HISTOPATHOLOGY SEGMENTATION

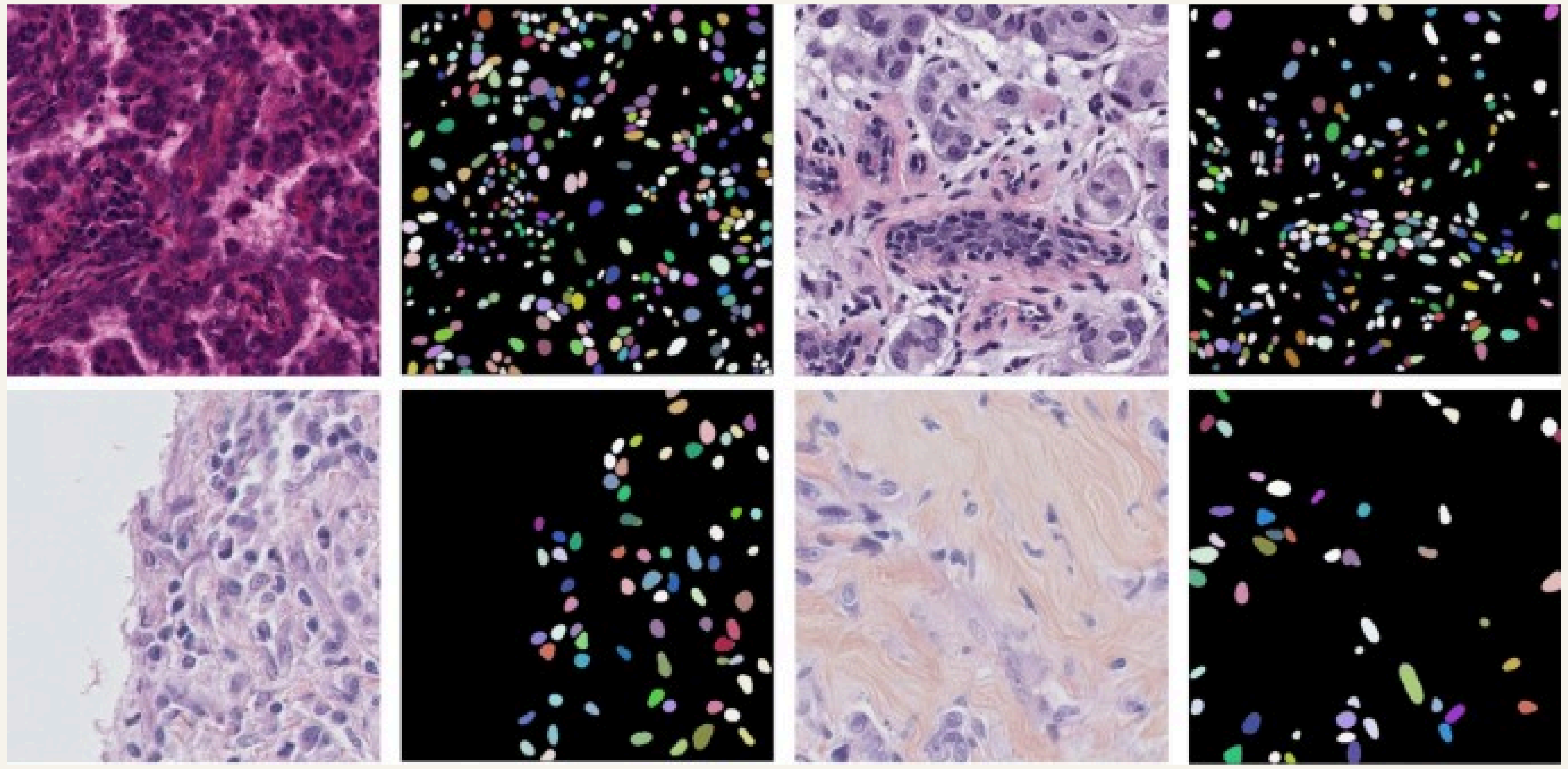
YAMAHA Hackathon

IIT Mandi | 2024

Group 32A

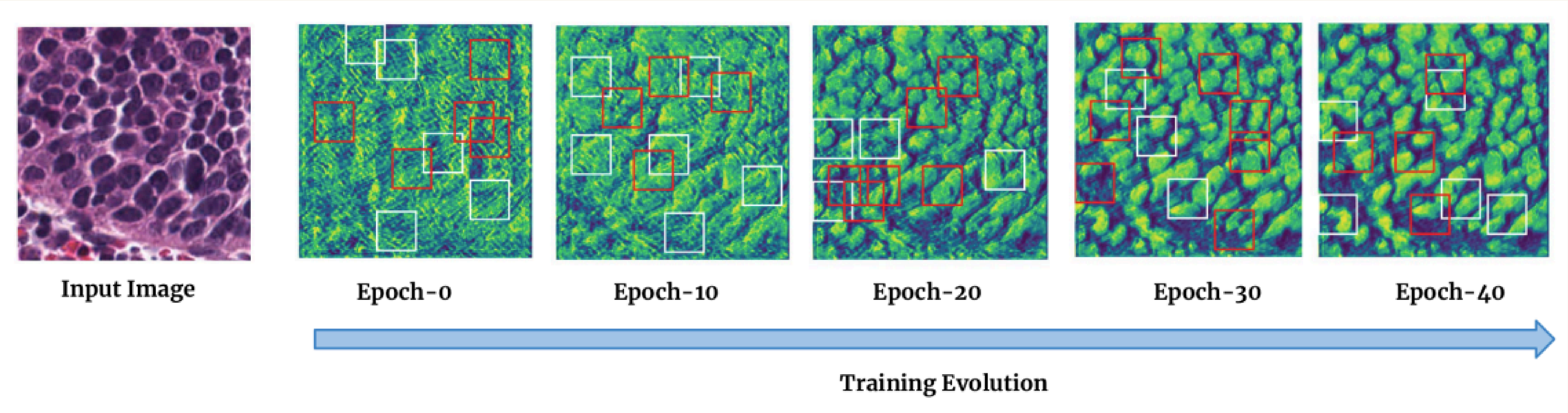
PROBLEM STATEMENT

Traditional annotation methods for histology images are time-consuming and costly. HistologyNet uses self-supervised learning to learn relationships over less available data and later finetunes it on labeled datasets for predicting diseased cells.



