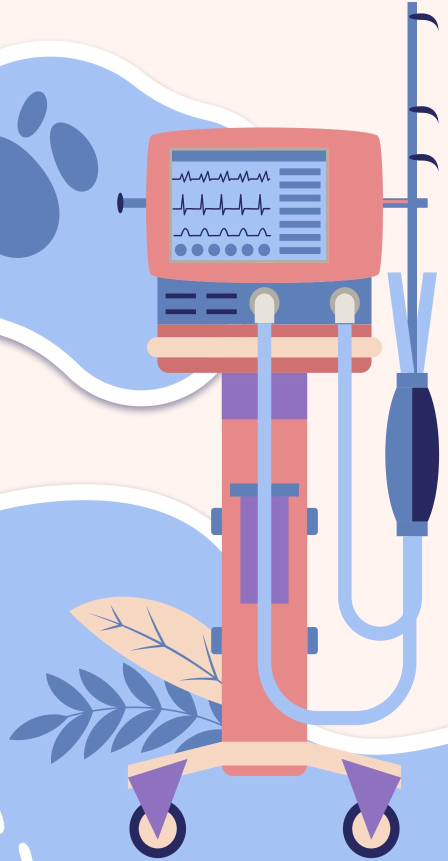
# Breast Cancer Segmentation

Borbála Fazakas



# Introduction

# The Goal

1. develop a model that can **categorize the cells** in breast cancer slides based on the **type of the tissue** to which they belong

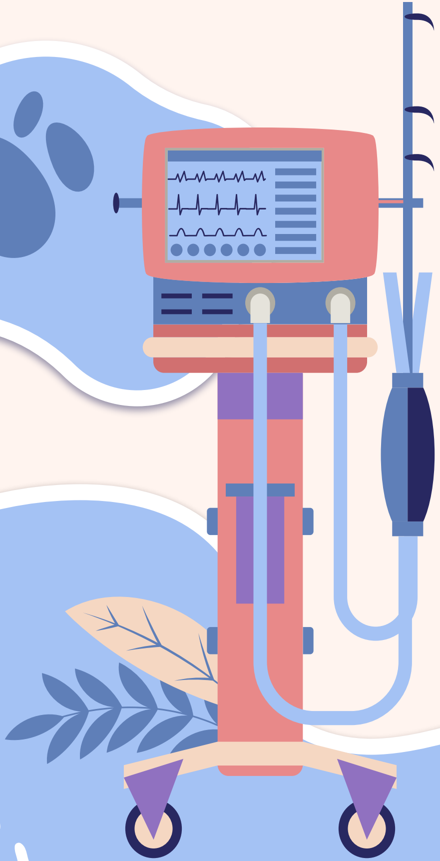
Multi-class Semantic Segmentation

2. develop a model that can **categorize the cells** in breast cancer slides as **cancerous/non-cancerous**

Binary Semantic Segmentation

# The Motivation

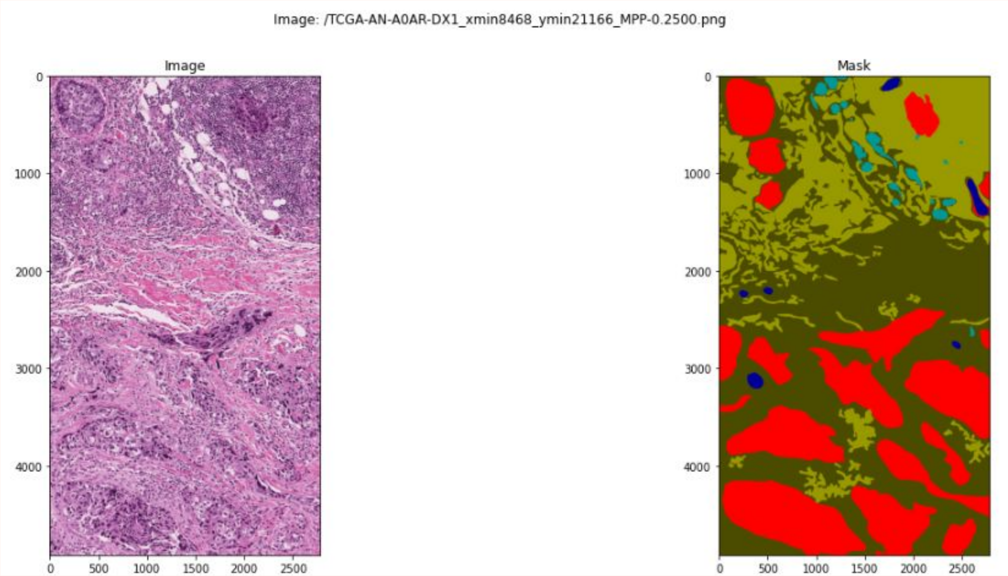
- Breast cancer is the most common type of Cancer in the UK
- In the UK, 1 in 8 women are diagnosed with breast cancer during their lifetime
- The segmentation of cancerous cells can help physicians quantify the volume of tissue in the breast for treatment planning

