Neural Networks for Pathology Image Classification

CS 640 AI, Fall 2023

Margrit Betke

Department of Computer Science

Boston University

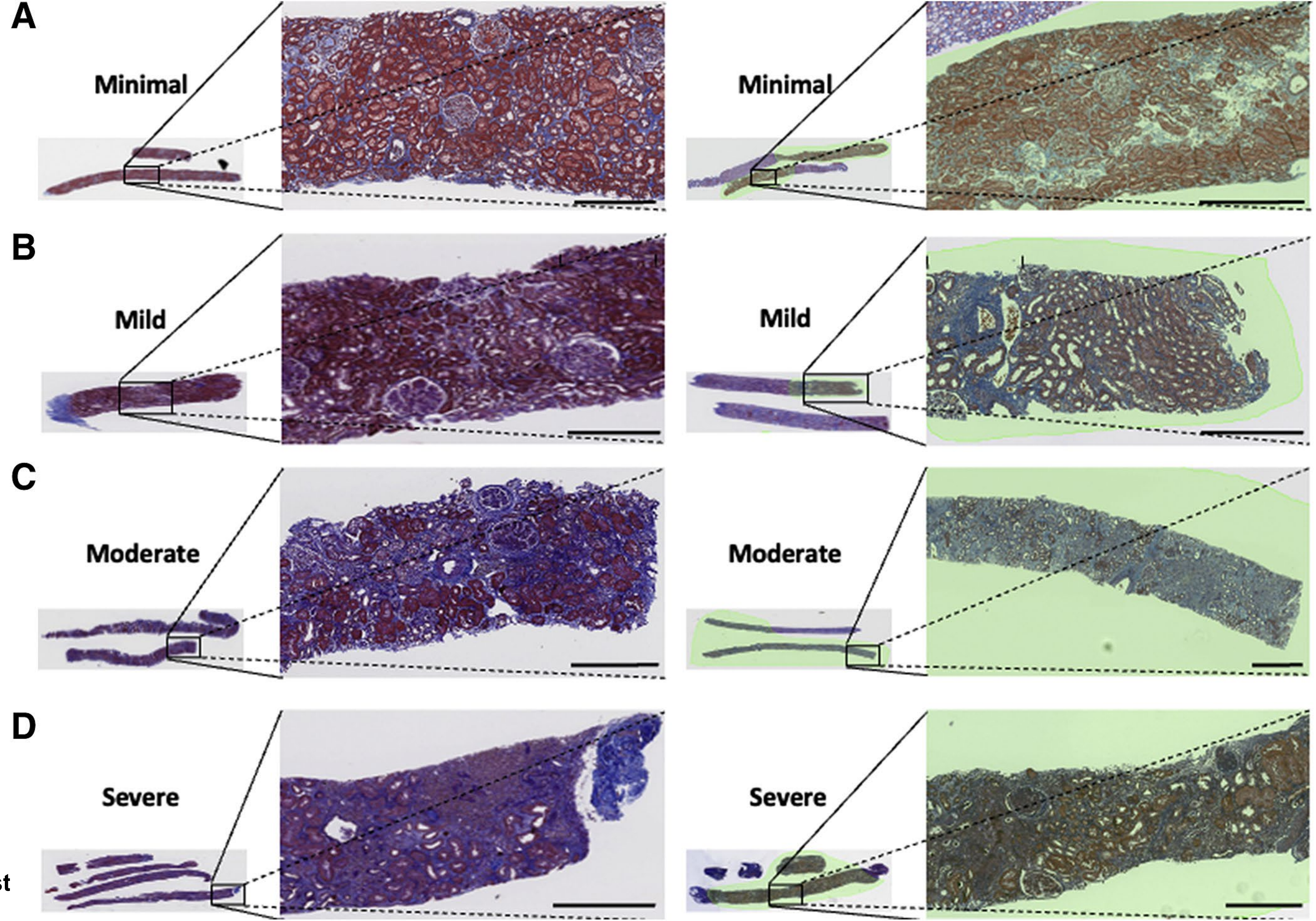
Learning Outcomes

- Learn about Whole Slide Images
- Learn about pathologists’ difficulty in establishing “ground truth”
- Learn about two AI models that interpret pathology images
    1. Feature Pyramid Network with Global/Local Feature Exchange
    2. Transformer with graph input and “activation map” output

