Liver Cancer Segmentation on Histopathology Images

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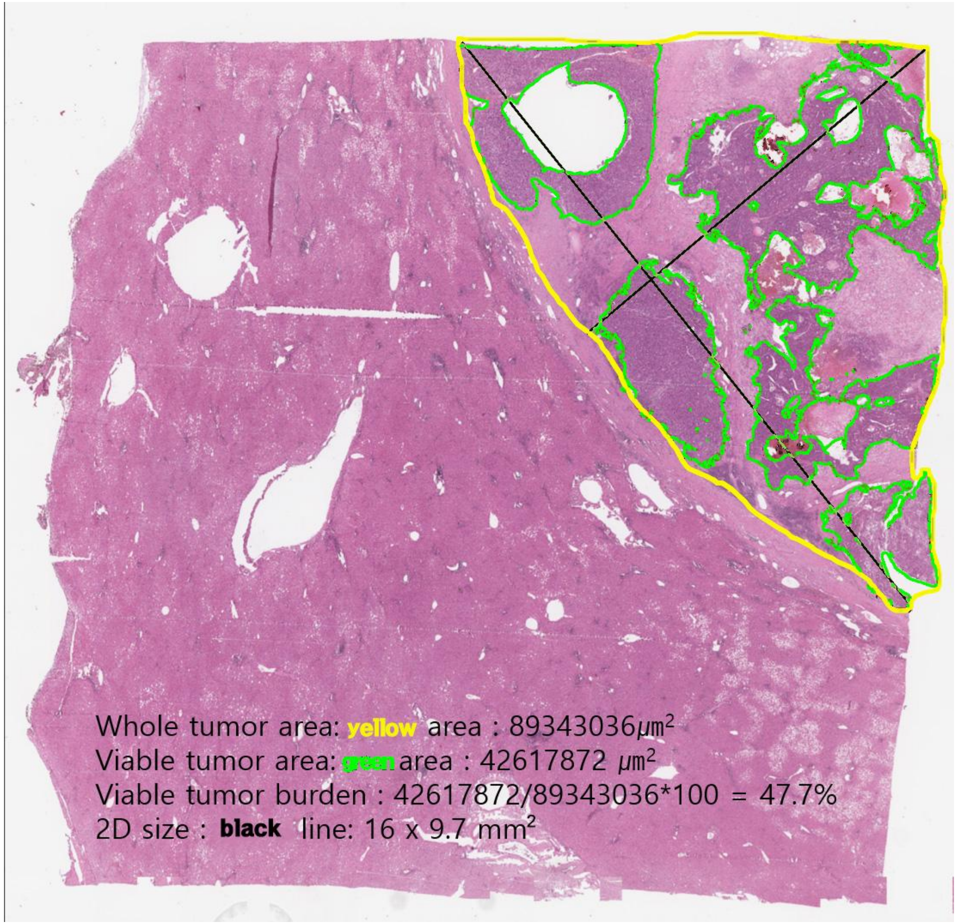
Introduction

- HCC is the 3rd leading cause of cancer deaths worldwide due to rise in non-alcoholic fatty liver disease and Hepatitis C
- Histopathology is primary prognostic tool to predict:
  - Response to treatments
- Current methods: semiquantitative grading system to estimate residual tumor burden or necrosis
  - Inefficient
  - Subjective