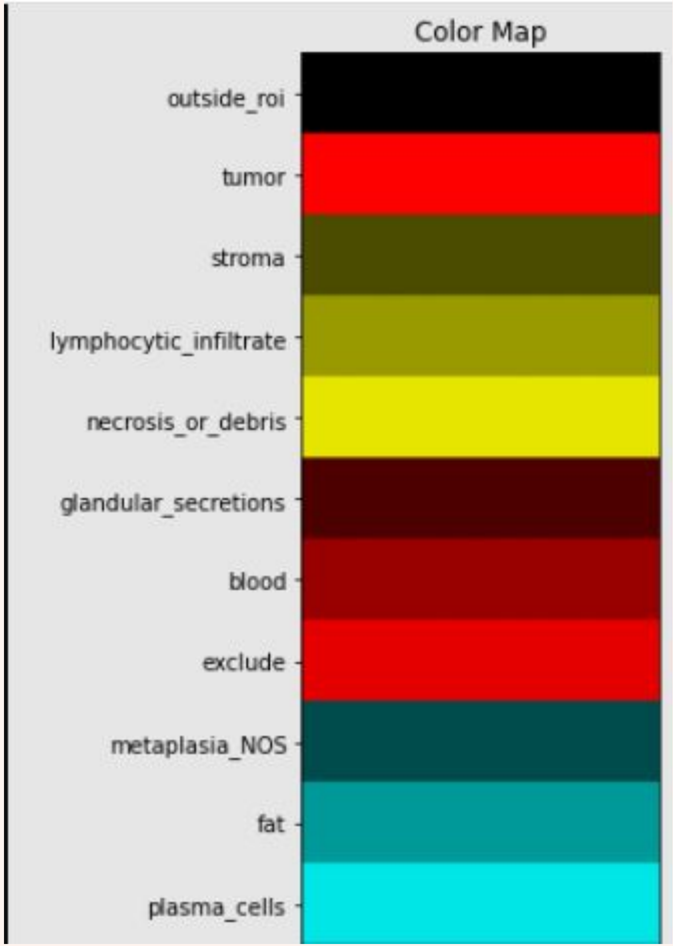
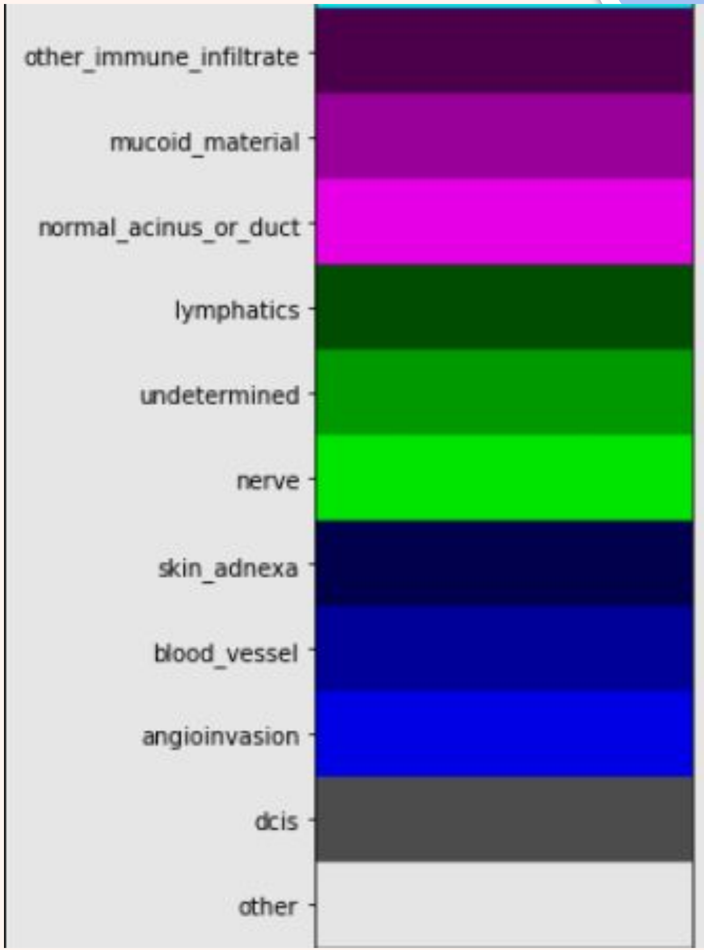


