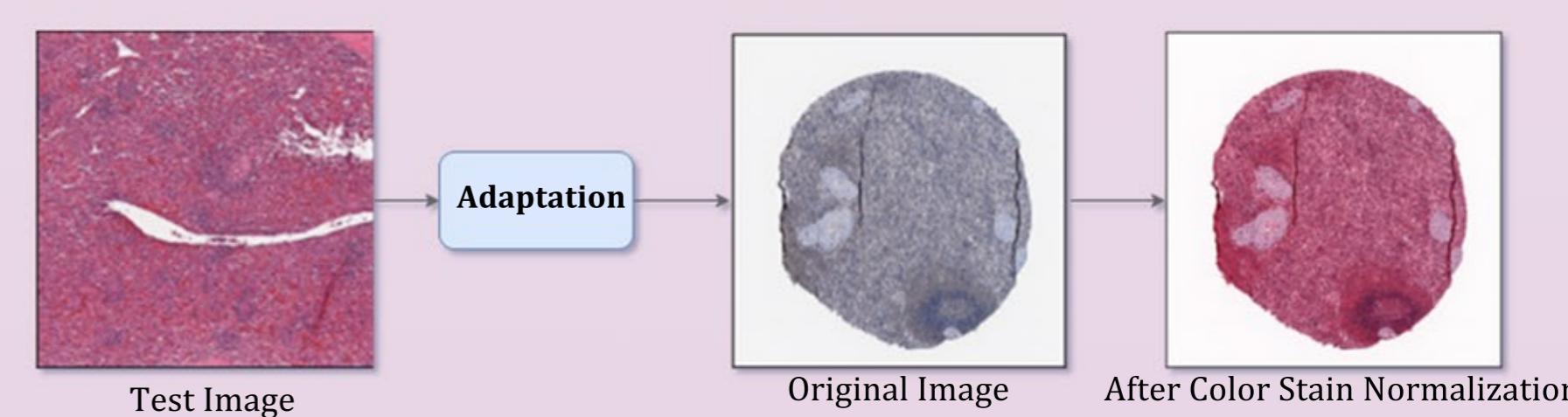
Convolutional Embedding Representation

Given the samples are of different types, which shows great **inter-class diversity** as illustrated in the histogram, **multimodal** based conditional segmentation is needed, which is realized by **additional channels and embedding layers** in the network.