Tasks

1. Viable Tumor Segmentation
   Cell nests within the whole tumor area

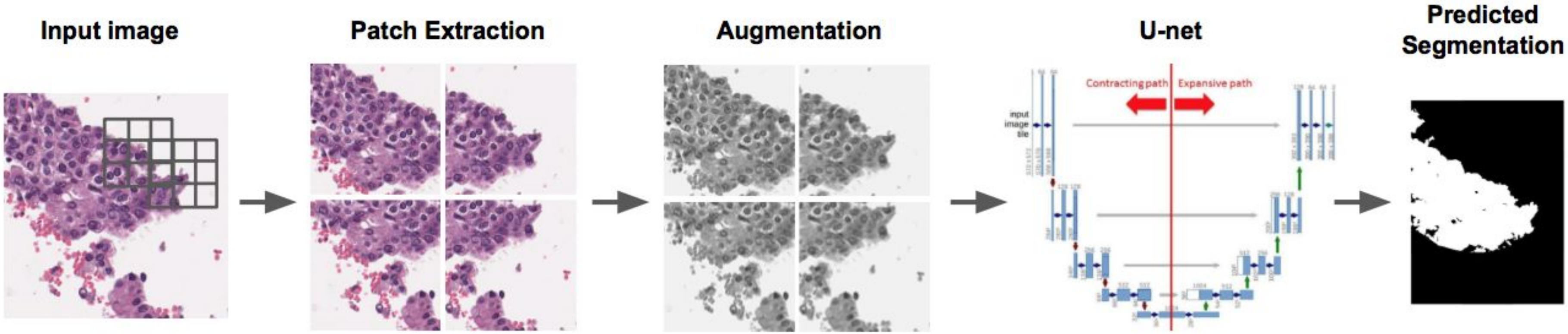
2. Model performance evaluation



Data Set

- PAIP 2019 Challenge
- Seoul National University Hospital.
- 20 WSI samples, with binary masks for viable tumor area identified by expert pathologists
- Slides scanned at 20X magnification.
- Each slide from one patient and contains one whole tumor region.

Methodology: Workflow



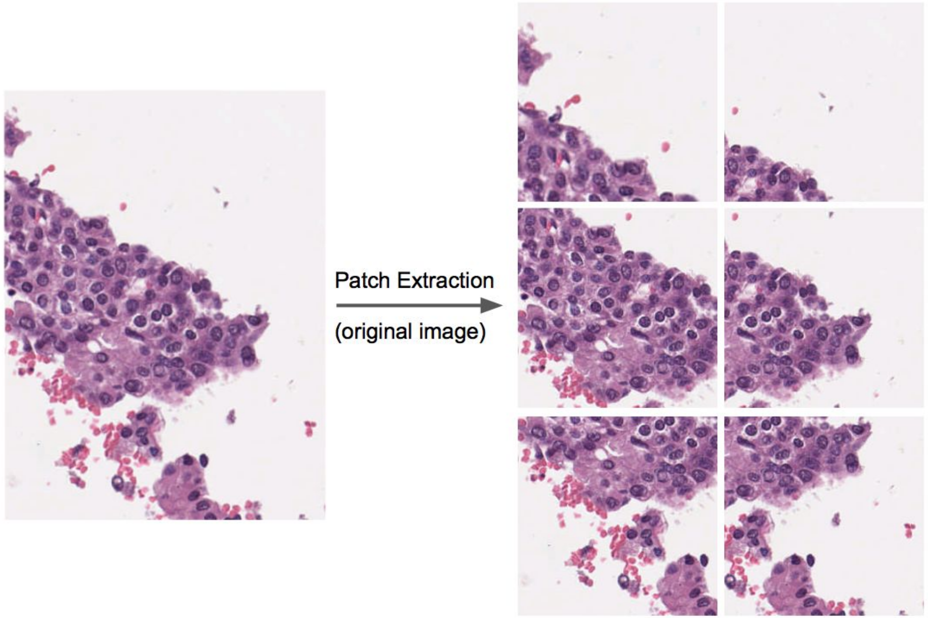
Methodology: Patch Extraction and Patch Preprocessing

Empty patch exclusion

Overlapping and non-overlapping patches

Patch size 256, 512 and1024

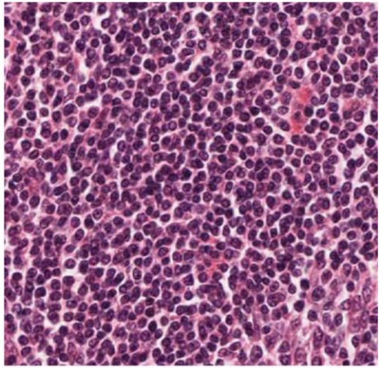
Majority vote patch stitching for final whole slide mask

