Multimodal Medical Imaging Optimization Lab
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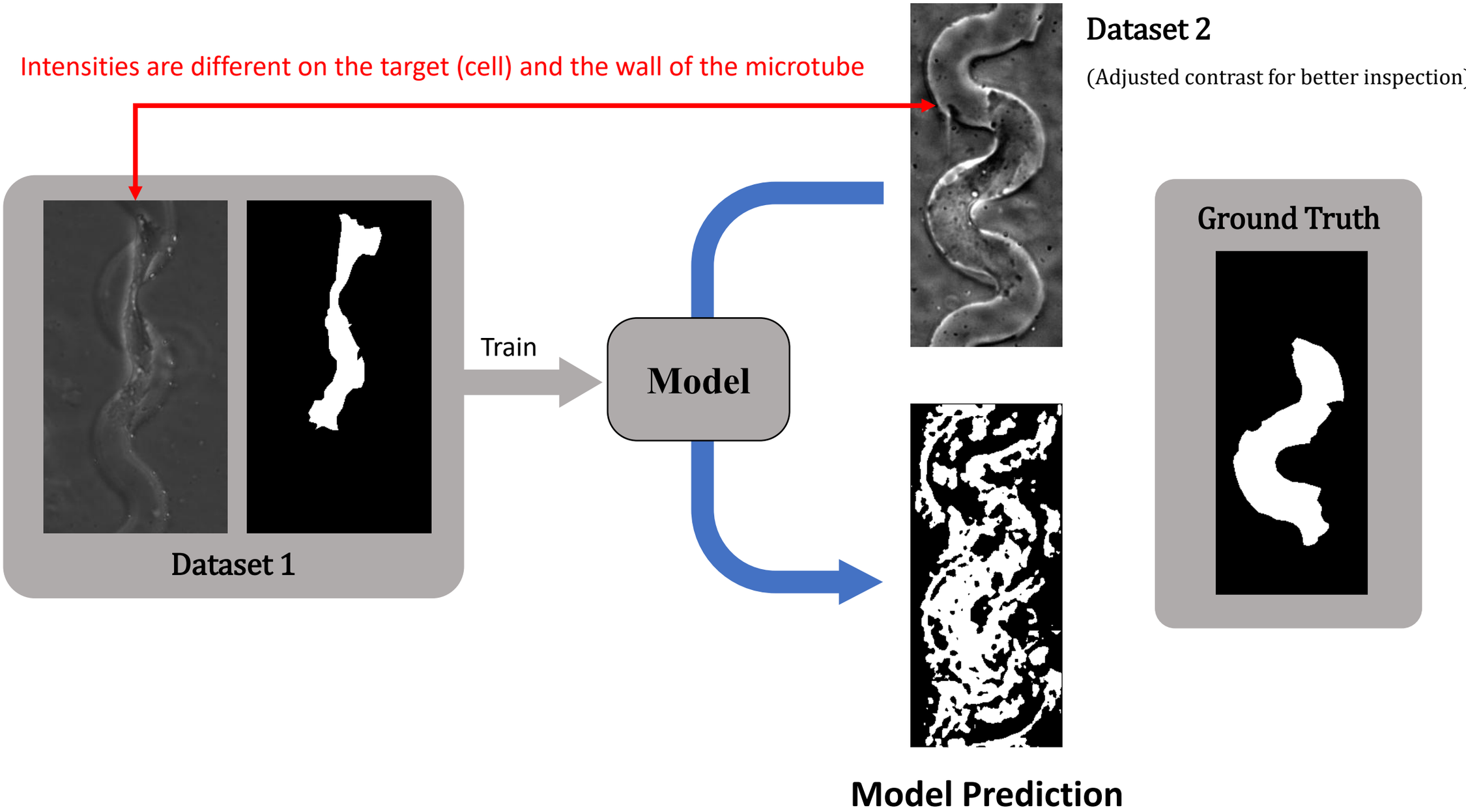
Finetuning existing models trained using Patch-based Attention U-Net for better generalization across different datasets

Introduction

- Image segmentation models which used our designed low-resource training strategy (patch-based preprocessing + Attention U-Net) **underperforms on datasets with similar morphology but different intensity distribution.**
- We expect that model can at least identify the same object in similar images as this is what we would expect a robust segmentation model can do.


