DETECTING PROSTATE CANCER USING A CONVOLUTIONAL NEURAL NETWORK WITH TRANSFER LEARNING APPROACH

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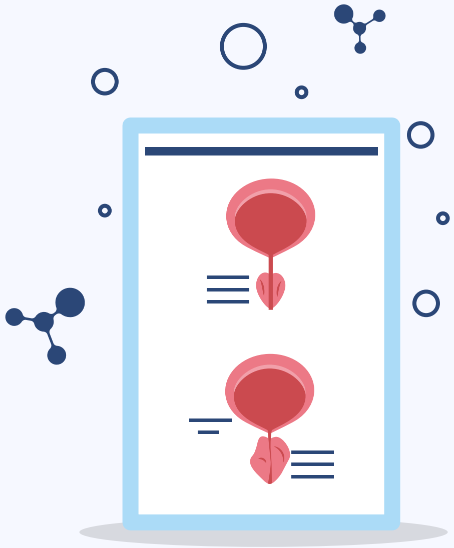


01

PROBLEM STATEMENT

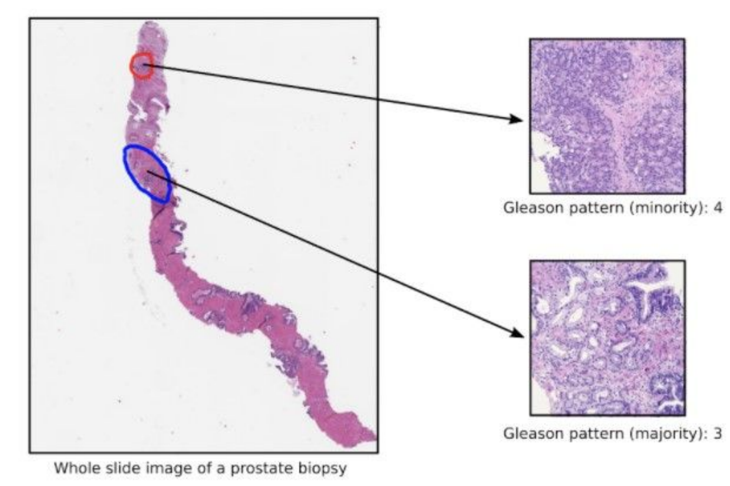
Introduction to the Disease

- Globally, around 1.1 million men are diagnosed with prostate cancer annually.
- The standard method for diagnosis is transrectal ultrasonography guided biopsy (TRUS), but it has a high rate of incorrect results and is a painful procedure.
- Given that prostate cancer is more common in older men, there is a need for less invasive and more accurate diagnostic techniques.

https://ncbi.nlm.nih.gov/pmc/articles/PMC7334337/

Prostate cANcer graDe Assessment (PANDA) Challenge

- The PANDA challenge took place on Kaggle in 2020, and featured over 1,000 teams competing for $25K in prizes.
- Automated deep learning systems exhibit potential in accurately grading prostate cancer (PCa)
- The training dataset includes around 11,000 whole-slide images of digitized H&E-stained biopsies from Radboud University Medical Center and Karolinska Institute
- It is the largest public whole-slide image dataset available, approximately eight times larger than the CAMELYON17 challenge
- For this project, the slide images in this data set will be used to build a CNN to diagnose prostate cancer



https://www.kaggle.com/competitions/prostate-cancer-grade-assessment

Process Overview

01

Break the slide into smaller 256x256 pixel tiles. Remove tiles with too much white space

02

Make note of the tile's location relative to the slide and cancer/benign label

03

Save the tiles down into folders separated by class/label

04

Train CNN model (pretrained ResNet50) on 80% of the data

05

Evaluate model performance on validation set (Confusion Matrix & ROC Curve)

06

Test model on new slide by tiling the slide and evaluating each tile separately

07

Apply a probability weighted shading to tiles based on likelihood of cancer

08

Stitch together tiles to output whole slide image with cancer mask overlayed, highlighting cancerous regions

