

Gleason grading of biopsies using an attention-based multi-resolution model ensembled with LGBM and XGBoost

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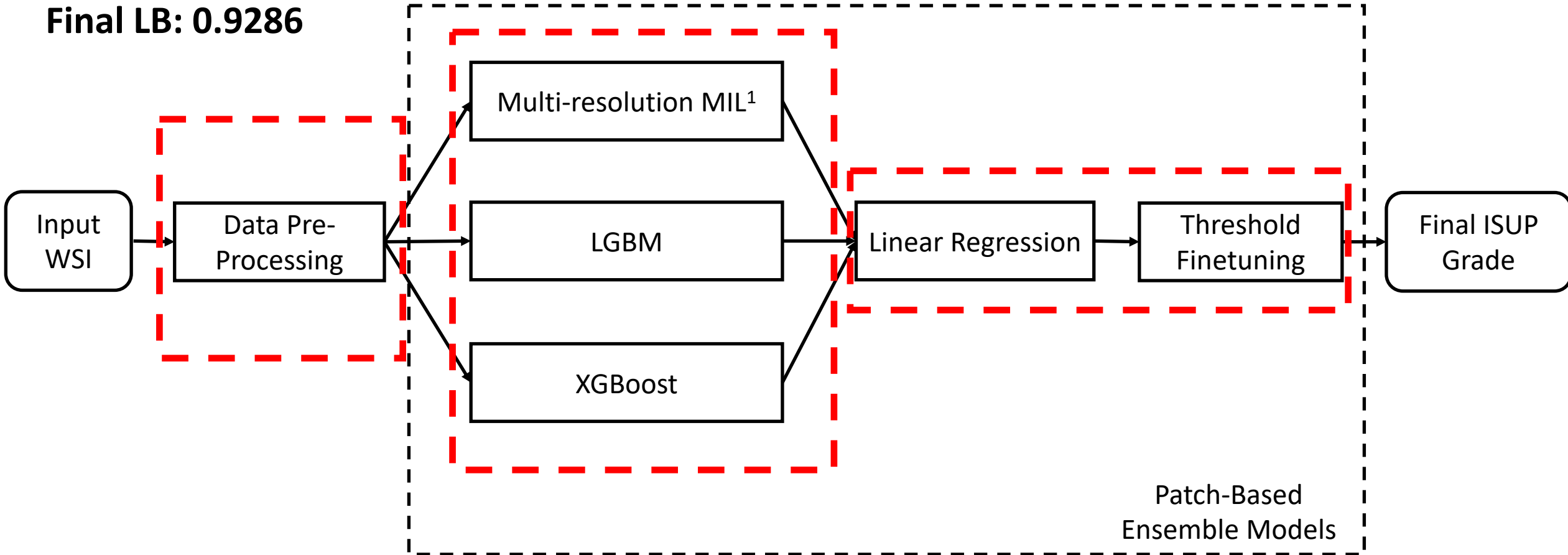


Group Photo of Medical Image Informatics

Computational Diagnostics (CDx)
Medical Imaging Informatics (MII)
University of California, Los Angeles, USA

Overall Solution

Final LB: 0.9286



¹ MIL: multi-instance learning.

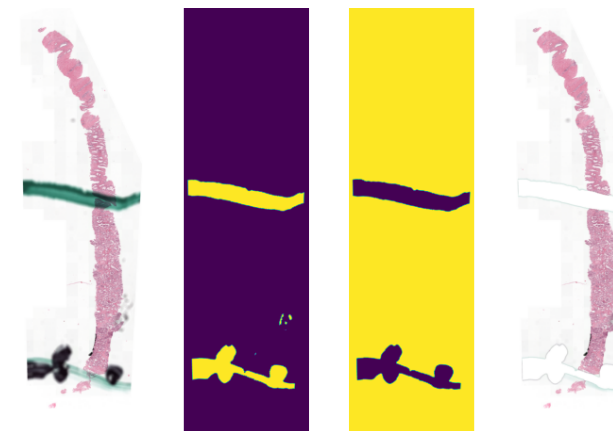
Data Cleaning



- Removal of Pen Marks by [akensert](#)
- Suspicious Slides by [Zac Dannelly](#)