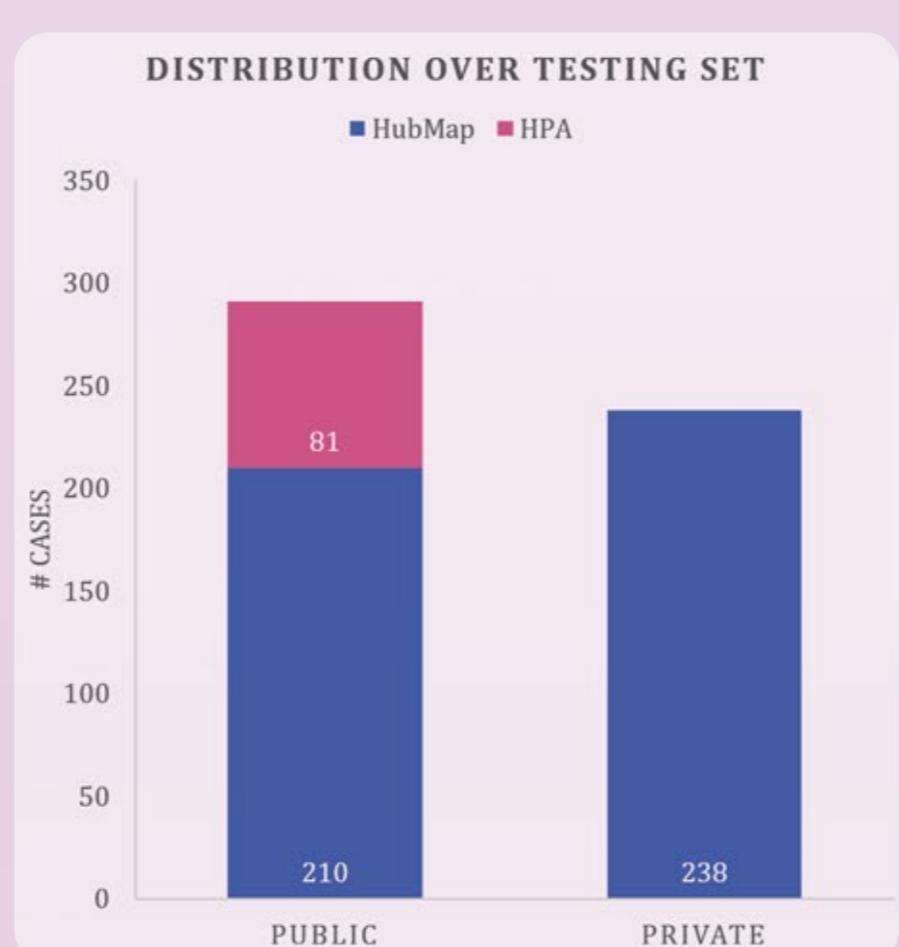
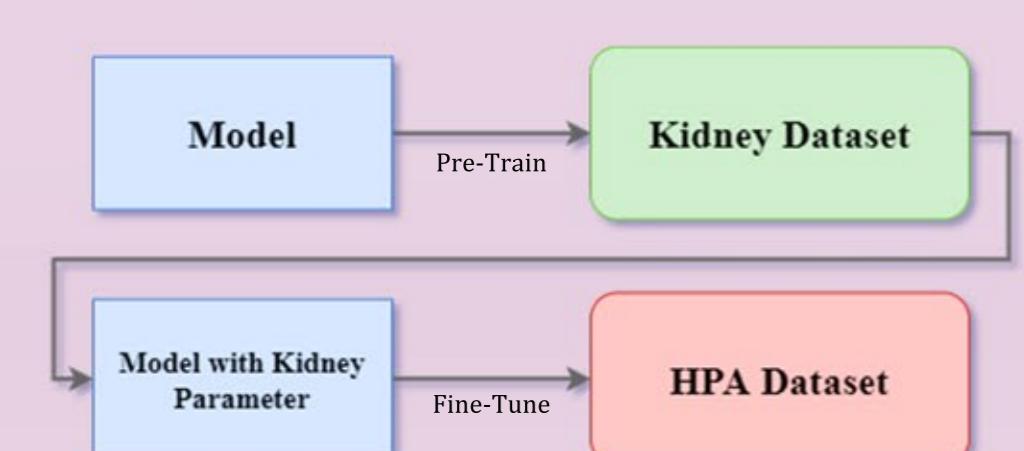
Color Stain Normalization Preprocessing

There are some differences between training images and testing images in terms of **color stain**. Thus, **Macenko** algorithm is used to produce **color normalized** training images and then combine them with the original training set.