02

DATA OVERVIEW & VISUALIZATION

10,617

Whole Slide Images

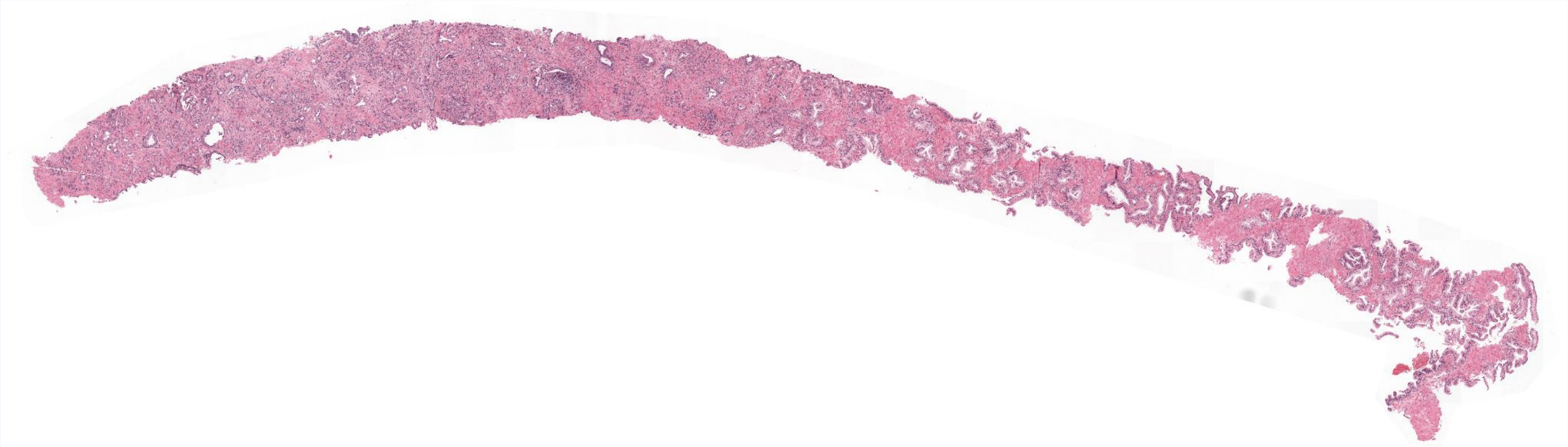
383 GB

Image Data

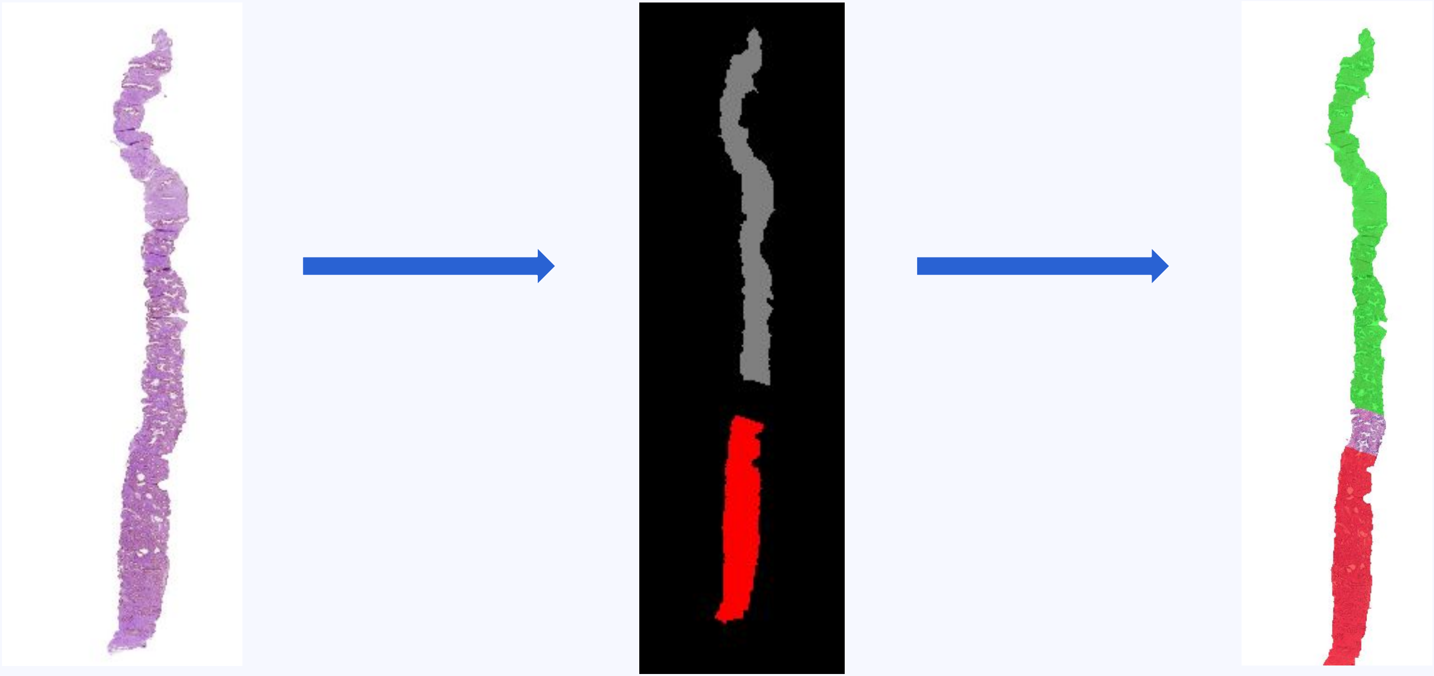
382,212

Tiled Images

Sample Slide



Sample Slide & Mask Overlay



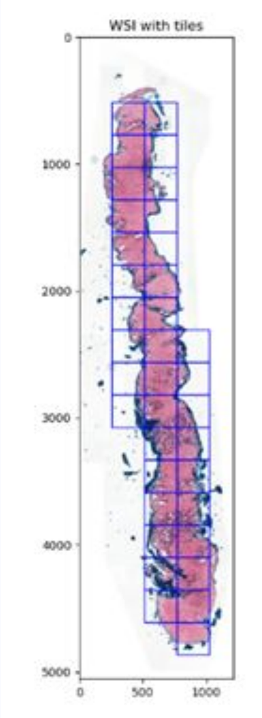
03

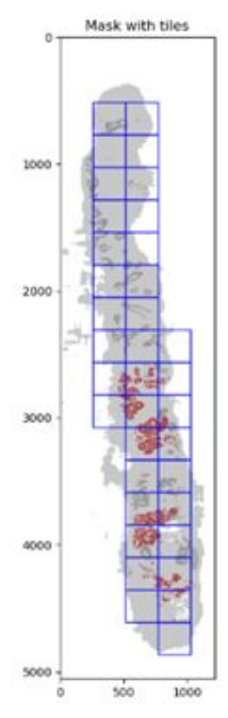
DATA PRE-PROCESSING

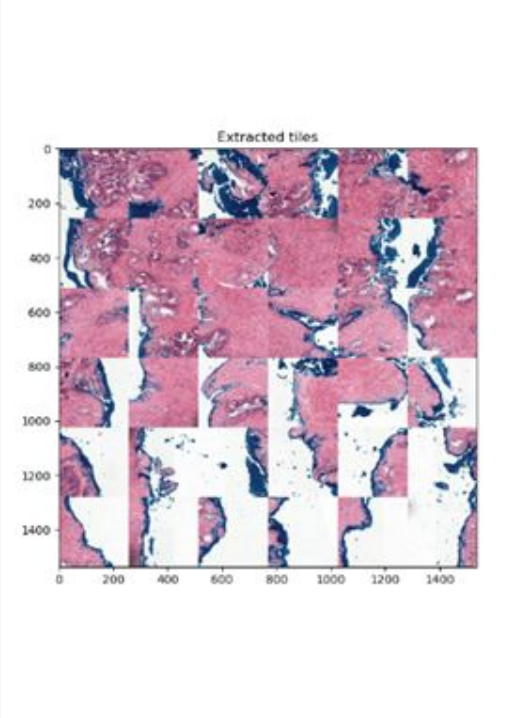
Tiling Process

Key Steps:

- Create function that breaks the slide up into tiles of a specified size and returns the (x, y) pixel coordinates of the top left corner
- The function then sums the total number of pixels in the tile, and sorts from high to low (to filter out tiles with too much white space)
- This function was then applied to extract the top 36 tiles of size 256x256 for each whole slide image