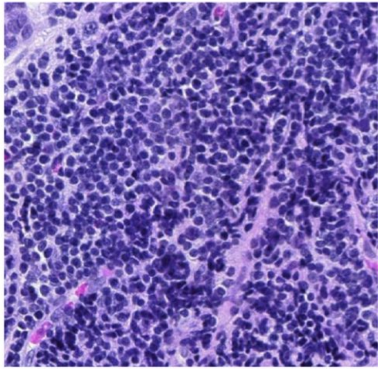


Methodology: Patch Extraction and Patch Preprocessing

Color jitter: Hue, Contrast, Saturation and brightness

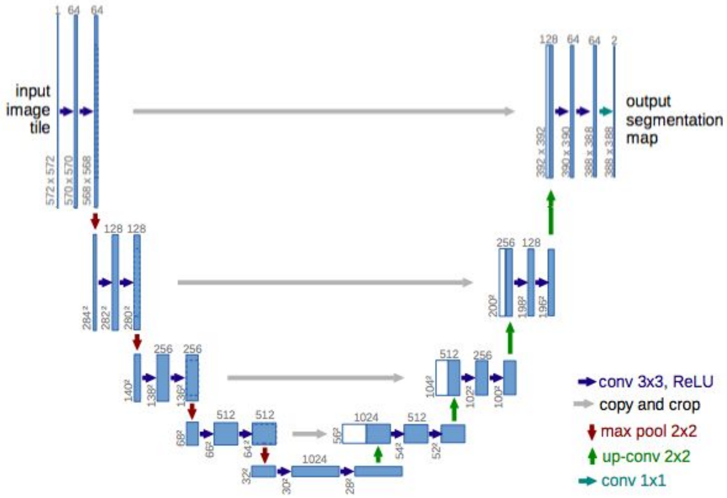
Rotation, width shift, height shift, shear, zoom, horizontal flip and fill with nearest





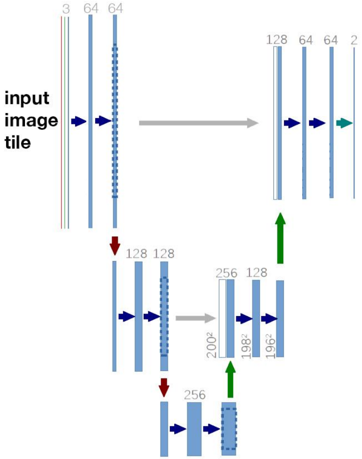
Methodology: U-Net

Default U-Net



10 convolution layers, depth 5

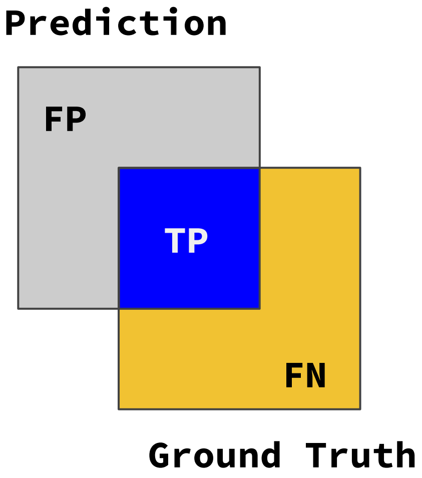
Modified U-Net



6 convolution layers, depth 3

Methodology: Performance Evaluation

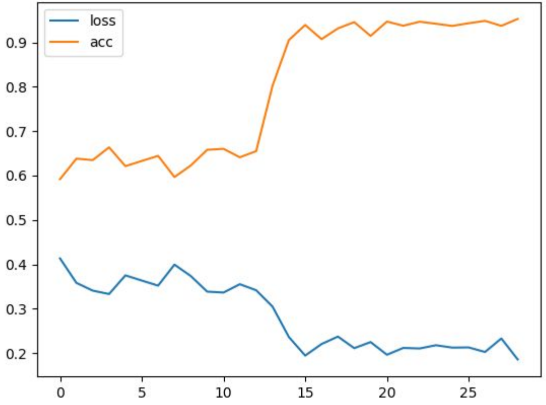
- Jaccard (IoU) $$\frac{TP}{TP + FP + FN}$$
- F1 score $$\frac{2*TP}{2*TP + FP + FN}$$
- Accuracy $$\frac{TP + TN}{TP + TN + FP + FN}$$