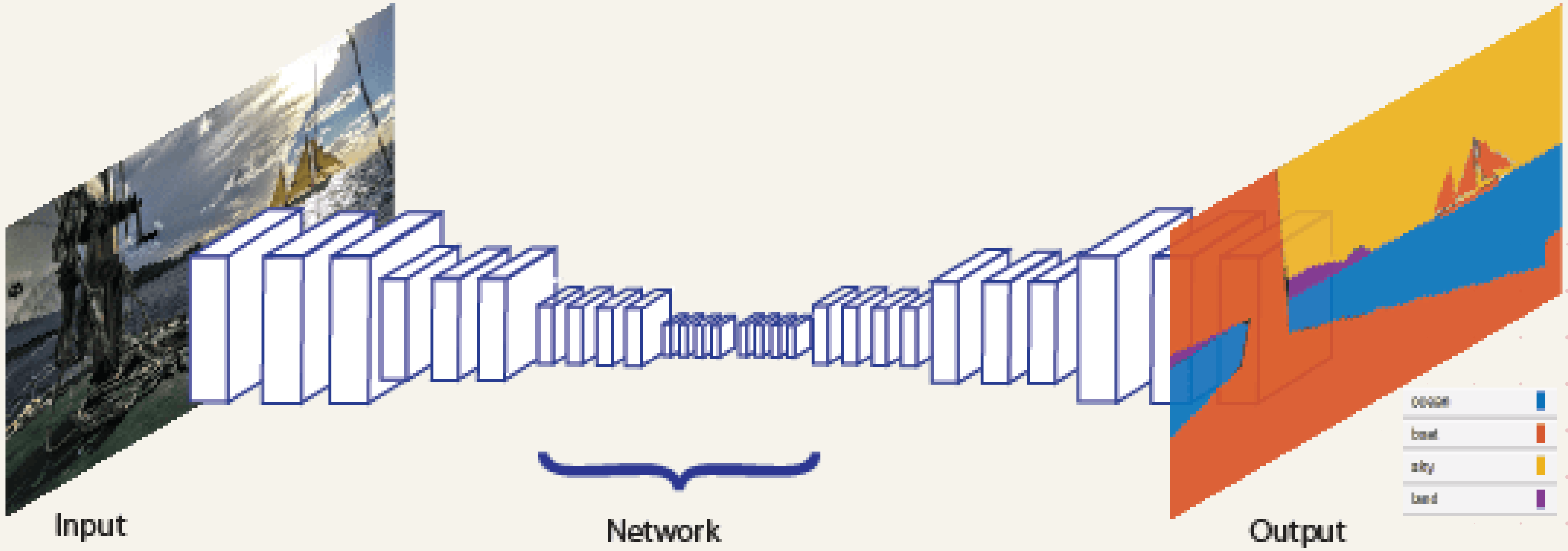
OVERVIEW

- Introduction
- Literature Review
- Methodology



INTRODUCTION

Segmentation models are widely used for identifying pixel-wise class distribution in a sample which can help us in problems like Histopathology.



INTRODUCTION

- Basic Segmentation architectures like UNet, which is an Encoder-Decoder Network, can learn simpler features, but for tasks like histopathology, more complex networks must be employed.

- Furthermore, these networks use supervised samples to calculate losses but often manually annotated datasets are difficult to acquire.

- Therefore, an unsupervised learning method is needed which can learn from pretext tasks such as color prediction, reconstruction, etc.

LITERATURE REVIEW

Papers Reviewed:

- Haq, M.M., Huang, J. (2022). Self-supervised Pre-training for Nuclei Segmentation. In: Wang, L., Dou, Q., Fletcher, P.T., Speidel, S., Li, S. (eds) Medical Image Computing and Computer Assisted Intervention – MICCAI 2022. MICCAI 2022. Lecture Notes in Computer Science, vol 13432. Springer, Cham. https://doi.org/10.1007/978-3-031-16434-7_3

- Boserup, N., & Selvan, R. (2022). Efficient Self-Supervision using Patch-based Contrastive Learning for Histopathology Image Segmentation. ArXiv. https://doi.org/10.7557/18.6798

LITERATURE REVIEW

- ## Approaches: Unsupervised Learning
  - Self-supervised learning based on patch contrastive loss optimization.
  - Region-level triplet loss to learn the embedding space. In the embedding space, it is expected that features should have similarities and dissimilarities among the same and different types of patches.
- ## Approaches: Supervised Learning for Finetuning
  - We finetune our networks like a combination of pre-trained color-based UNet and Patch-based segmentation, and TransUNet, which is Attention based UNet with Vision Transformer Backbone.