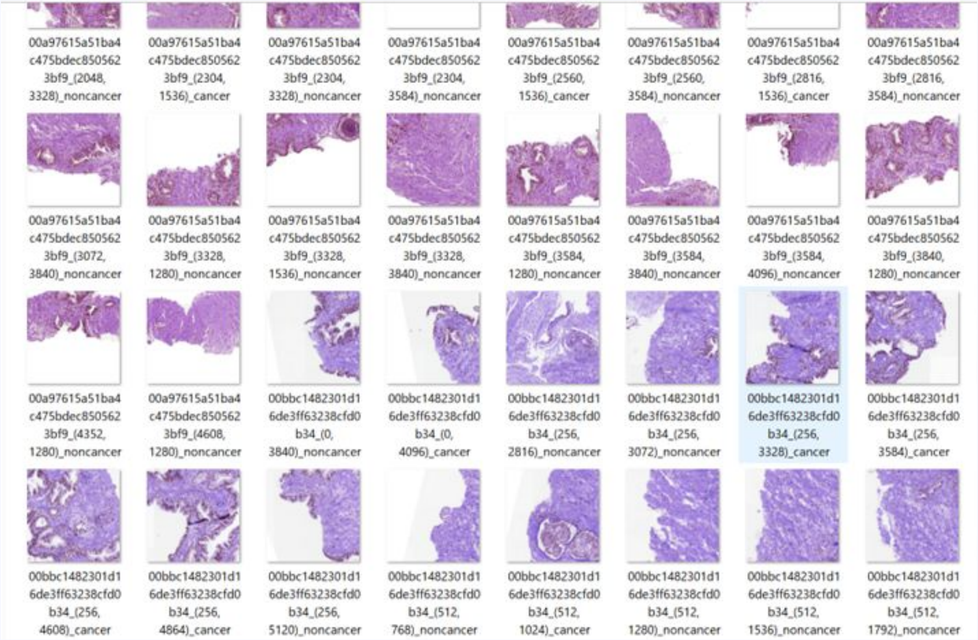




Saving Down Tiles

Key Steps:

- Create a function that determines if a tile is cancerous or benign based on the coordinates from its mask and associated Karolinska/Radboud label (2 for cancer in Karolinska and 3, 4, or 5 for Radboud)
- If at least one pixel in the associated region from the mask was cancerous, classify the entire tile as cancerous
- Loop through each WSI, to create tiled images with the following naming convention: slide-name_tile-coordinate_label