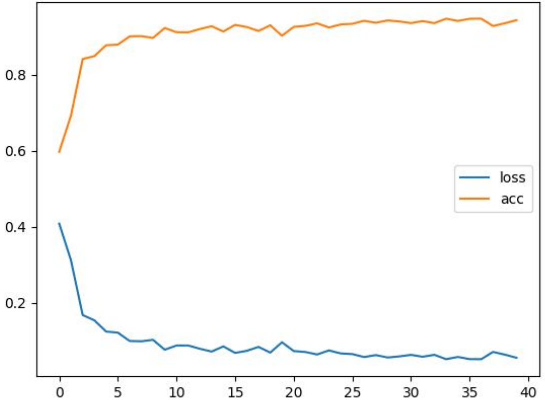
Comparison of network depth

Smaller network appears to be easier to converge

layer = 10
U-Net



layer = 6
U-Net (modified)

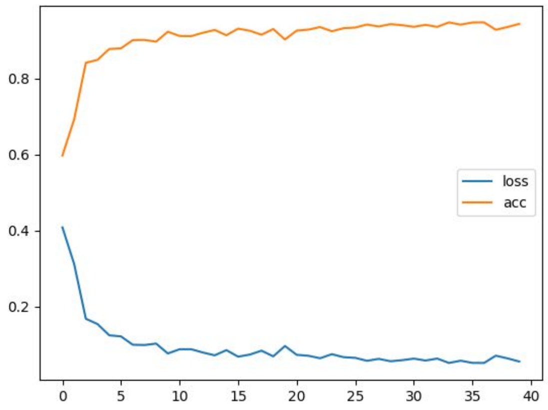


Comparison of input channels

More input channels, less time to converge

input = gray
(1 channel)

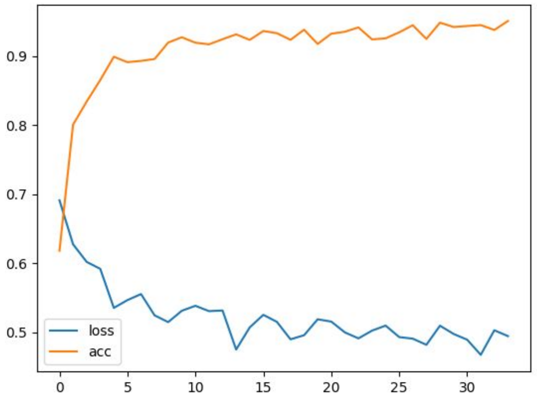
input = RGB
(3 channels)