No cancerous tissue but ISUP Grade > 0	85
Blank Slides	5

- Duplicate Slides by [Appian](#)



Original

Pen Marks
Removed



*65be0



*af93e

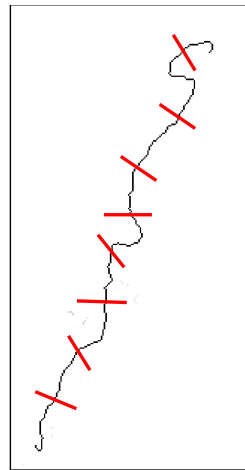
Data Pre-Processing



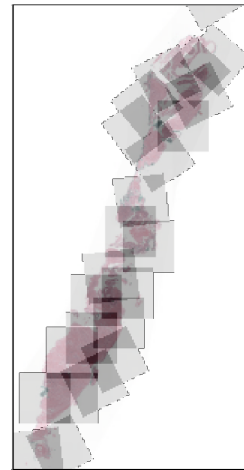
Original
Image



Tissue
Mask



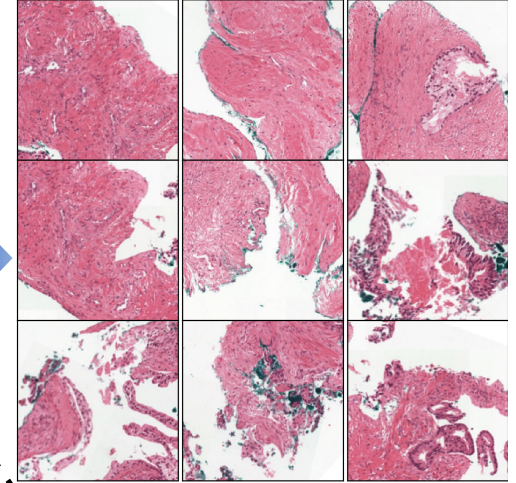
Midline



Spread Patches on
"Spine"



