# STAT 8002: Project Data Walkthrough

## Deep Learning Algorithms in Predicting Prostate Cancer

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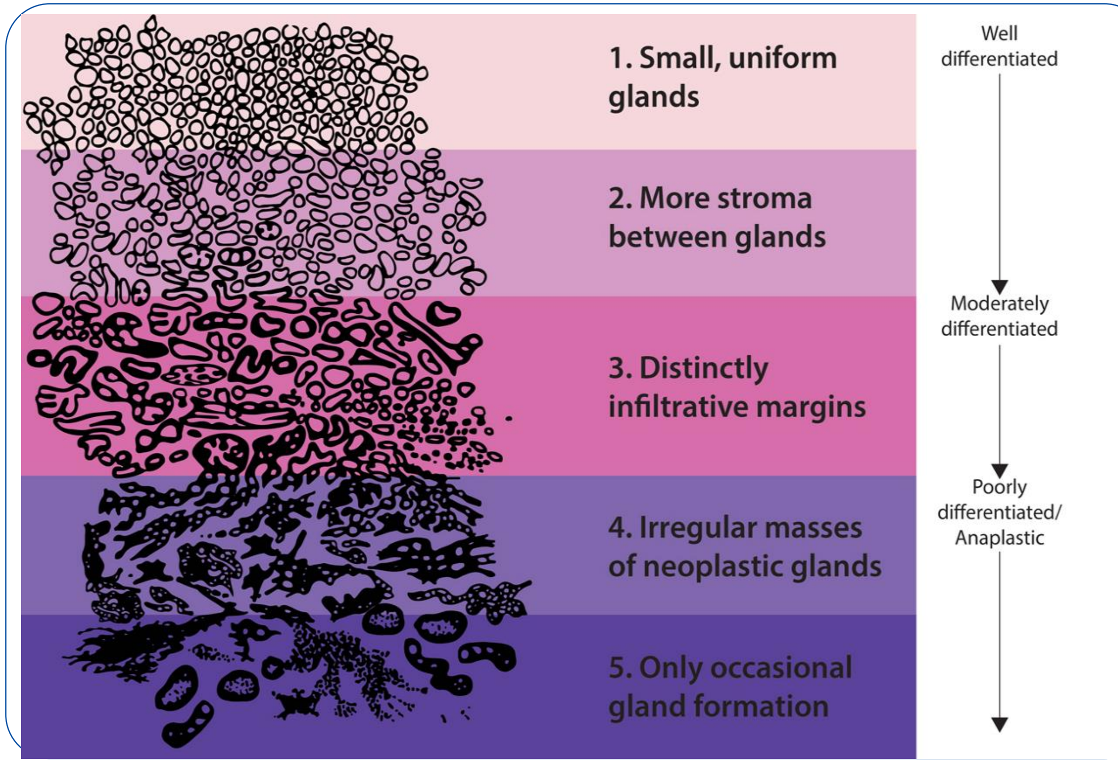
# Agenda

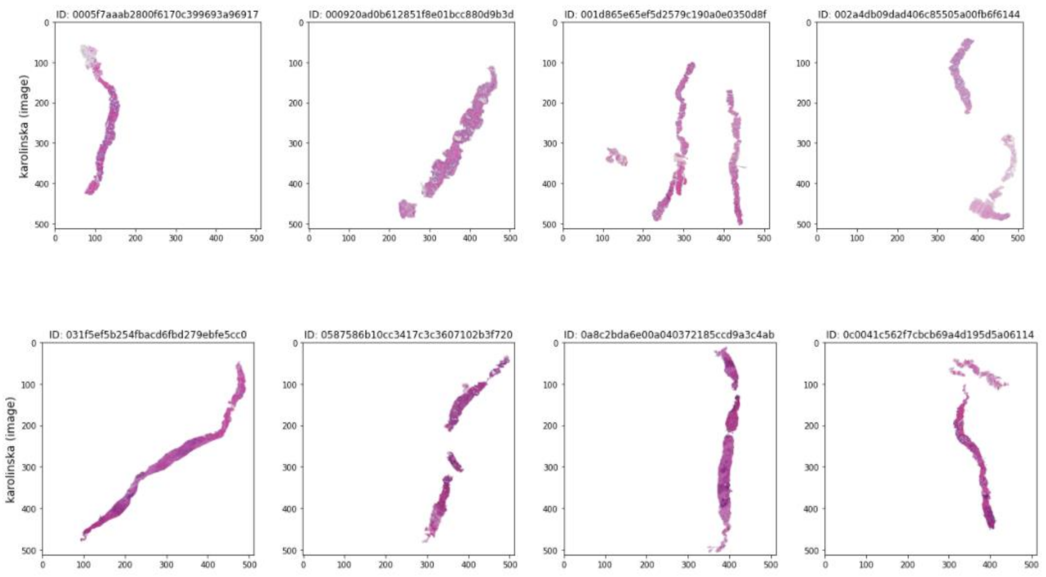
- Dataset Introduction
- Dataset Objective
- Masks Explanation
- Problems with Masks
- Possible Workflow Processes
- Evaluation Criteria
- Questions from my Side