METHODOLOGY

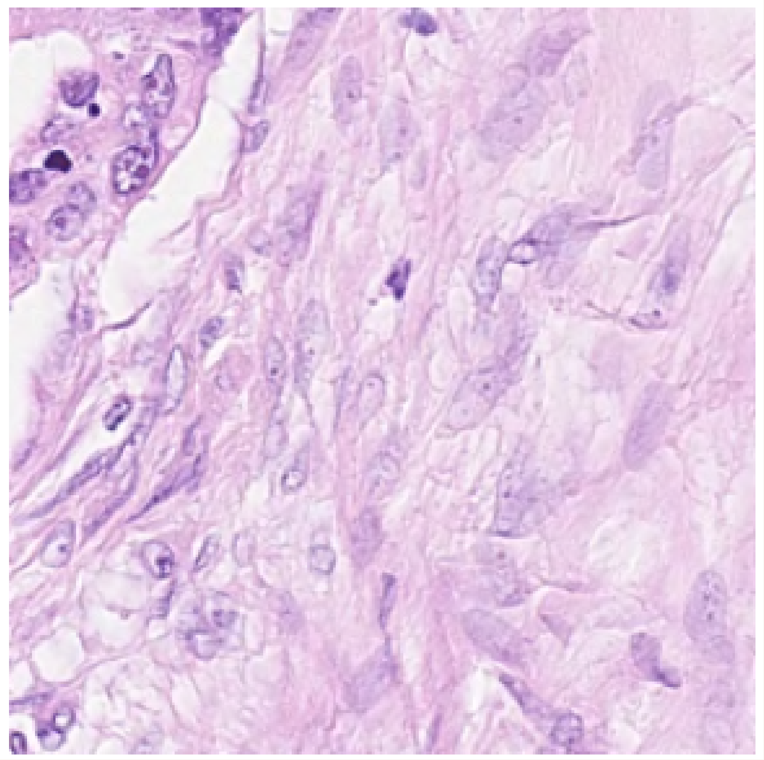
1 Pretraining UNet with Relevant Pretext Tasks

Designing of Specific Pretext Tasks plays an important role for capturing the information content of unlabelled data and leveraging it. We use the following Pretext tasks:

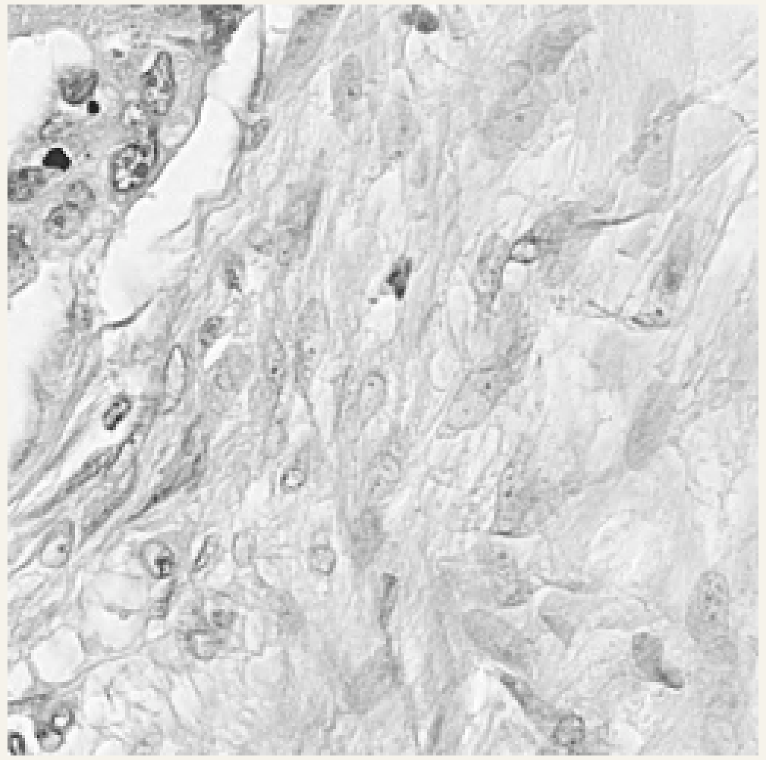
1. Coloration
2. BACH Constrastive Segmentation

A.