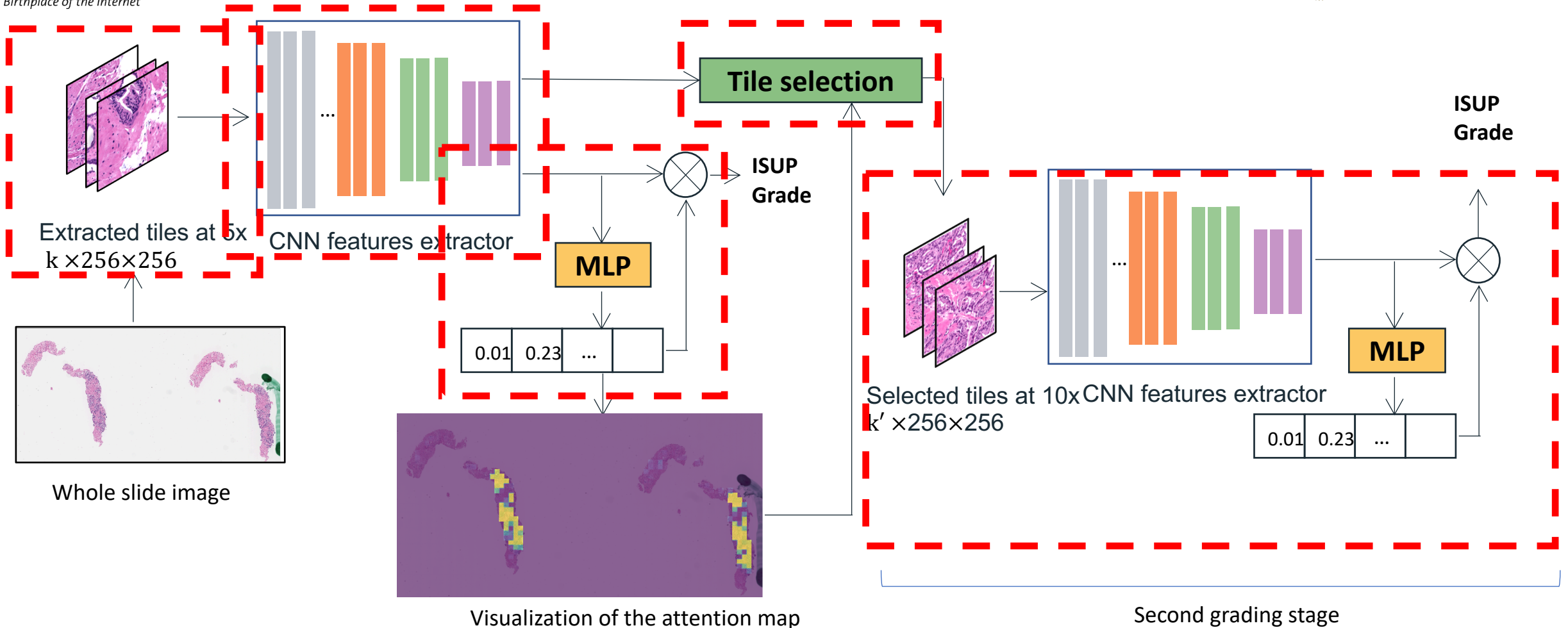
Blue Ratio
Selection



Top k Patches based
on BR

$$BR = \frac{100 \times B}{1 + R + G} \times \frac{256}{1 + R + G + B}$$

Multi-resolution MIL



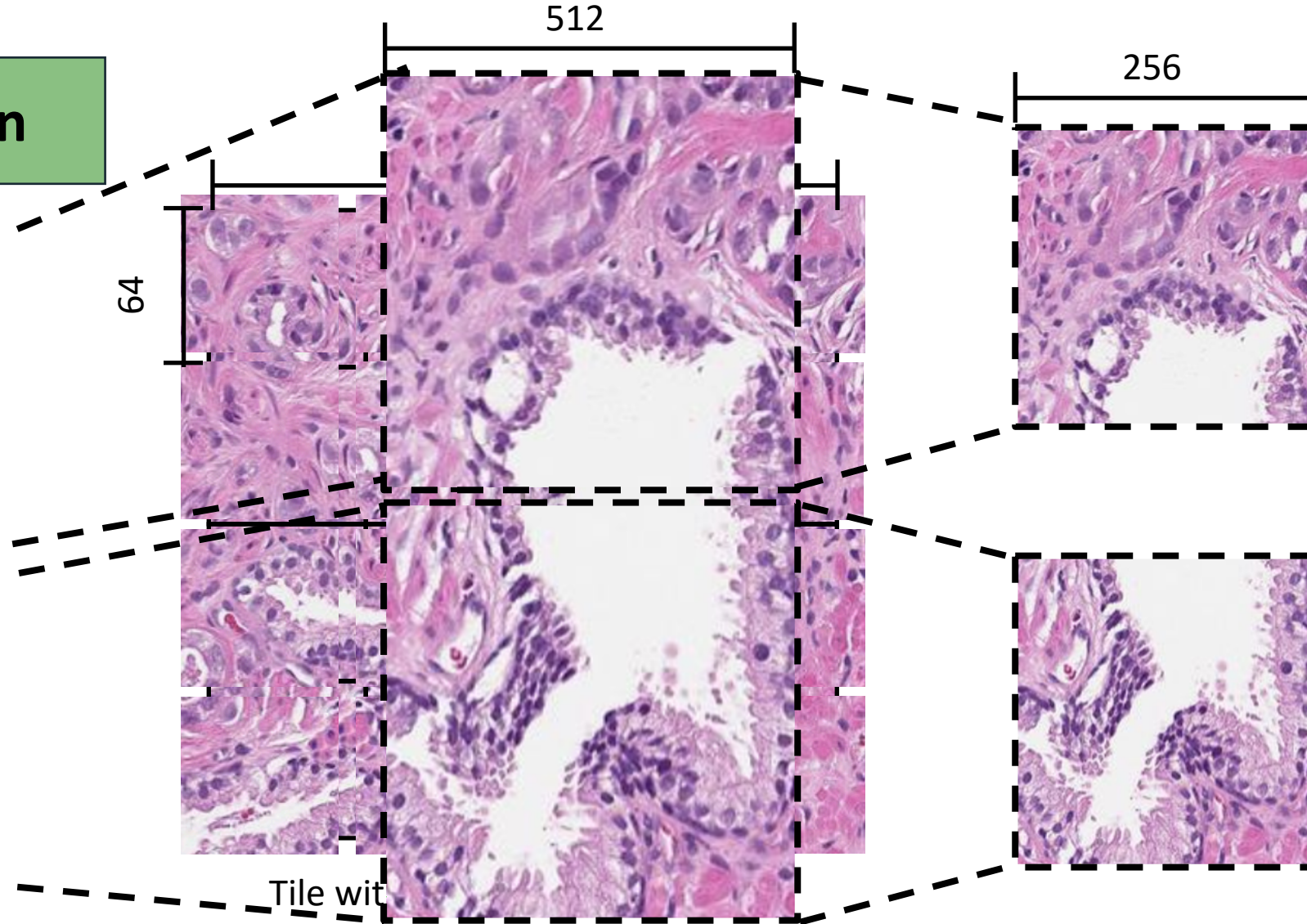
First screening stage