**Deep Learning Algorithms in Predicting Prostate Cancer**

# Dataset Introduction

## Dataset



**~21,000 H&E stained prostate biopsy images**

- **Size:** 383 GB
- **Format:** TIFF (high resolution)
- **Labels:** Yes (labelled by pathologists)
- **Masks:** Yes (labelled areas of interest by pathologists)

## Source from Organizations ~(50:50)

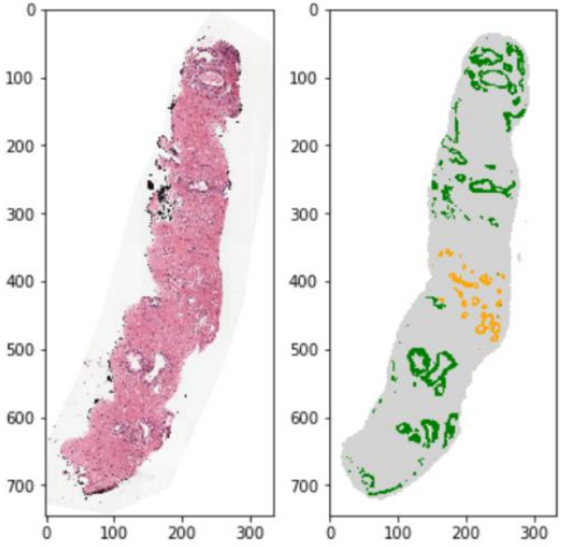


Image Mask*

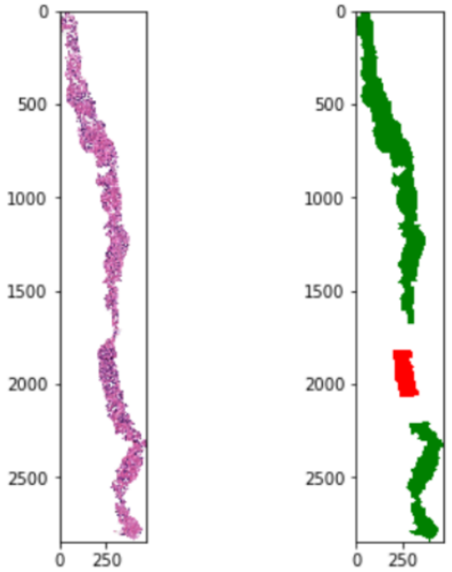


Image Mask*

Radboudumc university medical center

Karolinska Institutet

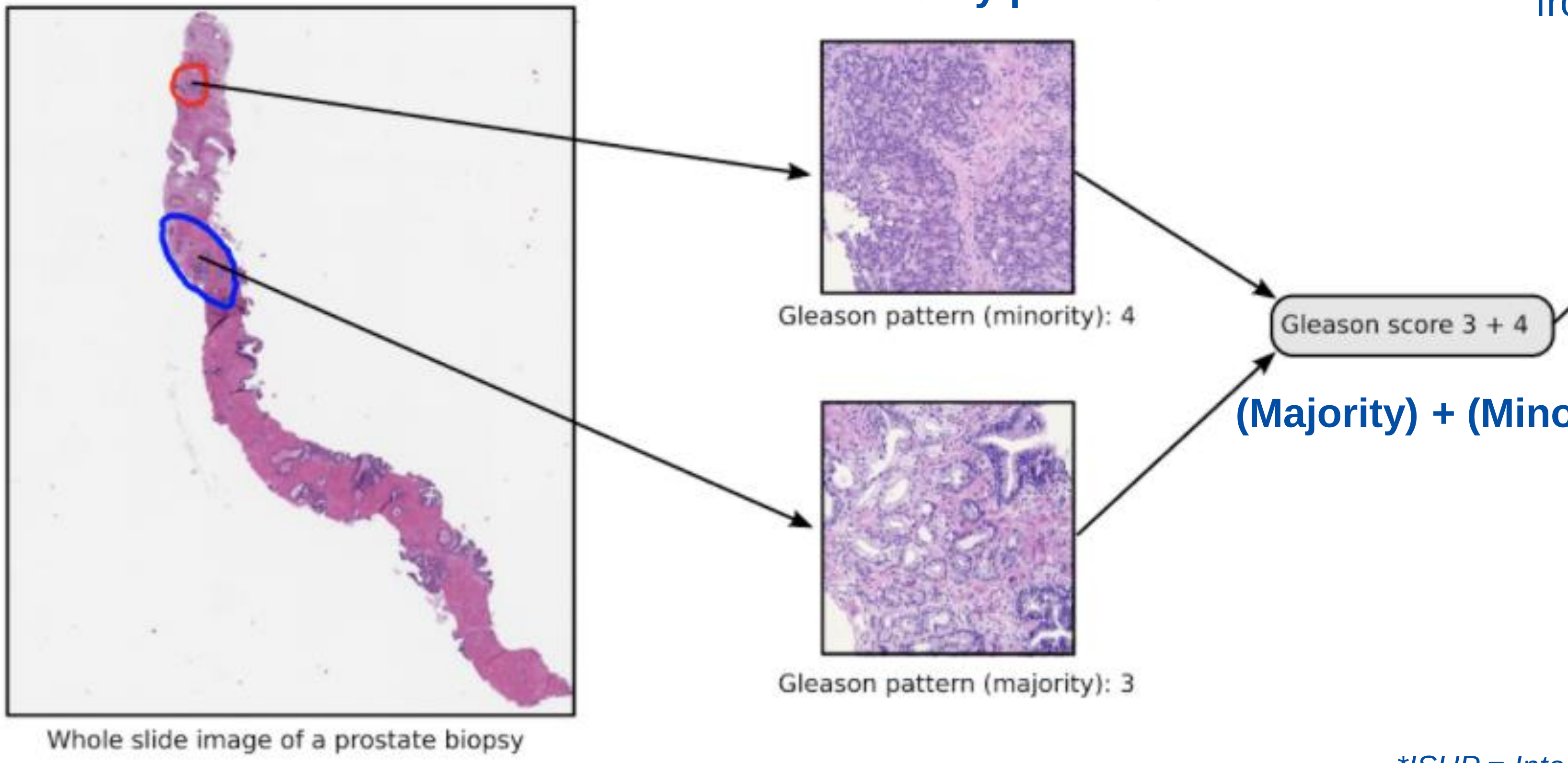