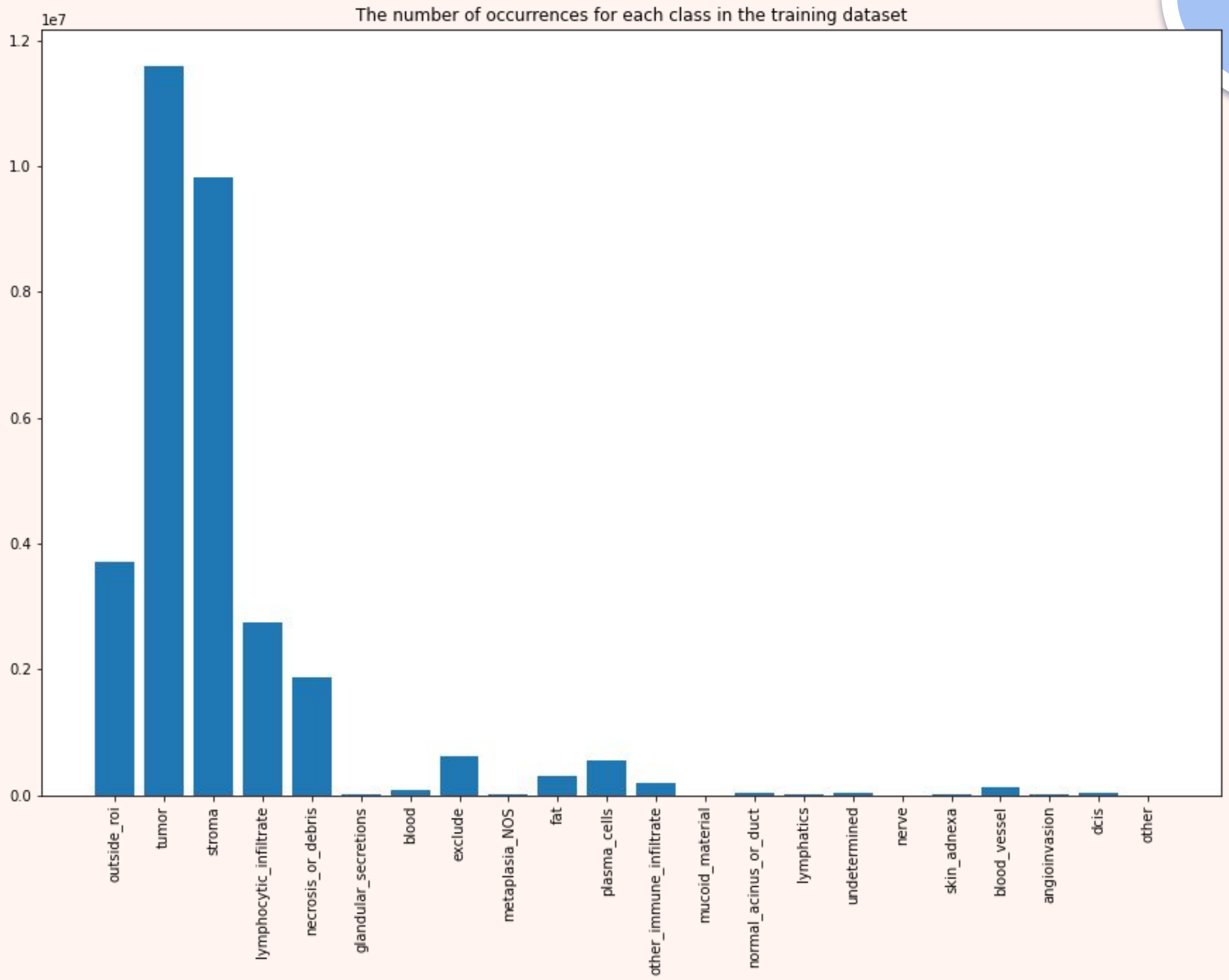
# Project Setup

# The Dataset

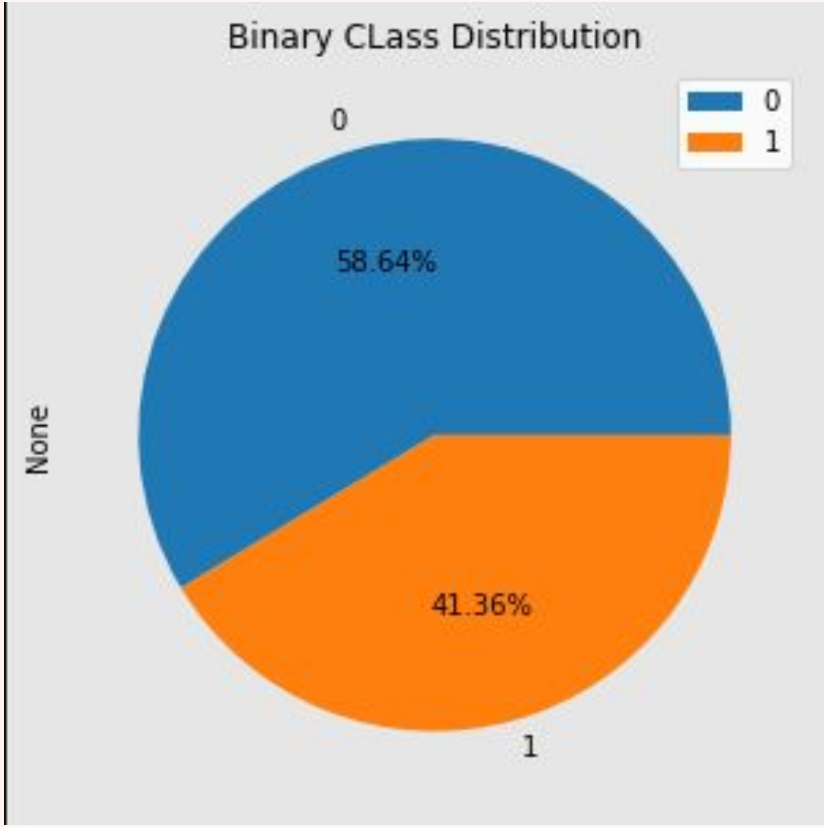
- 151 histology images with segmentation masks
  - images from the Cancer Genome Atlas (TCGA)
  - masks created through a crowd-sourcing method, by specialists