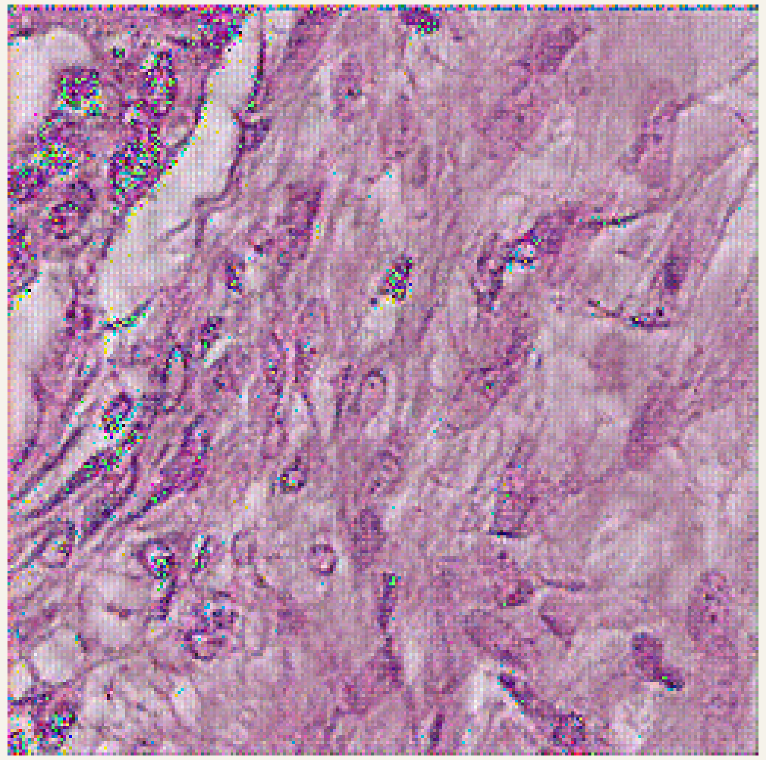
Coloration



Original



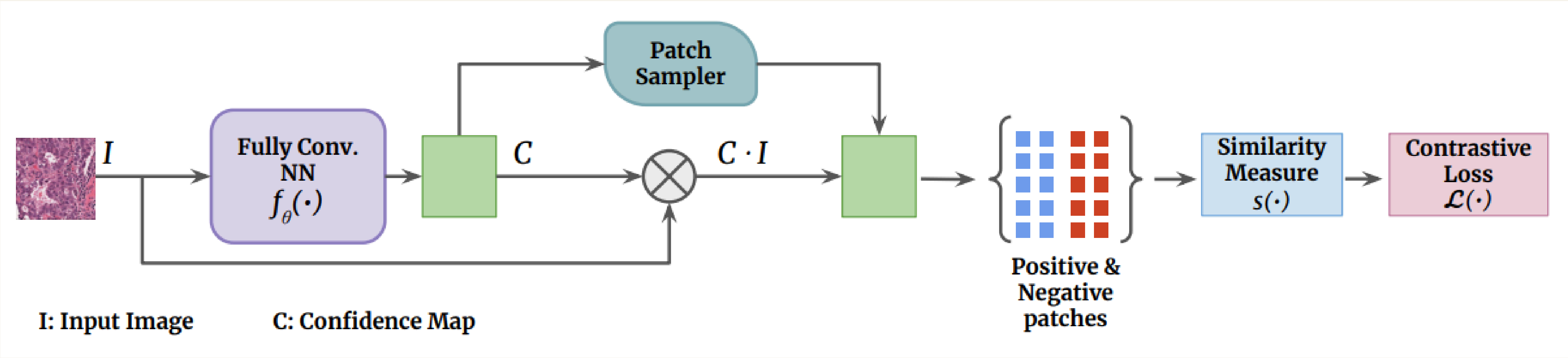
Greyscaled



Reconstructed

The UNet pretrained with coloration and then fine tuned on the labelled data gave a Dice Score of 0.7479 on unseen data. Specifically for the test data provided, the model acquired a Dice Score of 0.74