**Note that these 2 sources have different masking techniques*

# Dataset Objective

## Pathologist Labelling Process and response variable

**Pathologists labels the majority and minority patterns**

**ISUP* grade is what we want to predict.** 0 means not cancerous. ISUP from 0 to 5.




**(Majority) + (Minority)**

| Gleason score | ISUP grade |
|---|---|
| 3+3 | 1 |
| 3+4 | 2 |
| 4+3 | 3 |
| 4+4 | 4 |
| 3+5 | 4 |
| 5+3 | 4 |
| 4+5 | 5 |
| 5+4 | 5 |
| 5+5 | 5 |

**Less aggressive**

**Aggressive**

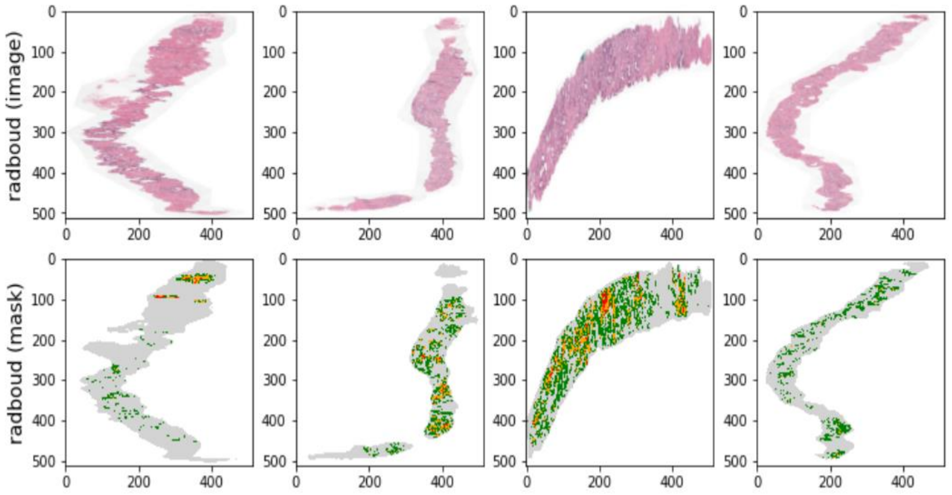
**ISUP = International Society of Urological Pathology*