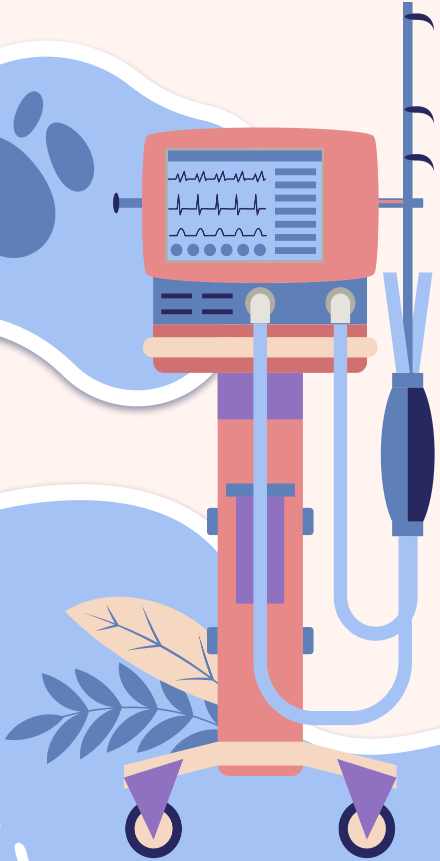

Color Map
outside_roi
tumor
stroma
lymphocytic_infiltrate
necrosis_or_debris
glandular_secretions
blood
exclude
metaplasia_NOS
fat
plasma_cells

other_immune_infiltrate
mucoid_material
normal_acinus_or_duct
lymphatics
undetermined
nerve
skin_adnexa
blood_vessel
angioinvasion
dcis
other



The number of occurrences for each class in the training dataset
1e7
1.2
1.0
0.8
0.6
0.4
0.2
0.0
outside_roi
tumor
stroma
lymphocytic_infiltrate
necrosis_or_debris
glandular_secretions
blood
exclude
metaplasia_NOS
fat
plasma_cells
other_immune_infiltrate
mucoid_material
normal_acinus_or_duct
lymphatics
undetermined
nerve
skin_adnexa
blood_vessel
angioinvasion
dcis
other




- 0 = non-tumor
- 1 = tumor



# Methodology and Results

# Two Network Architectures Considered...

## U-Net

- specifically developed for biomedical image segmentation
- encoder-decoder model, based on convolutional layers
- encoder: contracting part that captures the context
- decoder: enables precise localization
- published in 2015, achieved SOTA results in the ISBI cell tracking challenge and the Warping Error of the EM segmentation challenge

## SegFormer

- attention-based network architecture
- relies on a positional-encoding-free, hierarchical Transformer-encoder and a lightweight All-MLP decoder
- published in 2021, achieved SOTA results on common benchmarks, such as ADE20K, COCO-Stuff and Cityscapes

# Two Approaches...

## U-Net

- simple architecture, easy to implement

Implemented and Trained from Scratch

## SegFormer

- more complex architecture
- pretraining offers relevant knowledge

Fine-Tuned a pretrained checkpoint, from Huggingface

# But before the Training: Data Preprocessing

1. both models take fixed sized images → reshape
   - introduces a distortion
2. some parts of the images are outside the Region of Interest (ROI)
   - apply sample weights to ignore these pixels during the training
3. train-test split
   - 80-20%
   - no validation set used

# I. Multi-Class Problem

# Initial Results

## U-Net

(from scratch)

- converged in 30 epochs
- steady growth in accuracy, decrease in loss
- 56.29% test accuracy achieved

## SegFormer

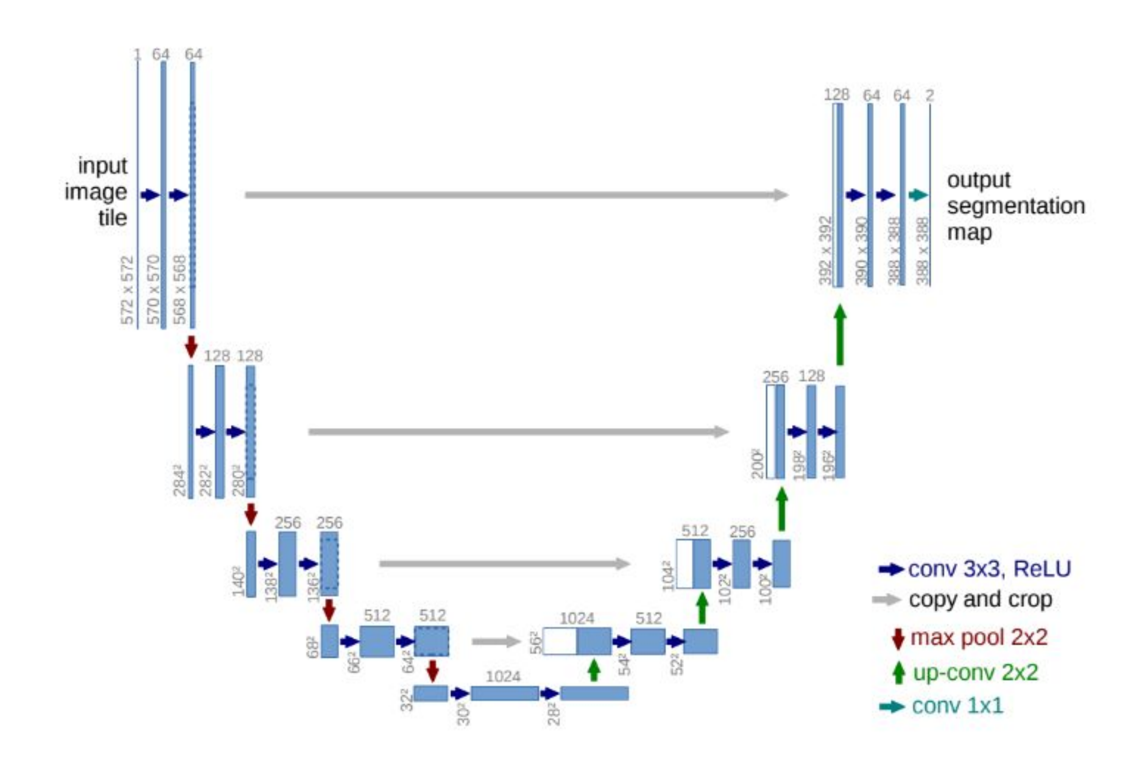
(transfer-learning)