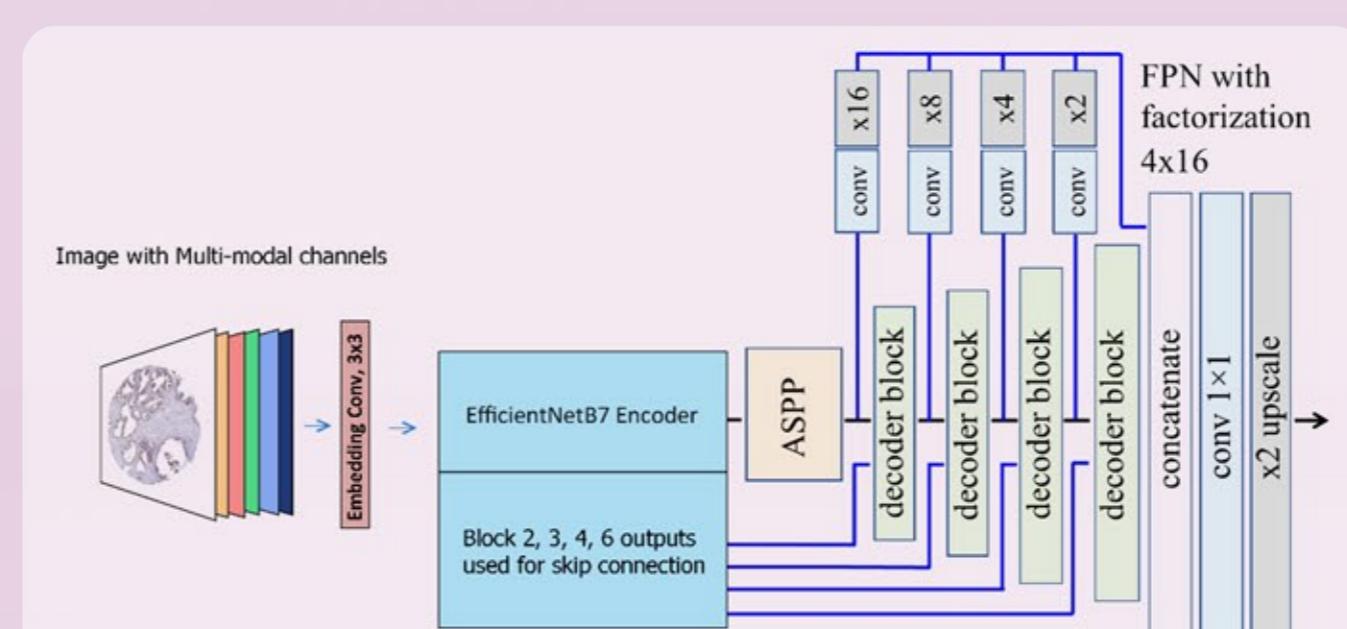
HubMap Transfer Learning

With consideration to the difference between our training set, **HPA dataset**, and the testing dataset contains many **HubMap samples**. The research team **pretrained** the model on a previous competition, and then **fine-tune** the model on current competition.



Model Architecture

The novel network is based on the **EffUNet** [3], in which the **EfficientNet encoder** creates a representation of features at different levels [4], while the **decoder** combines the features and generates a prediction as a segmentation mask.



Dice Coefficient

This competition is evaluated on the **mean Dice coefficient**, which can be used to compare the pixel-wise agreement between a predicted segmentation and its corresponding ground truth.

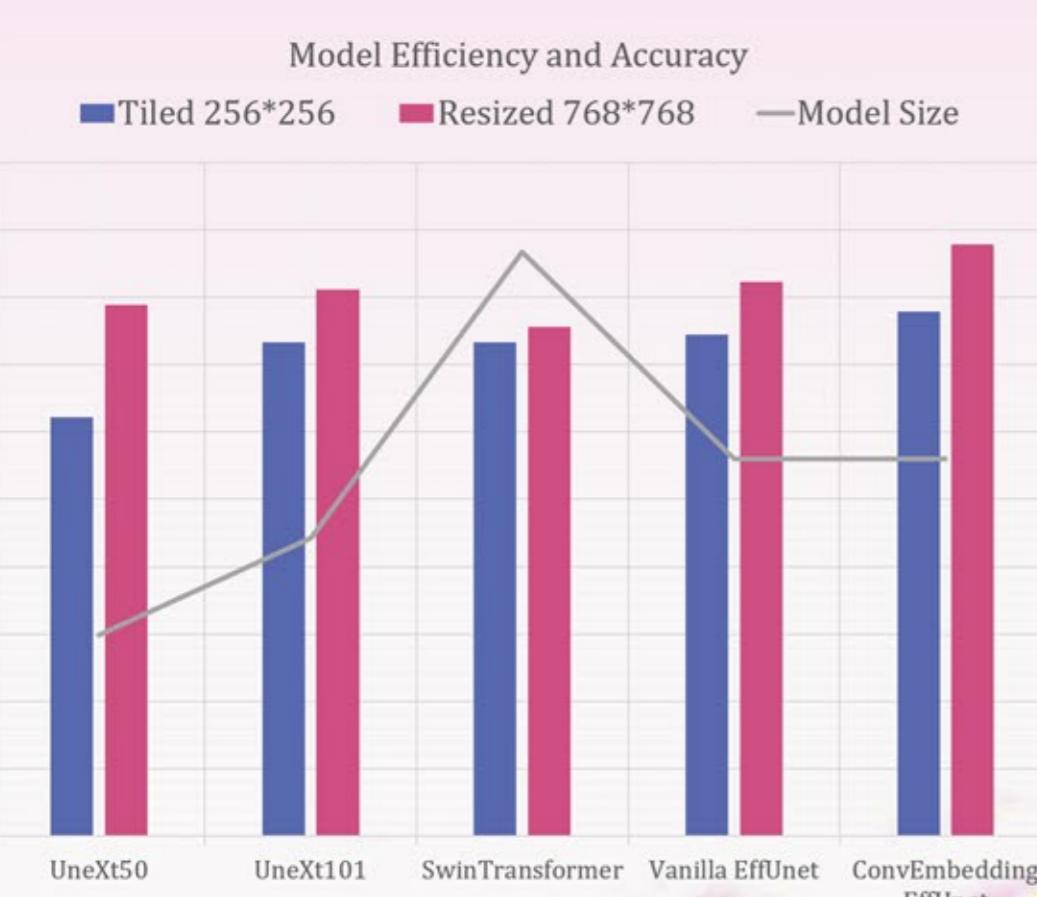
$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$