Intensities are different on the target (cell) and the wall of the microtube
Dataset 2
(Adjusted contrast for better inspection)
Ground Truth
Train
Model
Dataset 1
Model Prediction

Experiment design

- Train a model solely based on “Dataset 1” for finetuning
- Use images from Dataset 2 to finetune the raw model from Dataset 1
- Increase amount of image/mask pairs from dataset 2 to finetune base model and compare model performance

  (raw model / 5 image / 10 image / 15 image / 20 image)

Experiment design

- Training set: first 25 images from Dataset 2
- Finetuning dataset: 5/10/15/20 images from Dataset 2
- Test set: 6 remaining images from Dataset 1 + last 11 images from Dataset 2

Training settings

Preprocessing: Cropped to 128*128 patches and normalized

Model: Patch-based Attention U-Net (from our paper)

Loss function: Dynamic loss function selection (from our paper)

Epoch = 100

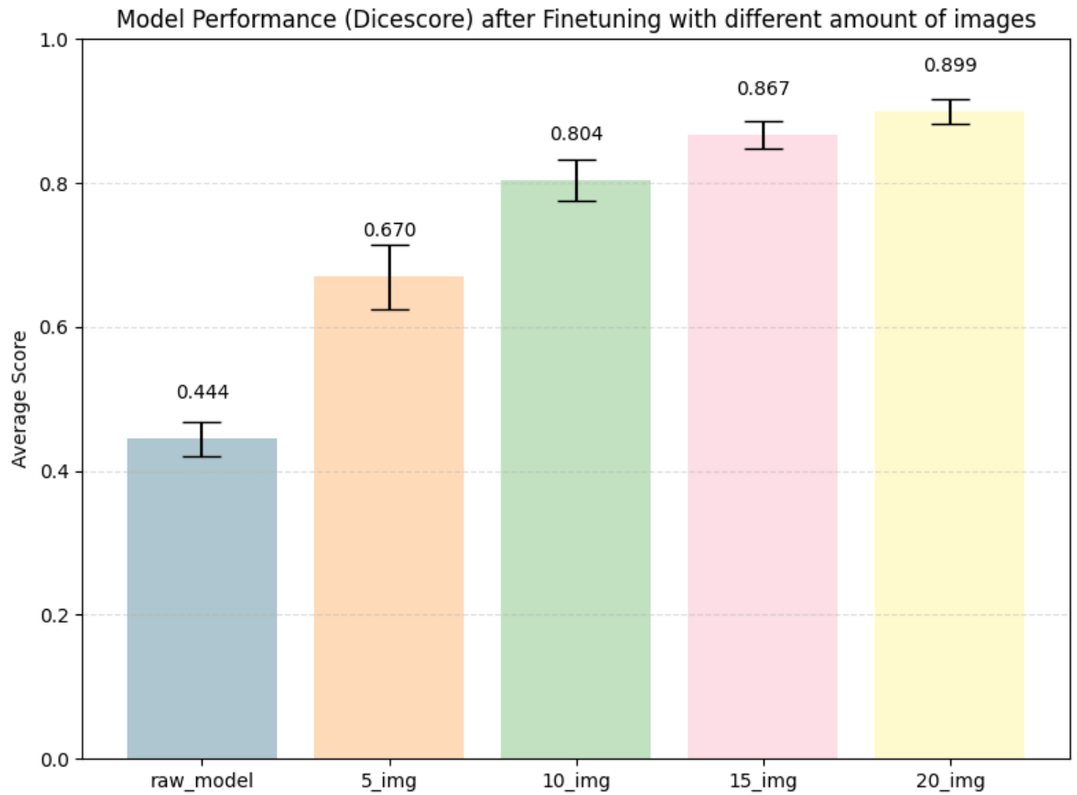
Batch_size = 4

Learning rate = 10^(-5)