- converged in 10 epochs
- oscillating loss and accuracy
- 20.84% accuracy achieved

(low performance probably because of the limited amount of data)

Decided to continue working with the U-Net

# U-Net



input image tile
output segmentation map
1
64
64
128
128
256
256
512
512
1024
1024
512
512
256
256
128
128
64
64
2
572 x 572
570 x 570
568 x 568
392 x 392
390 x 390
388 x 388
388 x 388
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

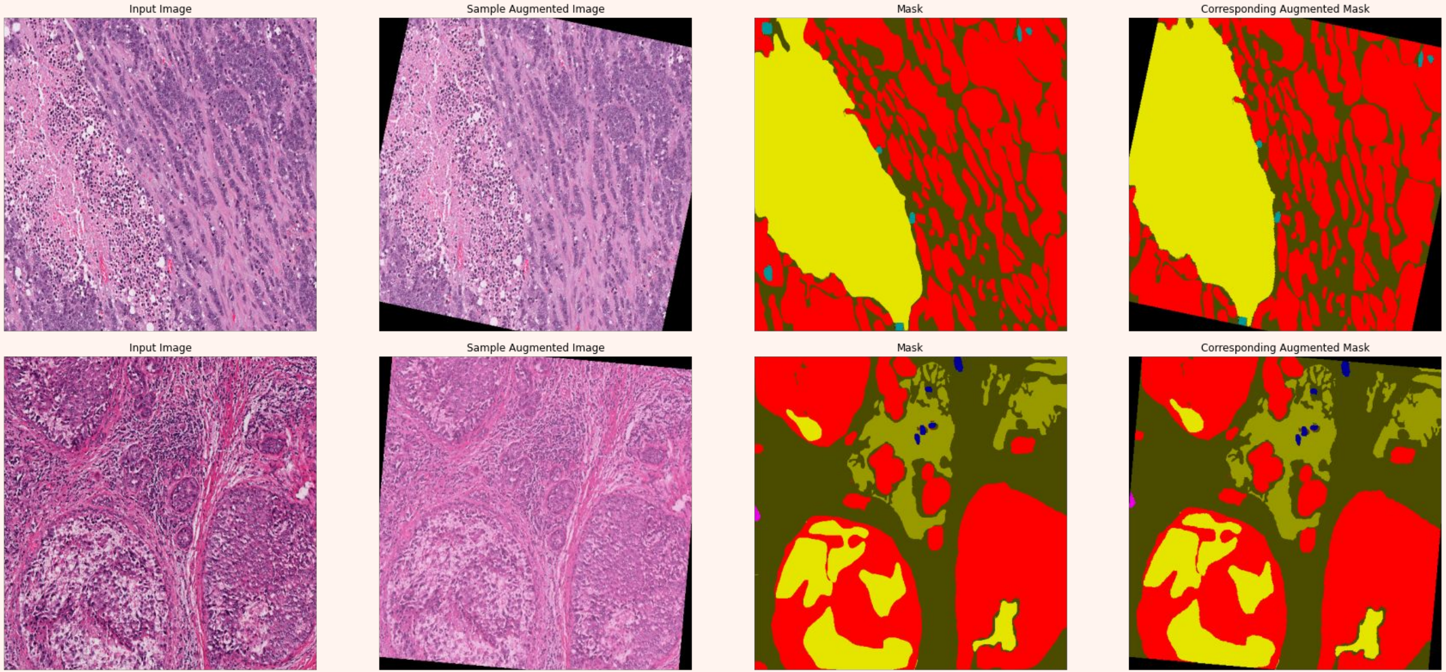
# 1st experiment:
# U-Net with balanced class weights

- motivation: the initial U-Net only detected the “tumor” and the “stroma” classes
- goal: balance out the over-representation of the above two-classes
- implementation: added balances sample weights on a pixel-level

# 2nd experiment:
# U-Net trained on an augmented dataset

- motivation: the original dataset contains relatively few images, not enough for the model to generalize well
- implementation: increased the dataset size 5x, by repeating each image 5x, with some simple preprocessing operations each time:
  - randomized brightness adjustments
  - randomized contrast adjustments
  - randomized rotations
  - randomized horizontal and vertical flips

# 2nd experiment:
# U-Net trained on an augmented dataset



# 3rd experiment: U-Net regularized

- goal: allow the model to generalize better, not to learn the particularities of the training dataset
- implementation:
  - applied a dropout after every double convolutional block (final dropout factor: 0.003)
  - applied L2-regularization on every convolutional layer (final dropout factor: 0.03)