# Masking Explanation

## Radbound

Image

Mask



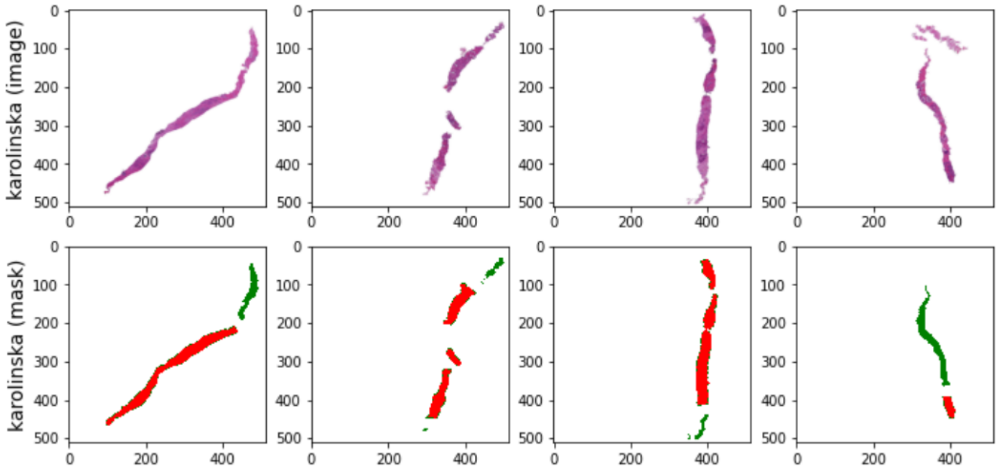

### Mask colors and description

- 0: background (non tissue) or unknown
- 1: stroma (connective tissue, non-epithelium tissue)
- 2: healthy (benign) epithelium
- 3: cancerous epithelium (Gleason 3)
- 4: cancerous epithelium (Gleason 4)
- 5: cancerous epithelium (Gleason 5)

## Karolinska

Image

Mask




### Mask colors and description

- [0]: background (non tissue) or unknown
- [1]: benign tissue (stroma and epithelium combined)
- [2]: cancerous tissue (stroma and epithelium combined)

# Problems with Masks

## Masks are not the same

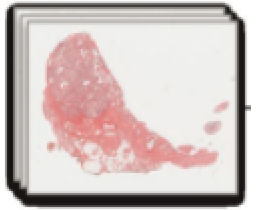
- From previous slide, obvious that both sources have different masking techniques
- If want to use masks, need to find way to standardize these masks such that they will be close to similar

## No masks in production

- In production, just the image will be available and no masks will be available
- A segmentation model must be trained to produce/predict masks of the images
- If predict using mask in test set, already considered data leakage

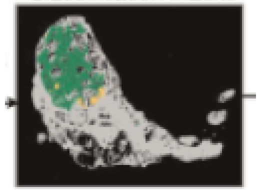
# Possible Workflow Processes

## Two Stage Model (Using Mask)

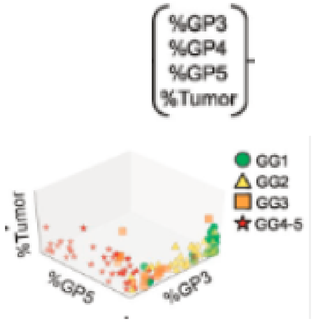


Biopsy Scan Images

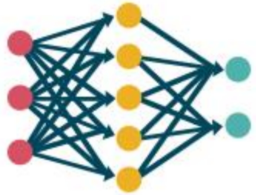
Convolutional Neural Network



Segmentation of Masks




Feature Extraction

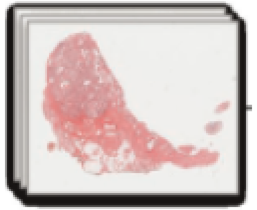


Deep Learning Model

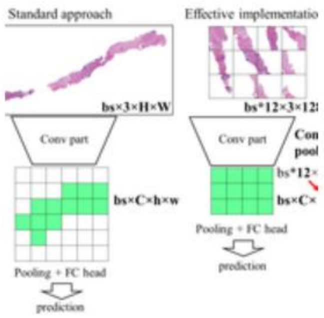
| isup_grade |
|---|
| 0 |
| 1 |
| 2 |
| 4 |
| 3 |
| 5 |