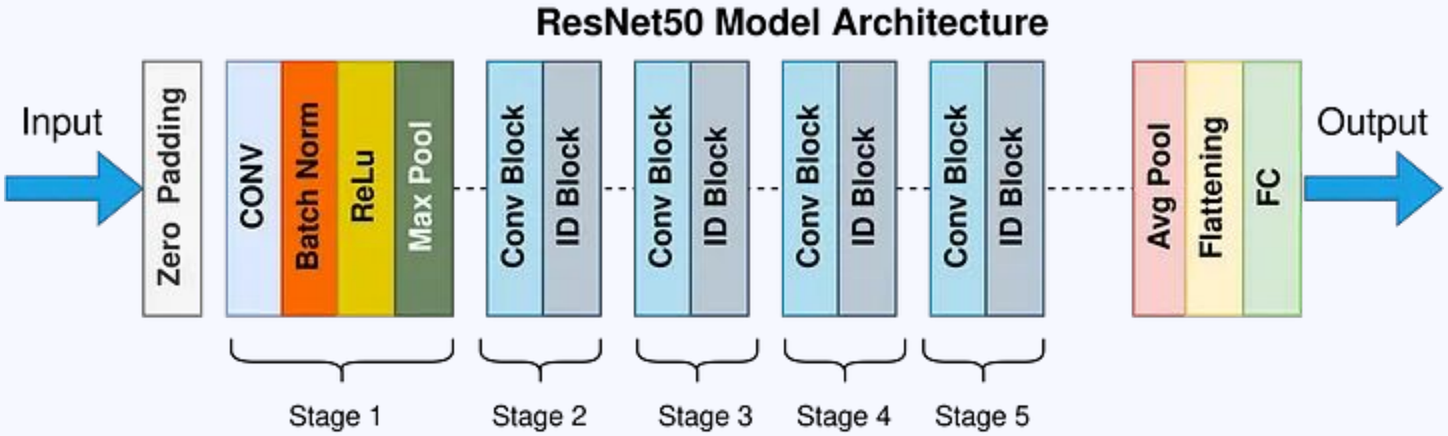


04

MODEL CONSTRUCTION & EVALUATION

ResNet50 Models in Cancer Detection

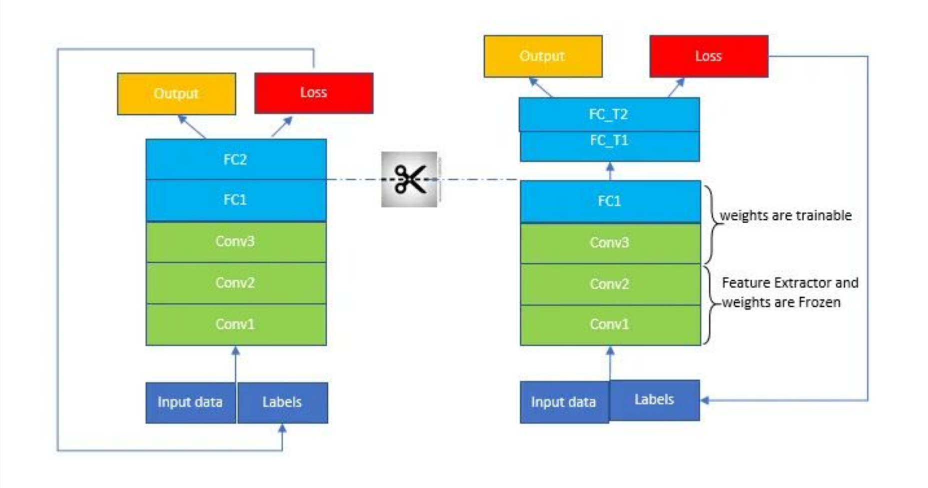
- ResNet50 models are a popular choice in medical image analysis, particularly for detecting breast, skin or breast cancer, providing the most reliable performance for accuracy, sensitivity, and specificity
- ResNet50 has been pre-trained on a large dataset, allowing it to learn intricate patterns and relevant features crucial for cancer detection
- In the realm of histopathology images, ResNet50 serves as a potent tool for extracting features and has demonstrated top-tier performance in distinguishing between malignant and benign tumors



https://www.sciencedirect.com/science/article/pii/S1877050921000284, https://towardsdatascience.com/the-annotated-resnet-50-a6c536034758

Transfer Learning - Fine Tuning

- A ResNet50 CNN mode will be used as the pre-trained model for fine tuning for Transfer Learning
- Transfer learning will be applied to the ResNet50 model by replacing its last predicting layer with custom predicting layers.
- The initial lower layers of the network, responsible for learning generic features from the pre-trained model, have frozen weights that remain unchanged during training.
- Task-specific features are learned in the higher layers, which are trainable or fine-tuned in the pre-trained models.