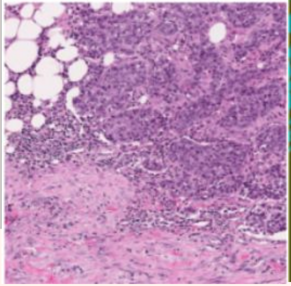
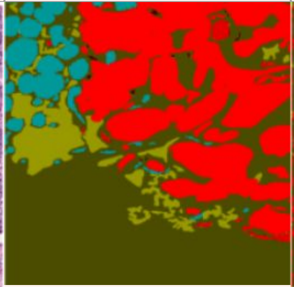
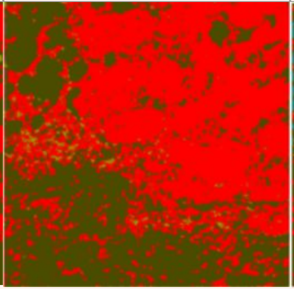
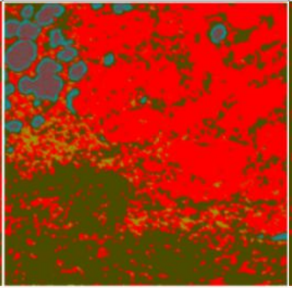
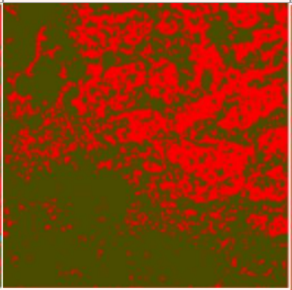
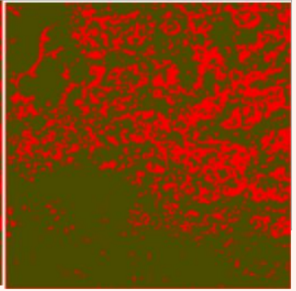
# 4th experiment:
# U-Net trained on an augmented dataset, with regularization

- experiment 2 and 3 combines

# Results

| Model | Test Accuracy |
|---|---|
| Simple U-Net | 56.29% |
| U-Net trained with balanced Sample Weights | 1.34% |
| **U-Net trained on the Augmented Dataset** | **57.76%** |
| Regularized U-Net | 56.33% |
| Regularized U-Net trained on the Augmented Dataset | 51.86% |

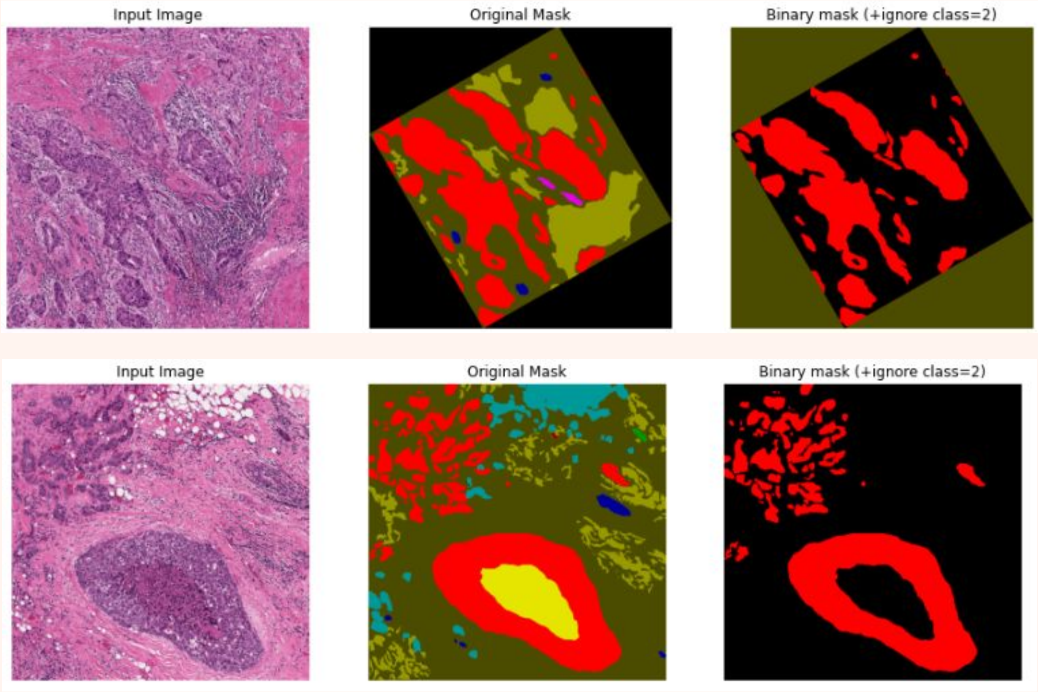
# Sample Predictions

| Input | True Mask | Simple U-Net - Output | U-Net trained on aug. dataset - Output | Regularized U-Net - Output | Regularized U-Net trained on aug. dataset - Output |
|---|---|---|---|---|---|
|  |  |  |  |  |  |