Classification

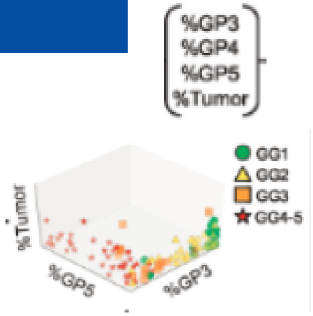
## One Stage Model (No Mask)



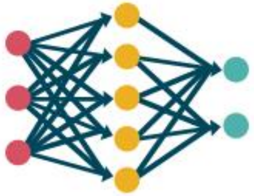
Biopsy Scan Images




Concatenate Tile Pooling




Feature Extraction



Deep Learning Model

| isup_grade |
|---|
| 0 |
| 1 |
| 2 |
| 4 |
| 3 |
| 5 |

Classification

# Evaluation – Quadratic Weighted Kappa (QWK)

## QWK with N classes

$$\kappa = 1 - \frac{\sum_{i,j} w_{i,j} O_{i,j}}{\sum_{i,j} w_{i,j} E_{i,j}}$$

*i = actual*

*j = predicted*

## Observed Confusion Matrix

N x N confusion matrix of prediction classification

## Expected Confusion Matrix

N x N confusion matrix under the assumption of no correlation among classes. Outer product of actual and predicted labels.

**E = np.outer(actual, predicted)**

## Penalty matrix, N x N

$$w_{i,j} = \frac{(i-j)^2}{(N-1)^2}$$

N x N confusion matrix of penalties. If predicted is equal to actual, zero penalty.

## Why use QWK?

- Allocate a **higher penalty score if our prediction is further away from the actual value.**
- Hierarchy matters in this case. Predicting ISUP grade 1 for sample supposedly grade 5 has huge consequences.

| isup_grade |
|---|
| 0 |
| 1 |
| 2 |
| 4 |
| 3 |
| 5 |

**Actual = 2 , Predicted = 1**

**Penalty:**

$$\frac{(2-1)^2}{(5-1)^2} = 0.0625$$

**Actual = 2 , Predicted = 4**

**Penalty:**

$$\frac{(2-4)^2}{(5-1)^2} = 0.25$$

# Evaluation – Quadratic Weighted Kappa (QWK)

## QWK Values Interpretation

| Range of Quadratic Weighted Kappa | Concordance |
|---|---|
| Negative | poor |
| 0.01–0.20 | slight |
| 0.21–0.40 | fair |
| 0.41–0.60 | moderate |
| 0.61–0.80 | substantial |
| 0.81–1 | almost perfect |

## Usage in Python

### From sklearn library

```
cohen_kappa_score(actual, pred, labels=None, weights= 'quadrati
c', sample_weight=None)
```

# Questions from my side

- Is the project name flexible? Or must I follow back the original one in the STAT 8002 Project list? If not, I was thinking of **Deep Learning Algorithms in Predicting Prostate Cancer.** Feel free to suggest otherwise.

- Based on your experience, is using or not using mask in modelling better?

- Is a triweekly (once in 3 weeks) catchup alright with you? With emails in between if needed (e.g significant findings/breakthrough, quick questions for you)

- Is there anything you feel I missed out in this session that you would like to know?

# Project Outline Recap (Flexible)

- **Introduction**
    - Dataset information
    - Refresh on domain knowledge of prostate cancer
- **Exploratory Data Analysis (EDA)**
    - EDA on ISUP score labels to see distribution of labels
    - Label distributions for age / other demographics
    - Images EDA
    - Masks EDA
    - Data cleansing process
- **Modelling & Algorithms**
    - Benchmark using Resnet/VGG/etc to get benchmark score on test set
    - Try a self built model to improve the results
    - Highlight structure of self built models
    - Compare the results of possible models used
    - Evaluated using quadratic weighted kappa or f1-weighted score
- **Explainability of model results (using best model)**
    - use SHAP to derive some explainability
    - visually show why/how the model makes the classification
- **Transfer Learning Potential (optional and if time permits)**
    - see if can be applied to similar H&E stained biopsy images of breast cancer
    - evaluate performance
- **Potential Improvements**
- **Conclusions**


THANK
YOU