Both AI models are available for you to use for your course project

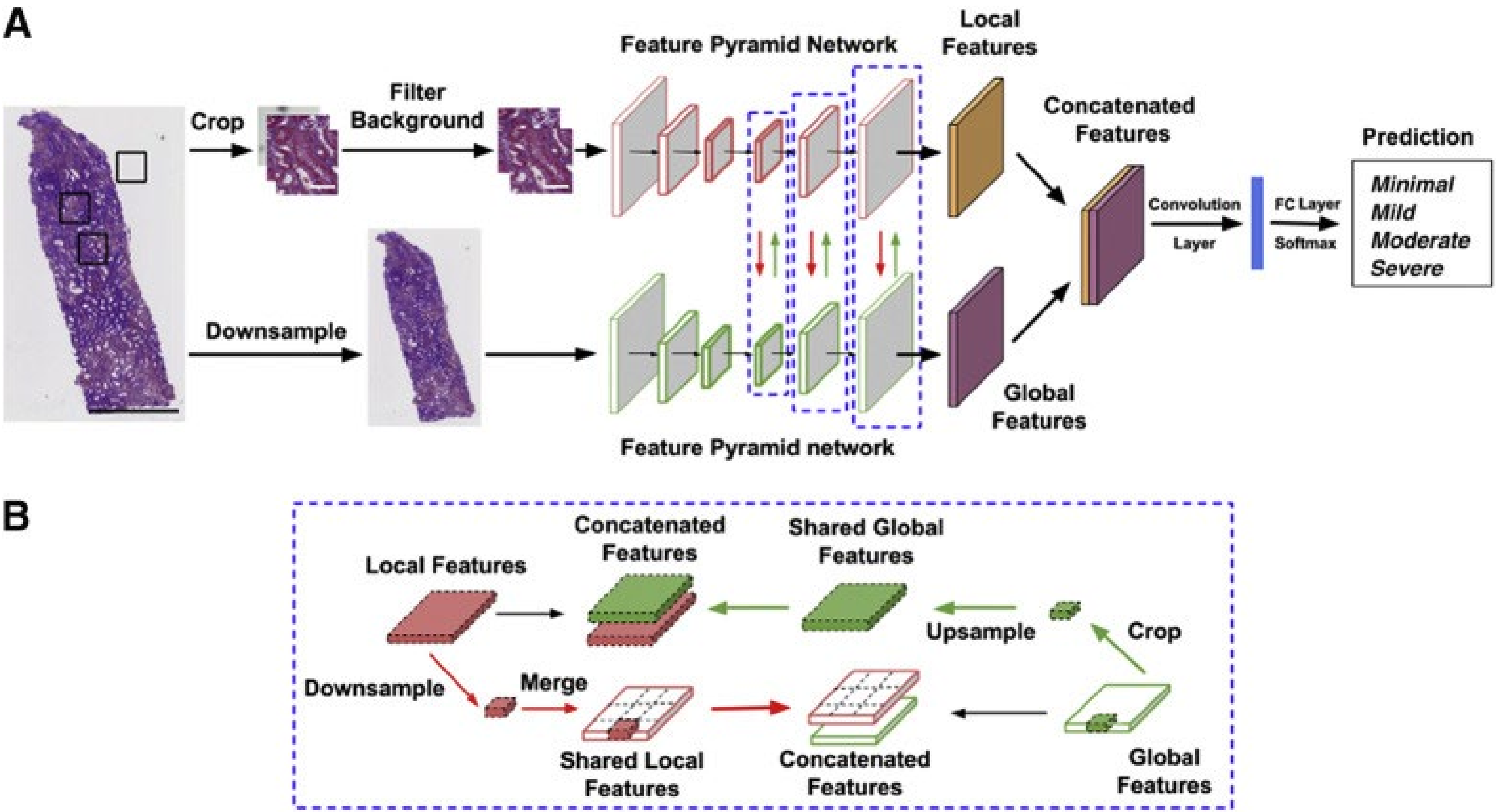
Yi Zheng, Clarissa A Cassol, Saemi Jung, Divya Veerapaneni, Vipul C. Chitalia, Kevin Ren, Shubha S. Bellur, Peter Boor, Laura M. Barisoni, Sushrut S. Waikar, Margrit Betke, and Vijaya B. Kolachalama.
Deep learning-driven quantification of interstitial fibrosis in digitized kidney biopsies.
The American Journal of Pathology: 191(8):1442-1453, August 2021.