# I. Binary Problem

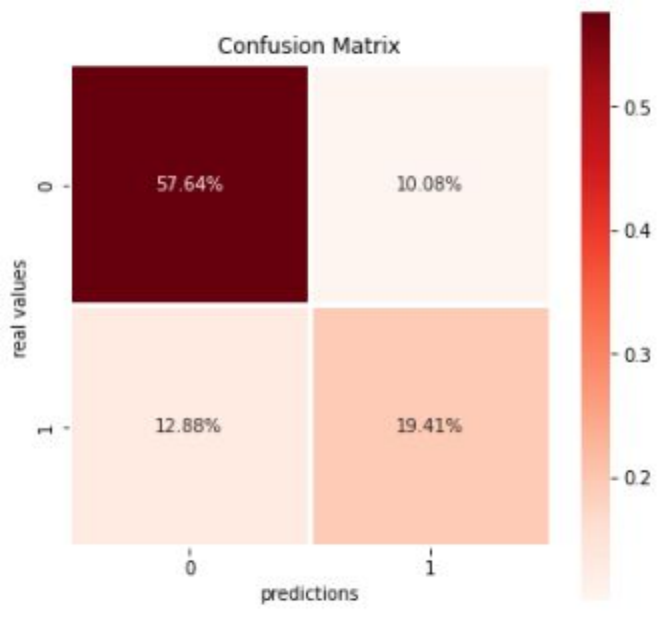
# Data Preprocessing

- preprocessed the masks:
  - tumor class: 1
  - no-tumor class: 0
  - outside ROI class: 2 (ignored in the loss and evaluation)