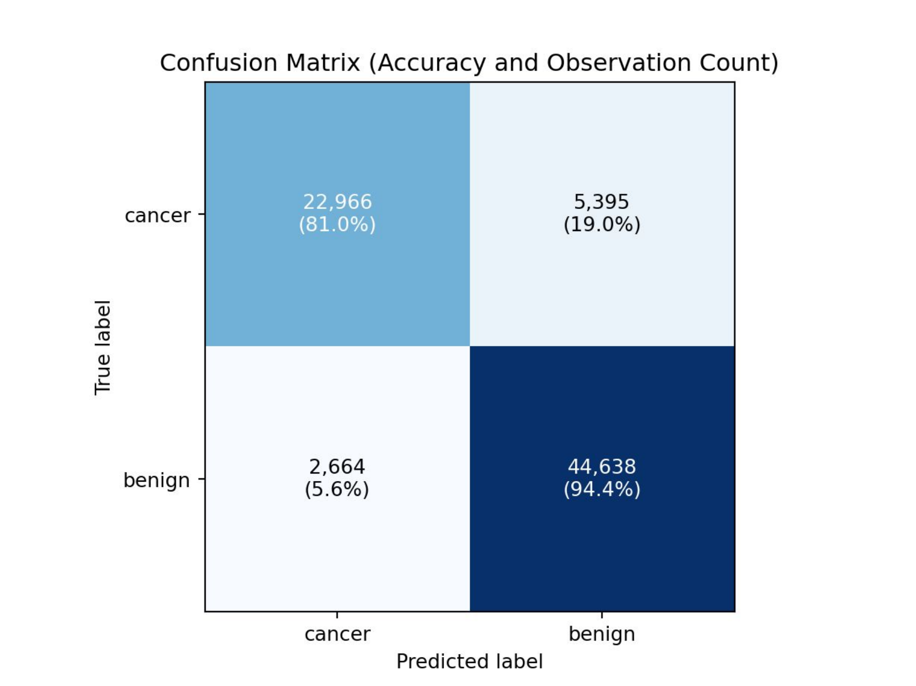
https://towardsdatascience.com/deep-learning-using-transfer-learning-python-code-for-resnet50-8acdfb3a2d38