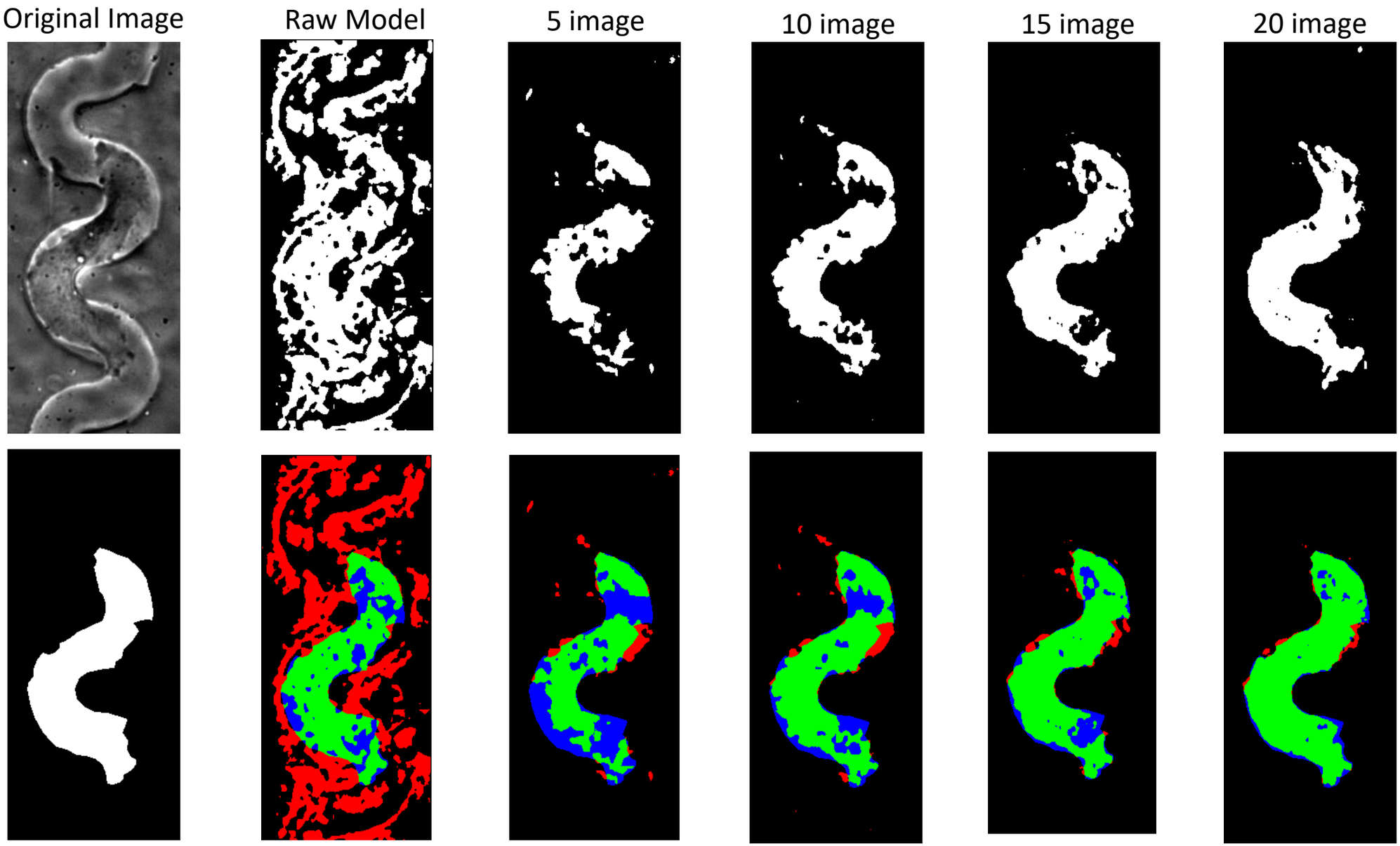
(same settings as training base model)

Results & Discussion

- Model Performance (Average Dice score)



- Model generalized better after feeding it more images from dataset 2 for finetuning
- Model didn't completely converge itself to the new dataset as more images from Dataset 2 is used for finetuning (Model didn't forget Dataset 1)


Original Image
Raw Model
5 image
10 image
15 image
20 image
Ground Truth
Overlay Comparison