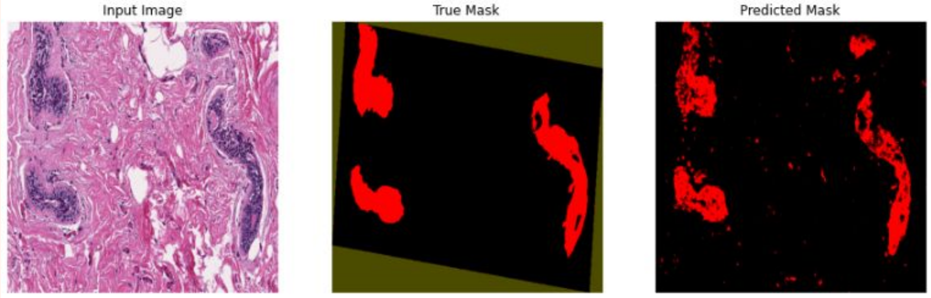


# Trained a Simple U-Net

- accuracy: 77.7%
- f1-score: 62.8%
- precision: 65.8%
- recall: 60.1%



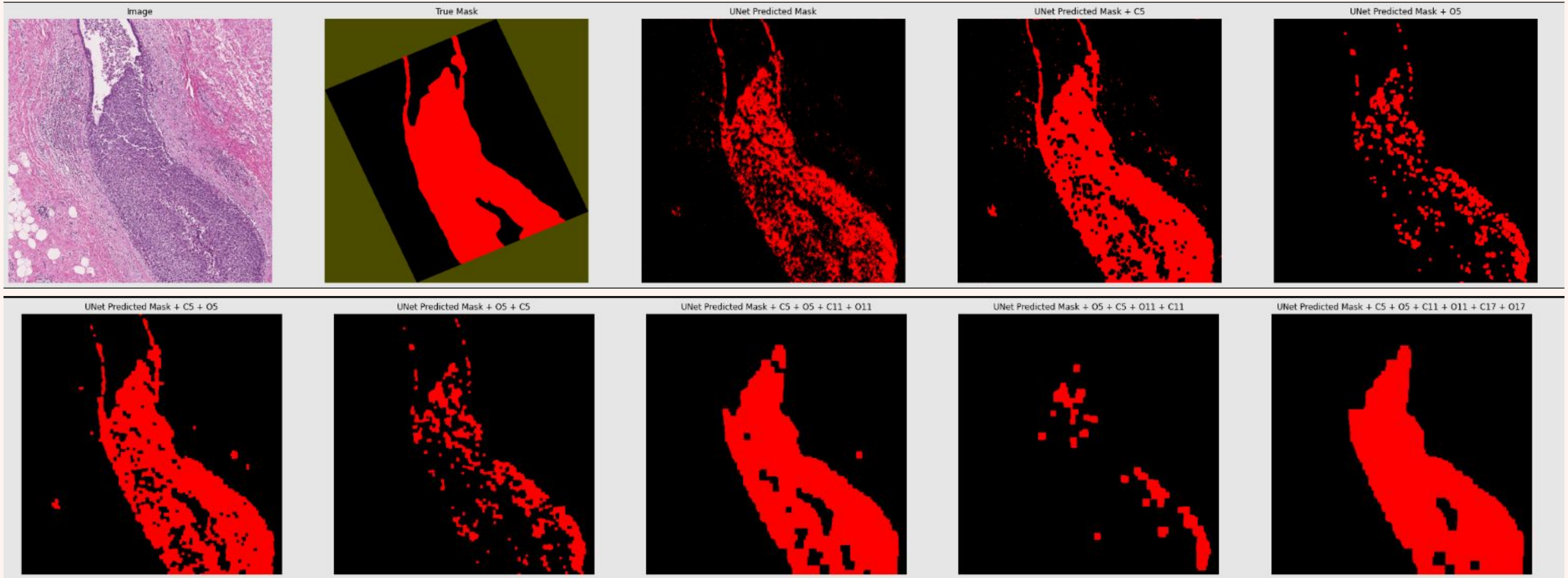
# Simple U-Net - Sample Predictions

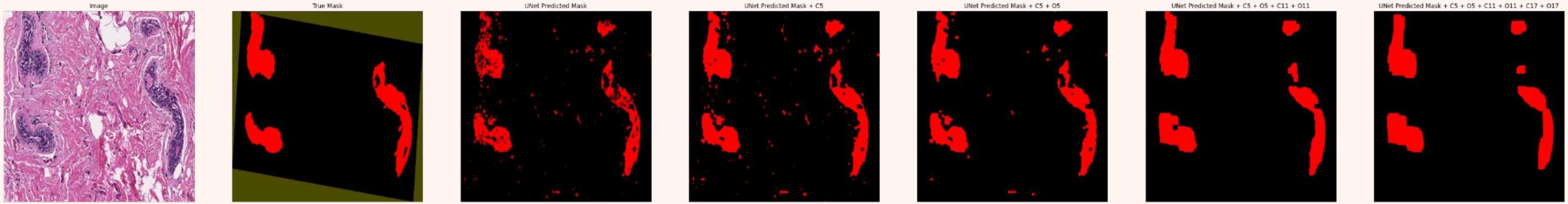


# Improvement: filter out the noise via morphological operations

- applied an alternating sequence of opening and closing operations, with increasing kernel size, on the predicted mask, to filter out the salt-and-pepper noise



# Morphological Post-processing - Example

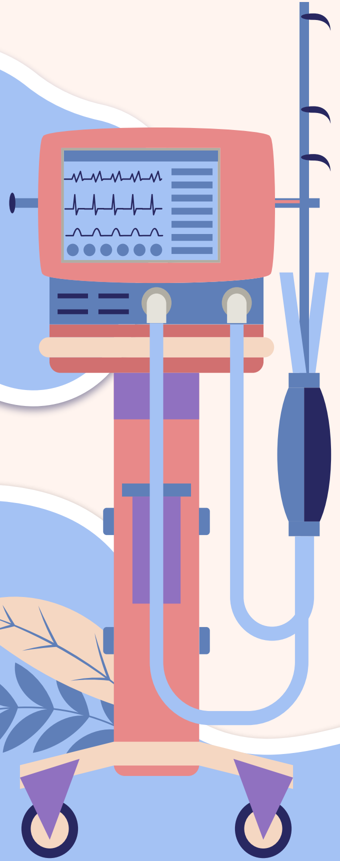


# Results

Experiments for post-processing:

- S1: closing (5) + opening (5)
- S2: closing (5) + opening (9)
- S3: closing (5) + opening (5) + closing (11) + opening (11)
- S4: closing (5) + opening (9) + closing (11) + opening (15)
- S5: closing (5) + opening (5) + closing (11) + opening (11) + closing (17) + opening (17)

| Post-processing sequence on the U-Net Prediction | Accuracy | F1 | Precision | Recall |
|---|---|---|---|---|
| None | 77.05% | 62.8% | **65.8%** | 60.1% |
| S1 | 76.9% | 67.2% | 61.9% | 73.5% |
| S2 | **78.2%** | 66.9% | 65.7% | 68.3% |
| S3 | 76.3% | **68.0%** | 60.2% | 78.0% |
| S4 | 78.1% | 66.8% | 65.3% | 68.4% |
| S5 | 75.3% | 67.2% | 58.9% | **78.3%** |



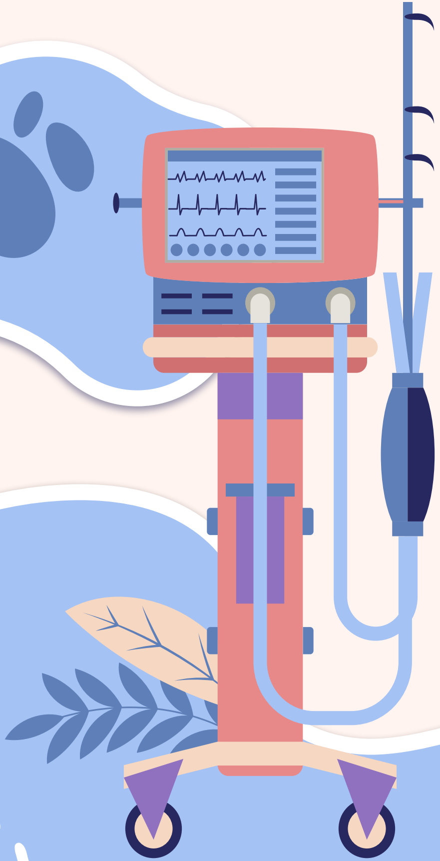
# Conclusions. Observations

# Conclusions

- the U-Net is better suited for this problem than the SegFormer
- data augmentation and regularization can bring significant model improvements
- morphological post-processing is helpful for filtering out the noise

# Further Observations

- data augmentation brings significant improvements in detecting under-represented classes
- data augmentation and regularization do not work well together on this problem
- noise filtering helps to make the output easier to interpret for humans, apart from increasing the accuracy



# Further Work

# Further Work

- trying networks, which allow varying input image sizes, to avoid distortions at the preprocessing steps
- trying “less balanced” class weights to learn the underrepresented classes
- trying other attention-based models
- ...

# Thank you for your attention!

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# References


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