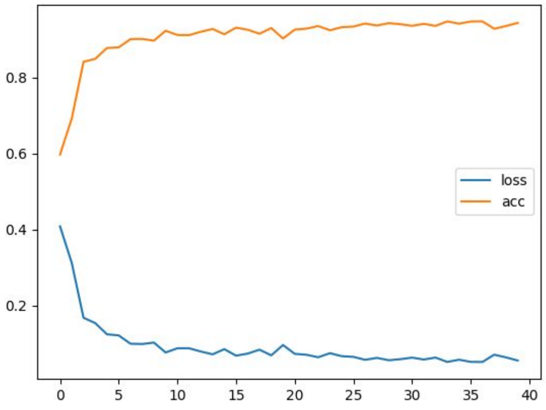
Comparison of loss function

Jaccard_distance (IoU) fits this task better

binary_crossentropy



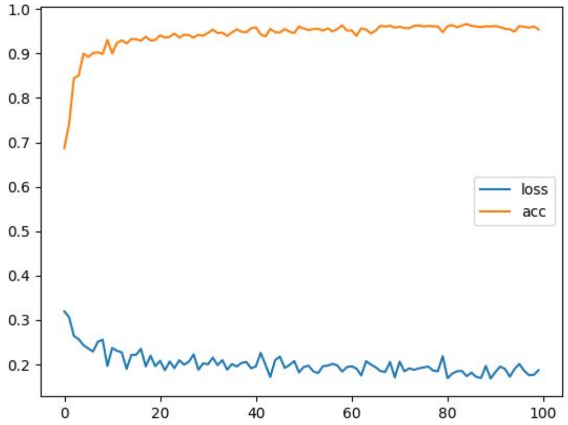
jaccard_distance



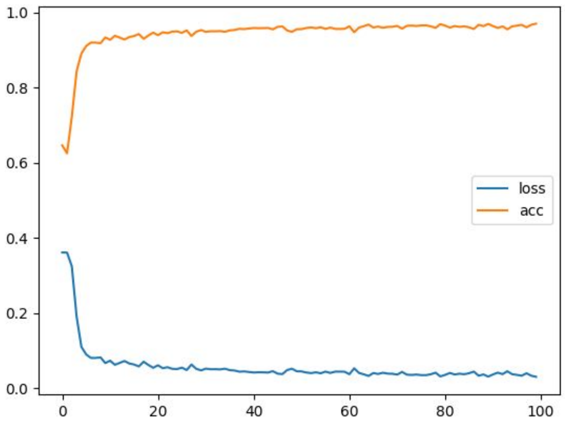
Comparison of batch size

Batch size = 8 achieves rapid convergence with good performance

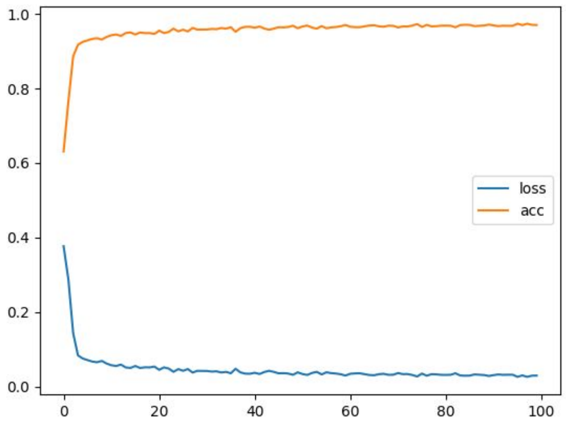
Batch size = 4



Batch size = 8



Batch size = 16

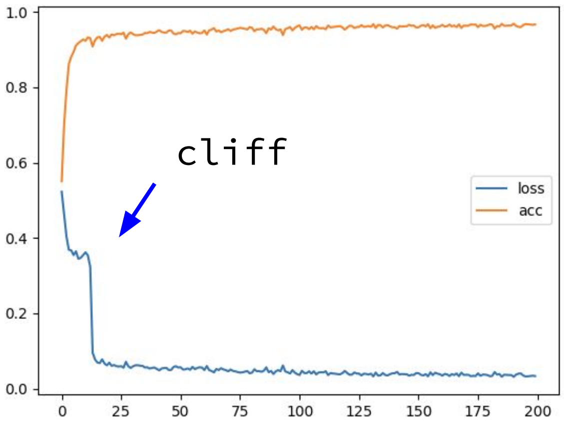


6 layer U-net, 100 epochs

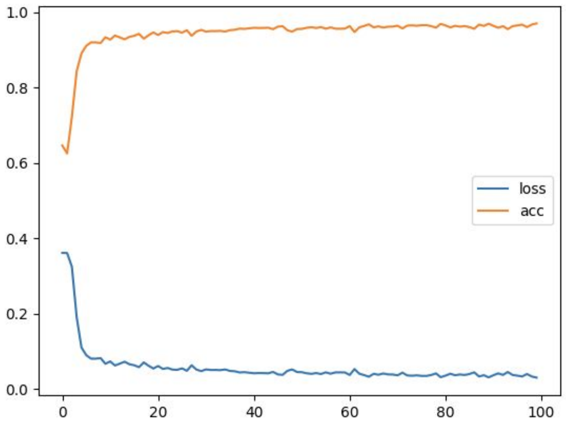
Comparison of learning rate

Smaller learning rate (1e-5) encounters local minima (cliff)