B. Contrastive Segmentation



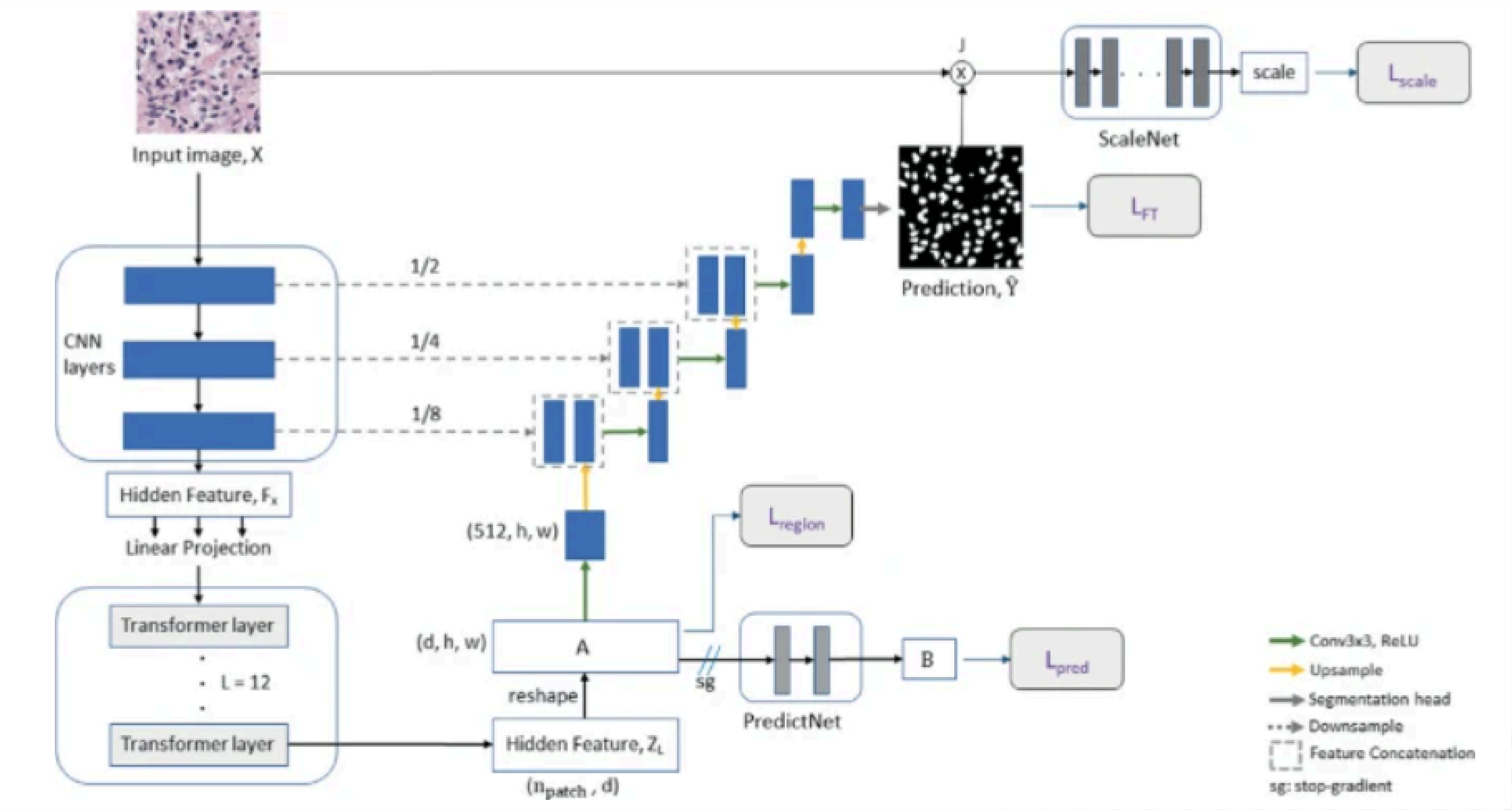
$$\mathcal{L}_{\text{intra}} = -\sum_{k=1}^{K} \frac{1}{|P_k|^2} \sum_{r,p\in P_k} \log \frac{\exp(s(r,p))}{\sum_{n\in N_k}\exp(s(r,n))}.$$