Second grading stage

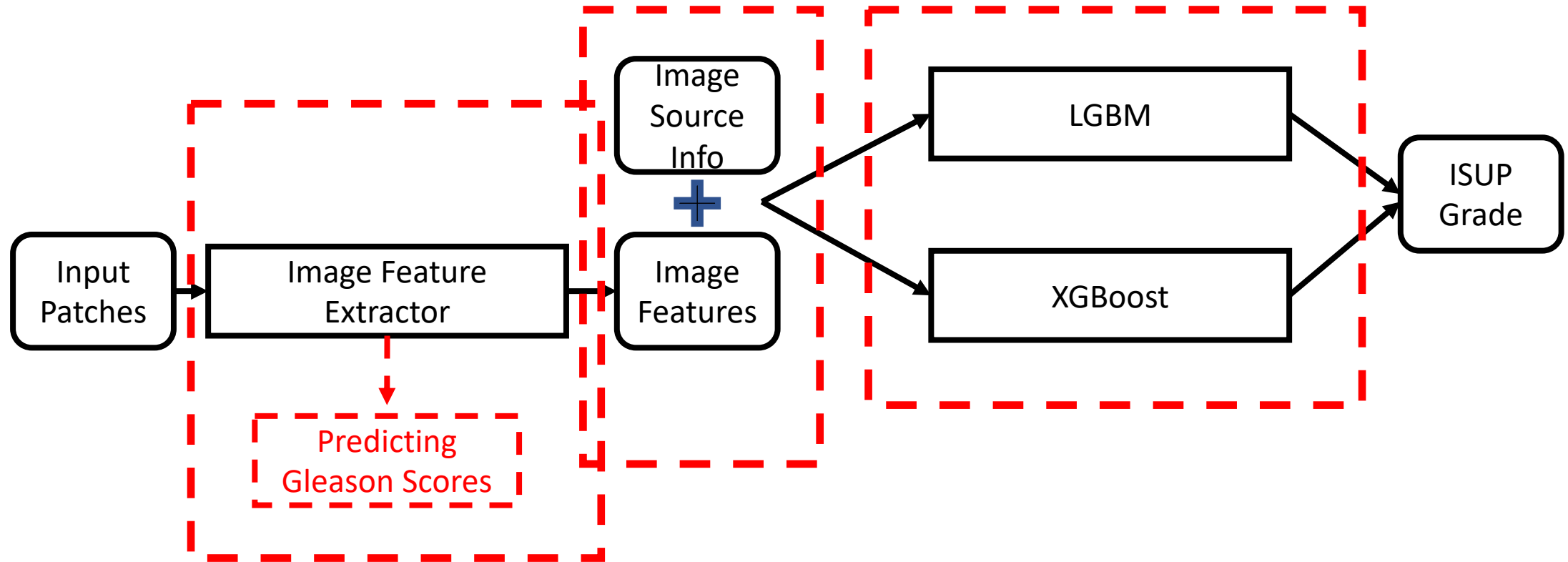
Li, J., Li, W., Gertych, A., Knudsen, B. S., Speier, W., & Arnold, C. W. (2019). An attention-based multi-resolution model for prostate whole slide image classification and localization. *CVPR Workshops (2019)*.