Model Performance – Confusion Matrix

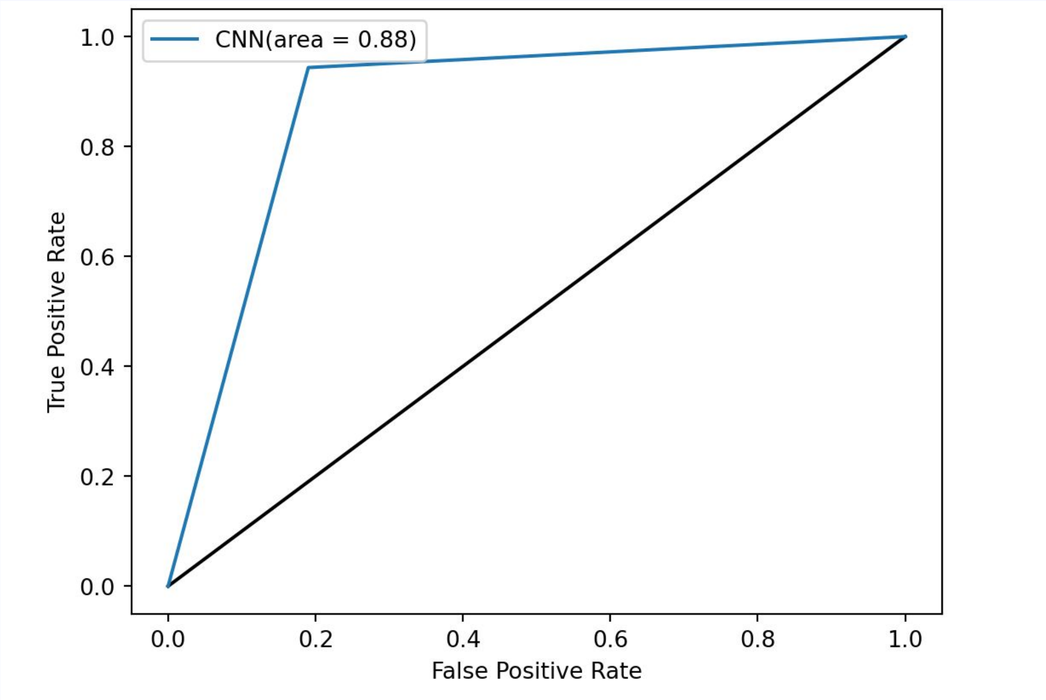
89% Accuracy

81% Sensitivity

94% Specificity



Model Performance – ROC Curve

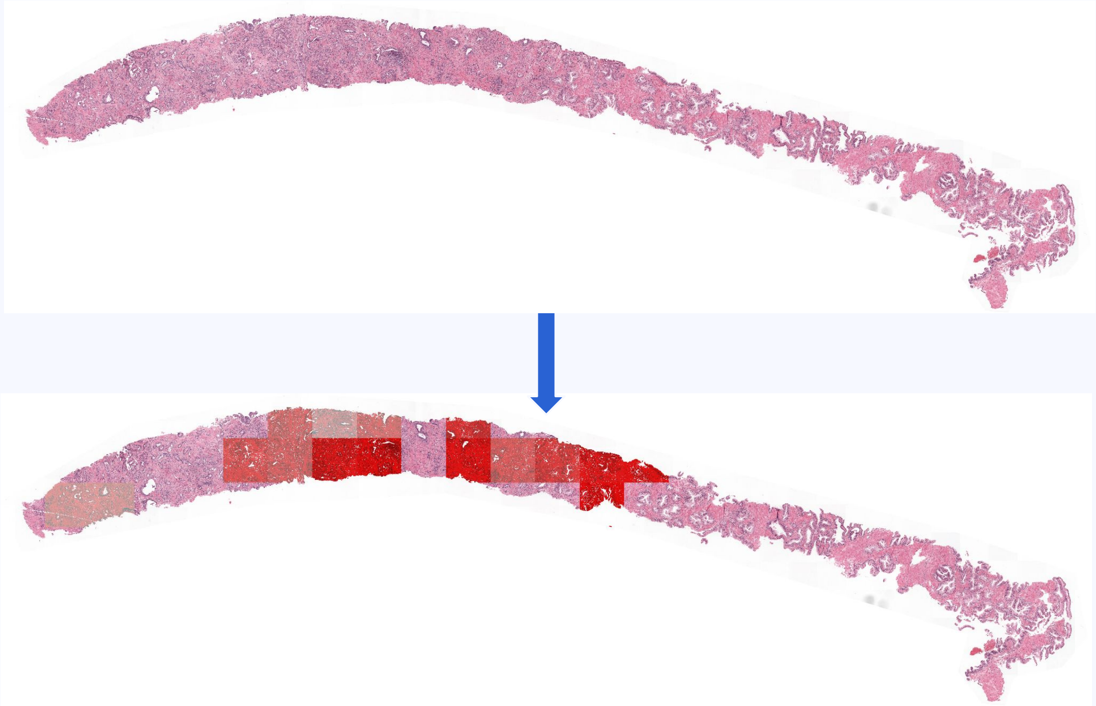


05

MODEL INFERENCE & CONCLUSIONS

Determine Cancerous Regions on Slide

- Run model on whole slide image and apply cancer mask
- Create a function that breaks a slide into tiles, runs the model on each tile and applies the mask (probability shaded)
- Then stitch together the tiles, and output the whole slide image with the mask overlayed
- Shading the regions of the slide with the highest probability of cancer can help save a pathologist time and improve their accuracy (especially sensitivity)



06

STREAMLIT APP

Prostate Cancer Detector

Please upload a tissue sample below

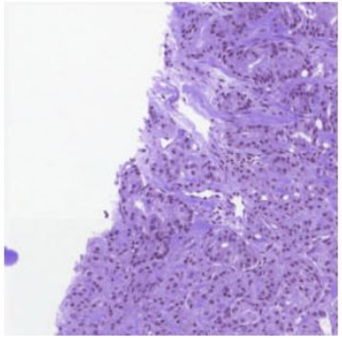
Upload an image

Drag and drop file here

Limit 200MB per file • PNG, JPG, TIFF, JPEG, TIF

Browse files

0018ae58b01bdadc8e347995b69f99aa_(256, 1024)_cancer.png 132.8KB



Uploaded Image.

This sample is **cancerous**

Prostate Cancer Detector

Please upload a tissue sample below

Upload an image

Drag and drop file here

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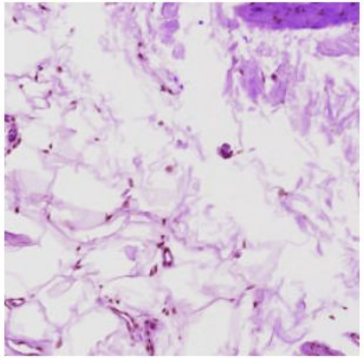
Browse files

0005f7aaab2800f6170c399693a96917_(1024, 1024)_noncancer.png 126.1KB



Uploaded Image.

This sample is **benign**