$$\mathcal{L}_{\text{inter}} = -\sum_{k=1}^{K}\frac{1}{|P_k|^2}\sum_{r,p_k\in P_k}\frac{\exp(s(r,p_k))}{\sum_{i=1,[i\neq k]}^{K}\sum_{p\in P_i}\exp(s(r,p))}$$

- We divide our output from an FCNN which returns 2 channels into patches. These patches belong to a single class (Positive or Negative) and contribute to inter channel and intra channel losses which decrease distances in positive patches in intra channel loss and increase in inter channel loss. The opposite is done for negative patches and positive patches.

2

TransNuSS



Input image, X
ScaleNet
scale
L_{scale}
Prediction, $\hat{Y}$
L_{FT}
CNN layers
1/2
1/4
1/8
Hidden Feature, F_x
Linear Projection
(512, h, w)
L_{region}
Transformer layer
L = 12
Transformer layer
(d, h, w)
A
reshape
Hidden Feature, Z_L
(n_{patch}, d)
sg
PredictNet
B
L_{pred}
Conv3x3, ReLU
Upsample
Segmentation head
Downsample
Feature Concatenation
sg: stop-gradient

Results and Conclusions

We Finally ensembled the three models to obtain our inferences.
Here are the outputs:

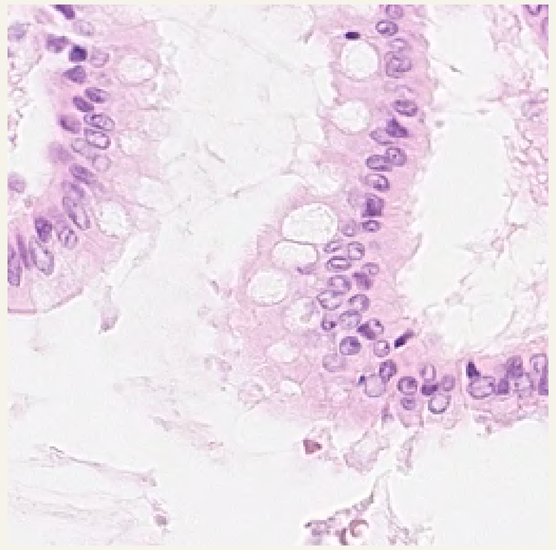
Validation Scores:

- Dice: 0.7987

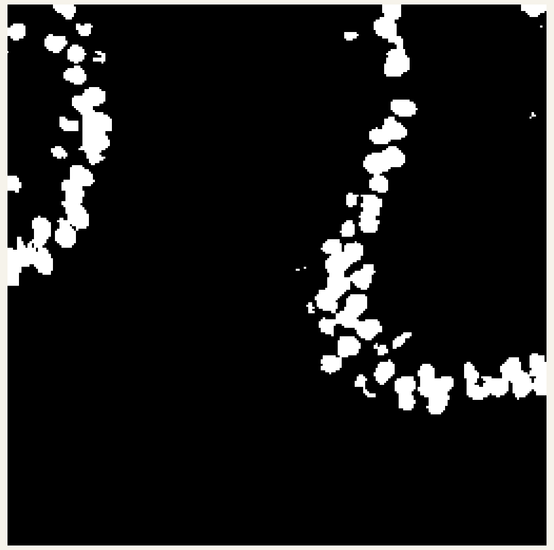
Metrics:

- First Evaluation: Dice: 0.7443 JI: 0.6080
- Second Evaluation: Dice: 0.7547 JI: 0.6219