Tile Selection of Multi-reso MIL

Tile selection



LGBM & XGBoost



Threshold Finetuning

- Optimizer of threshold for QWK: Brute force search
- Optimizer of threshold for QWK: Partial differentiation

Pseudo Code of Partial Differentiation Method

```
def fit(X, y):  
    ## construct partial differential equation  
    loss_partial = partial(kappa_loss, X=X, y=y)  
    ## initialize the threshold  
    initial_coef = [0.5, 1.5, 2.5, 3.5]  
    ## optimize the coefficient by specified method  
    coef_ = optimize.minimize(loss_partial, initial_coef, method='nelder-mead')
```

Training Details



- 4-fold Cross Validation:
 - Result $4 * 3$ (# of models, i.e. MIL, LGBM, XGBoost) = 12 models at inference time
- Network Architecture:
 - **ResNext 50**, EfficientNetB0
- Optimizer:
 - Adam Optimizer with Cosine Annealing Learning Rate Scheduler
- Loss Function: adopt ordinal regression (binning strategy)
 - Label = [0,0,0,0,0] means target 0, label = [1,1,0,0,0] means target 2, and label = [1,1,1,1,1] means target 5.

Performances Comparison

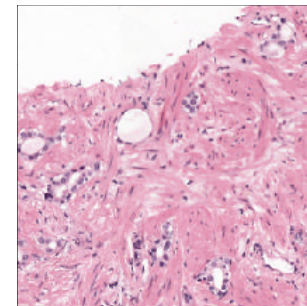


Method	Public LB Score	Private LB Score
LGBM	0.9135	0.9239
LGBM + XGBoost	0.9121	0.9248
MIL (w/o threshold optimization)	0.9161	0.8968
MIL	0.9018	0.9185
MIL + LGBM + XGBoost (w data source) ¹	0.9132	0.9262
MIL + LGBM + XGBoost	0.9061	0.9286

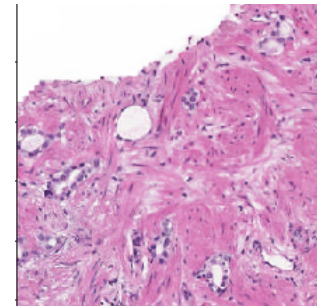
¹ “w data source” means we used data source information as input feature.

Discussions

- Things we have tried:
 - Stitching v.s Stacking
 - Stain Normalization: Reinhard v.s CycleGAN
 - Segmentation
 - Multi-task learning with Gleason score
 - Multi-resolution input
- Things we think can be improved:
 - Noisy samples detection
 - Self-supervised pre-training for feature extractor
 - Reinforcement learning or RNN for dynamic tile selection



Stain Normalization
(CycleGAN)



Acknowledgement

- Thanks to organizers for this fantastic Kaggle challenge.
- Thanks all the competitors for helpful discussions and kernels:
 - Data cleaning & pre-processing:
 - Removal of Pen Marks by [akensert](#)
 - Suspicious Slides by [Zac Dannelly](#)
 - Duplicate Slides by [Appian](#)
 - Imaging Tiling by [rftexas](#)
 - Network architectures & Training Details
 - Concatenate tile pooling by [lafoss](#)
 - Binning loss strategy by [haiqishen](#)
 - Optimizer for QWK by [abhishek](#)

Q & A

Thank you for your attention!