Learning rate = 1e-5

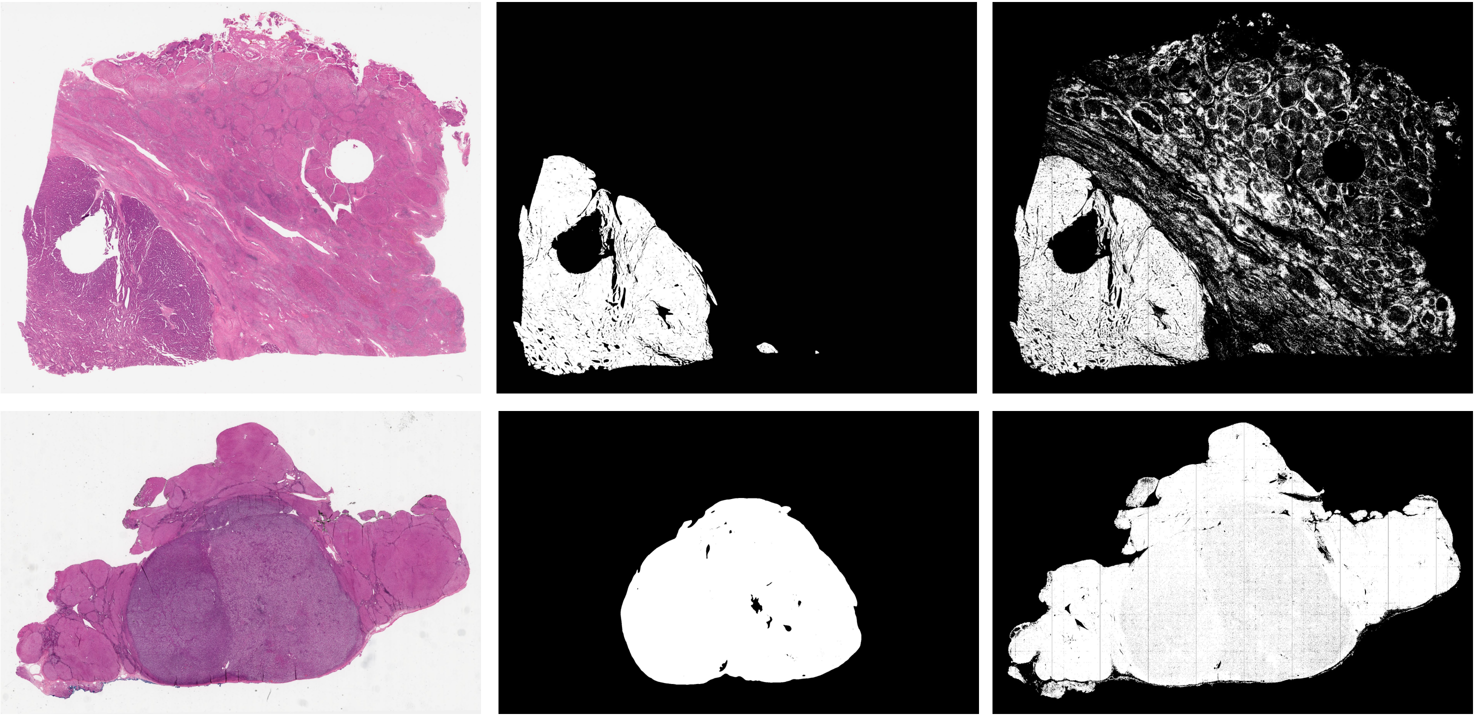


Learning rate = 3e-5



Differences in WSI staining affect mask prediction

WSI | Ground truth mask | Predicted mask



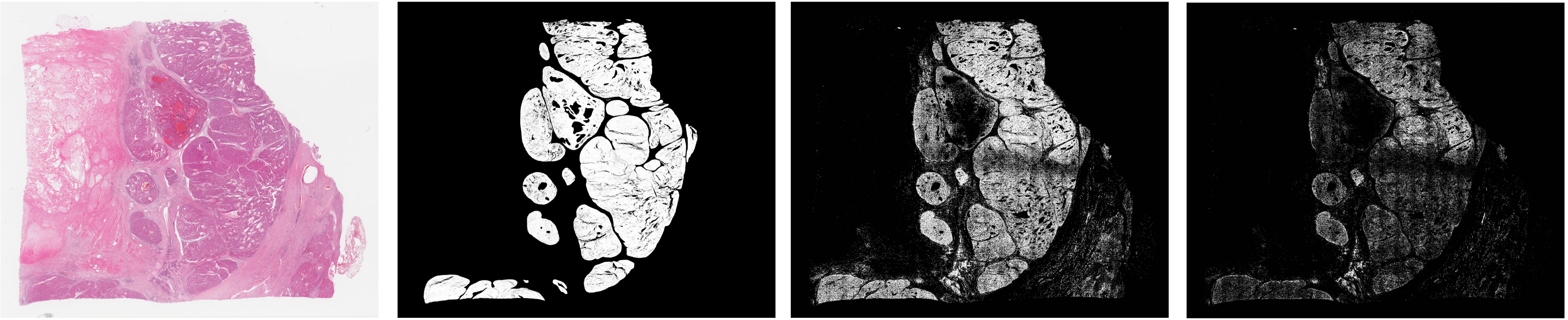
IoU = 0.726
F1 = 0.788
Accu = 0.737

IoU = 0.524
F1 = 0.624
Accu = 0.533

Color jittering augmentation improves model prediction

Predicted masks

WSI | Ground truth mask | 20% color jittering | 5% color jittering

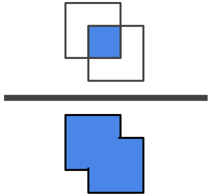
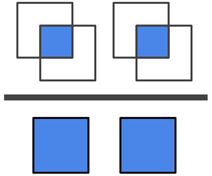


Conclusions

- Successfully trained modified U-net model using high resolution WSI image patches to predict viable tumor regions of liver cancer