Inference Time: 27 ms

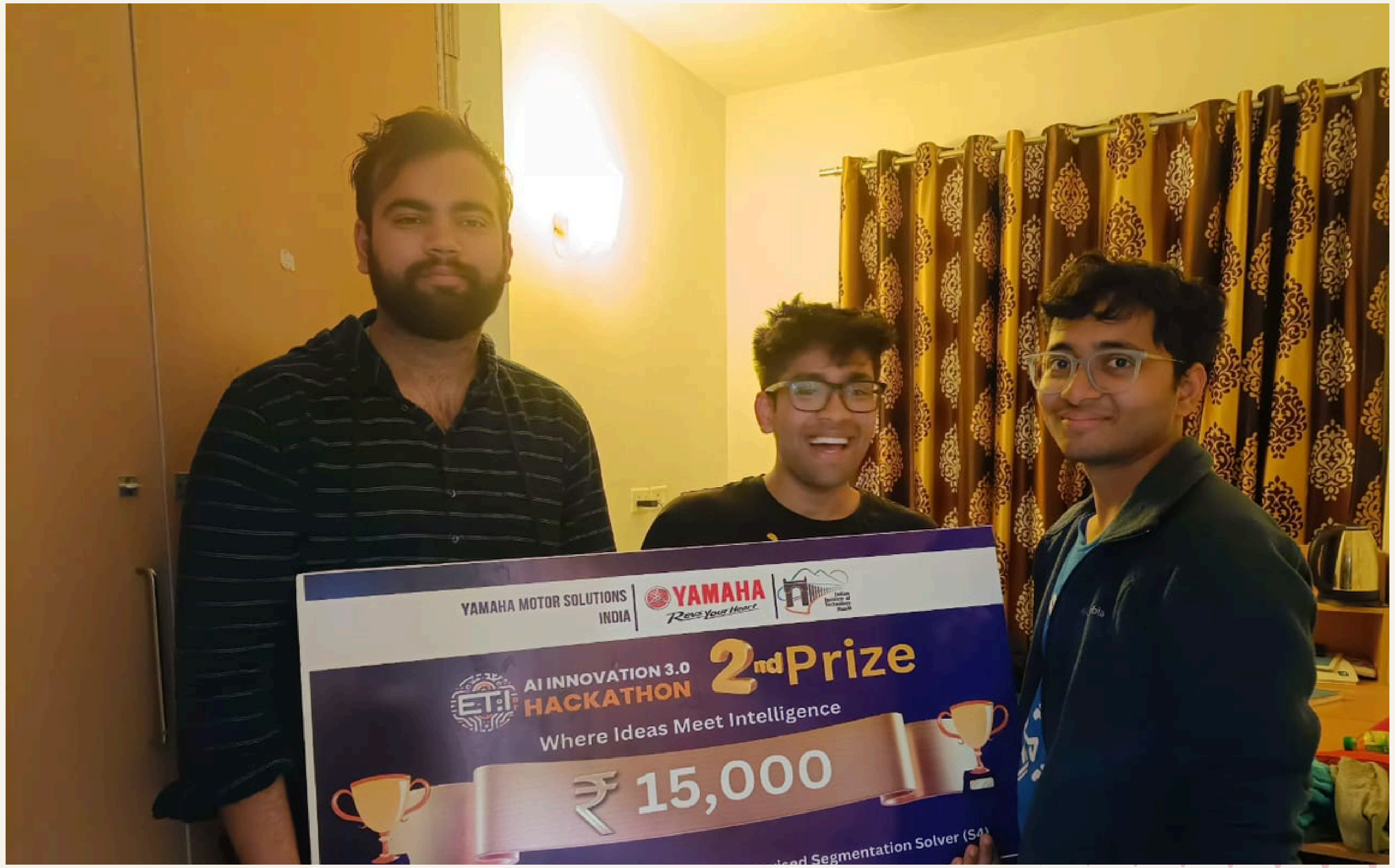


Original Image



Segmentation Masks

THANK YOU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