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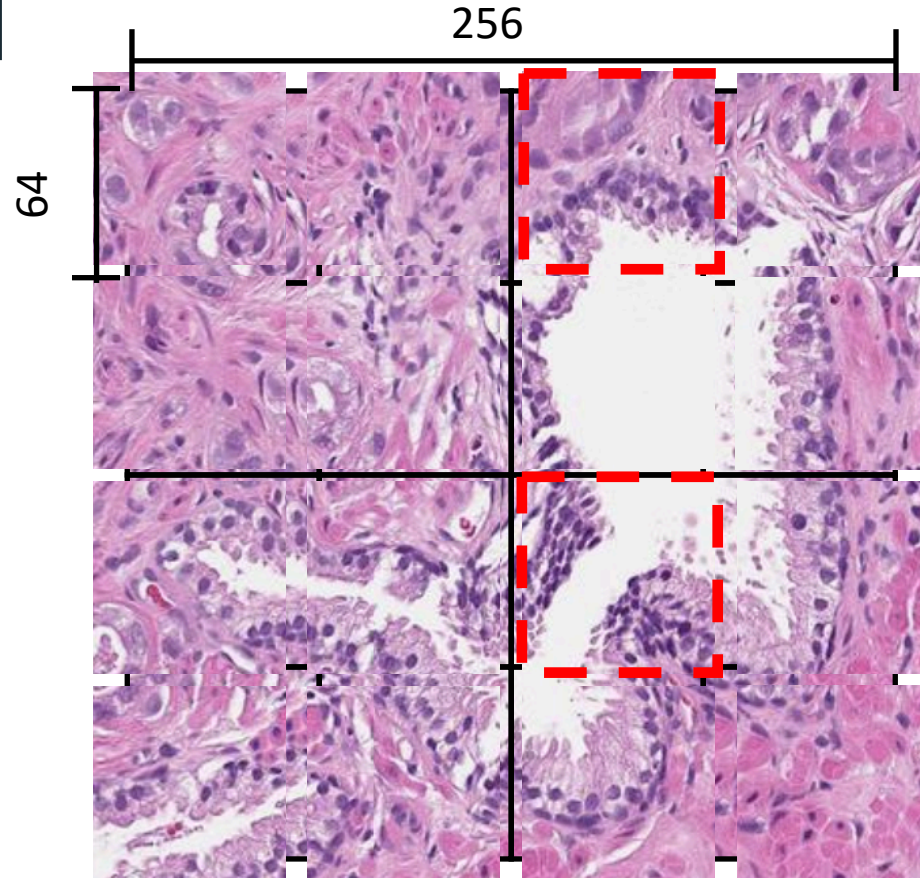
Homepage: <https://wenyuan-vincent-li.github.io/>