Lovász Loss

Lovász loss is a **differentiable surrogate** of Dice coefficient and can be used for optimizer [5]. The loss formula is given by:

$$\text{loss}(f) = \frac{1}{|\mathcal{C}|} \sum_{c \in \mathcal{C}} \overline{\Delta}_{J_c}(m(c))$$

Results



Discussion

Applying Transformers to Computer Vision is a prevailing research area. Many researchers claims that **Vision Transformer** is always a superior to **Convolutional Networks** in terms of **Domain Adaptation**, it lacks embedding information capabilities to overcome data diversity.

However, our team has tested several networks in the competition, and as a result, our novel **Convolutional Embedding** method is not only outperforming in terms of **accuracy**, but also more **efficient** than those **Transformer counterparts**. The model achieves a Dice score of 0.88 on local validation and 0.81 in testing set which is **11% higher** than SwinTransformer's score, while the size of the model is **as small as 60%** of the SwinTransformer [7] solution.

Conclusion

Our novel **Convolutional Embedding strategy** successfully enhanced the final accuracy result to **81%**, showing that embeddings of **organ metadata** helps in **improving performance** of a simpler convolutional model in Medical Segmentation.

Achievement:

Gold Prize

5 SURF2022_SC440



0.81

We have reached **5th rank out of 920 teams** with a score very close to the top placeholder's score **0.82**.

Reference

- [1] Shubham, S., Jain, N., Gupta, V., Mohan, S., Ariffin, M. M., & Ahmadian, A. (2021). Identify glomeruli in human kidney tissue images using a deep learning approach. *Soft Computing*, 1-12.
- [2] HuBMAP + HPA - Hacking the Human Body, Segment multi-organ functional tissue units, <https://www.kaggle.com/competitions/hubmap-organ-segmentation>
- [3] Tan, M., & Le, Q. V. (2019). Efficientnet: rethinking model scaling for convolutional neural networks.
- [4] Baheti, B., Innani, S., Gajre, S., & Talbar, S. (2020). EffUNet: A Novel Architecture for Semantic Segmentation in Unstructured Environment. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, IEEE.
- [5] Berman, M., Triki, A. R., & Blaschko, M. B. (2018). The Lovasz-Softmax Loss: A Tractable Surrogate for the Optimization of the Intersection-Over-Union Measure in Neural Networks. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE.
- [6] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., & Zhang, Z., et al. (2021). Swin transformer: hierarchical vision transformer using shifted windows.