- Hyperparameter tuning of network depth, input channels, loss function, batch size, and learning rate improved model performance
- Training image augmentation is important for consistent and robust prediction across different WSIs

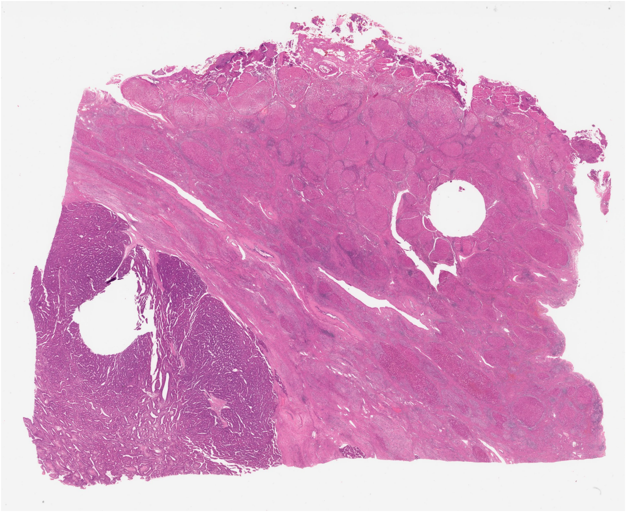
Extra Slides (TBD)

Methodology: Performance Evaluation

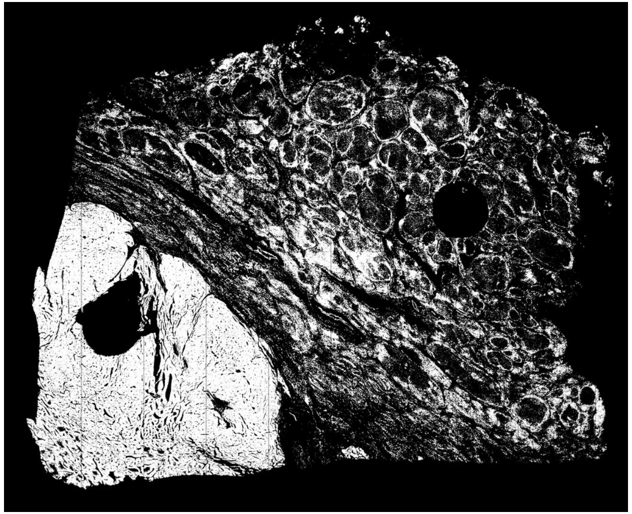
- Jaccard Index $$\frac{|AB|}{|A \cup B|}$$ 
- Dice Similarity $$\frac{2|AB|}{|A| + |B|}$$ 
- Pixel Accuracy

Results

WSI



Predicted mask



Ground truth mask

Jaccard score = 0.726

Results