Linkedin: <https://www.linkedin.com/in/wen-yuan-li-ucla/>

Tile Selection of Multi-reso MIL



Tile selection

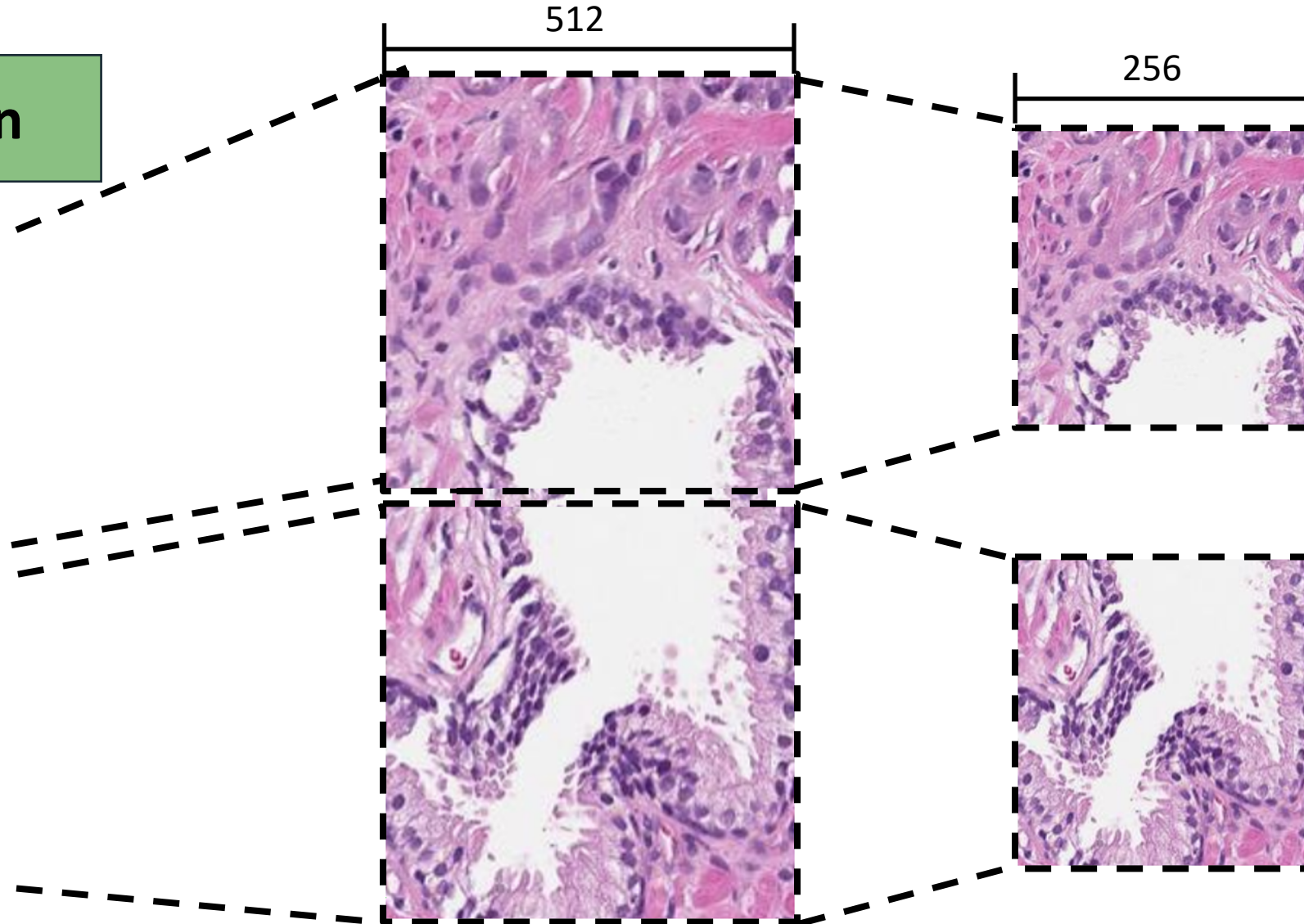


Tile with high attention weights

Tile Selection of Multi-reso MIL



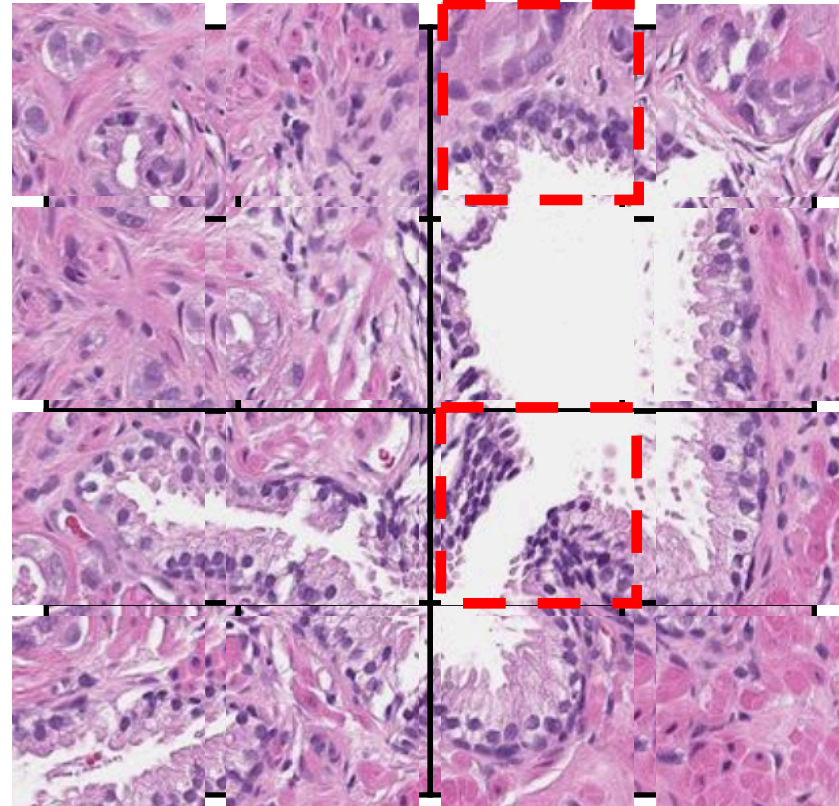
Tile selection



Tile Selection of Multi-reso MIL



Tile selection

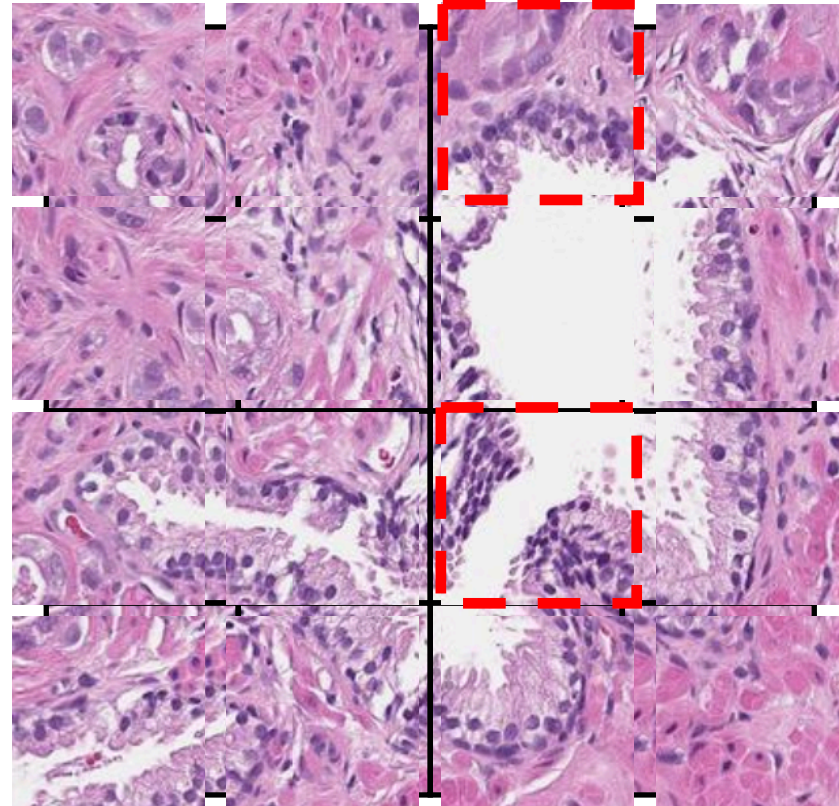


Tile with high attention weights

Tile Selection of Multi-reso MIL



Tile selection



Tile with high attention weights