https://doi.org/10.1016/j.ajpath.2021.05.005



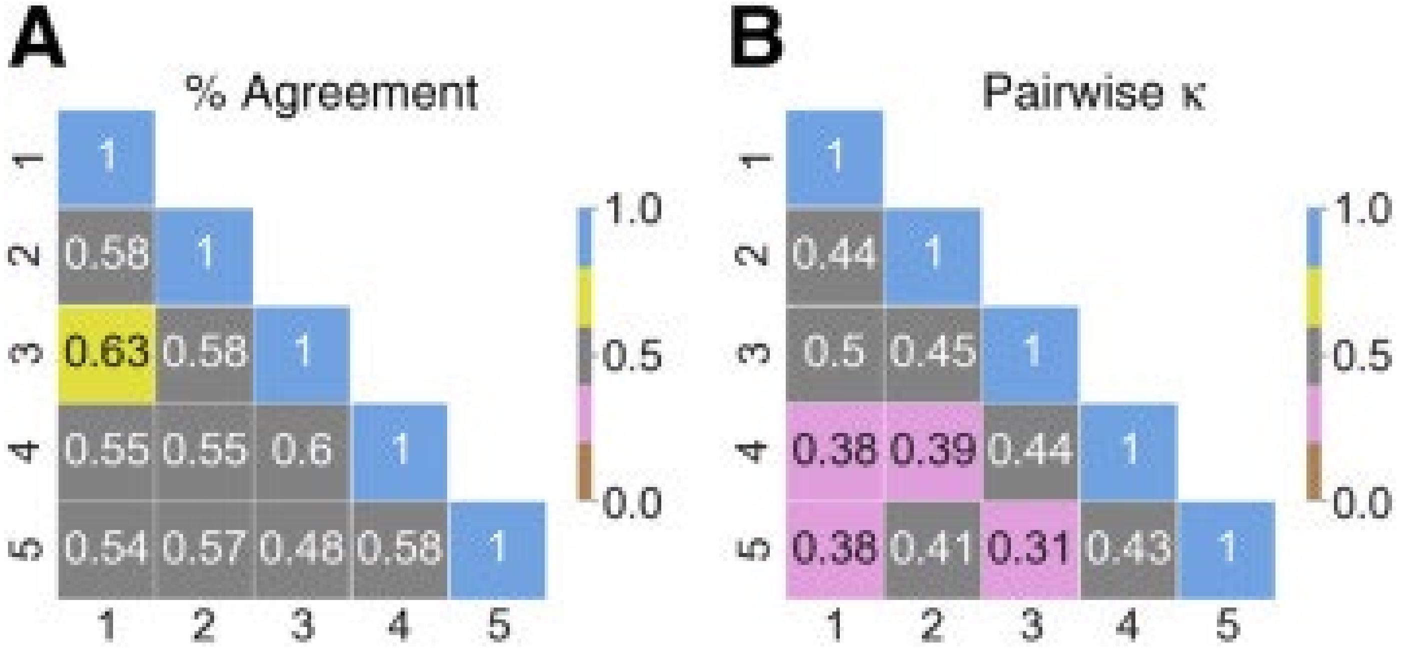
Bost

BOSTON UNIVERSITY

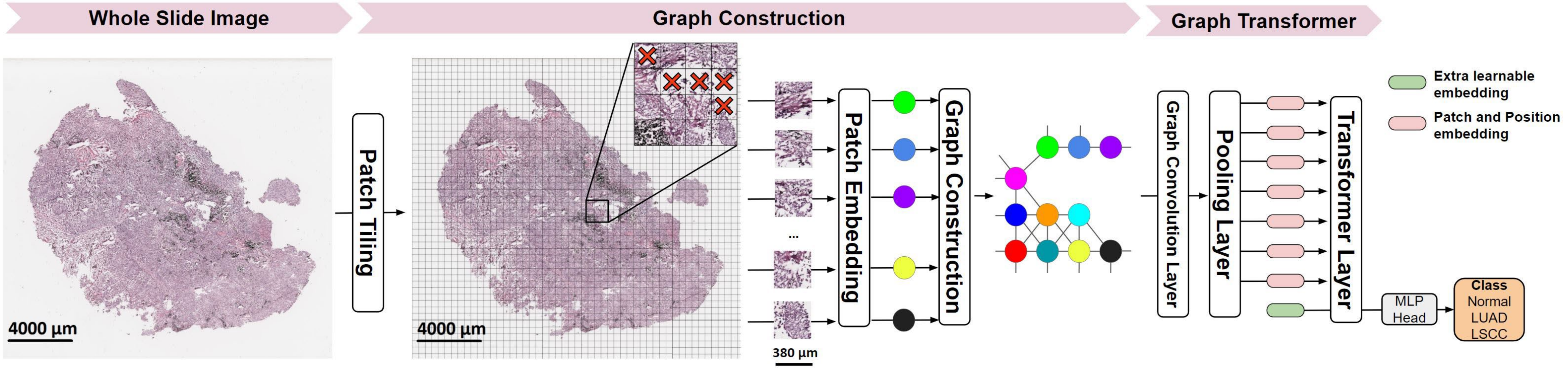

A
Crop
Filter
Background
Feature Pyramid Network
Local
Features
Concatenated
Features
Prediction
Minimal
Mild
Moderate
Severe
Convolution
Layer
FC Layer
Softmax
Downsample
Global
Features
Feature Pyramid network
B
Local Features
Concatenated
Features
Shared Global
Features
Upsample
Crop
Downsample
Merge
Shared Local
Features
Concatenated
Features
Global
Features

Pathologists often do not agree with each other

5 Pathologists and their mutual agreement



Overview of Our Graph Transformer Classification Model to Distinguish Two Lung Cancer Types and Healthy Pathology



Yi Zheng, Rushin H. Gindra, Emily J. Green, Eric J. Burks, Margrit Betke, Jennifer E. Bean, and Vijaya B. Kolachalama. A graph transformer for whole slide image classification. IEEE Trans Med Imaging 41(11):3003-3015, November 2022. https://doi.org/10.1109/TMI.2022.3176598

Data & Goal

Data:

4, 818 Whole Slide Images (WSIs) from

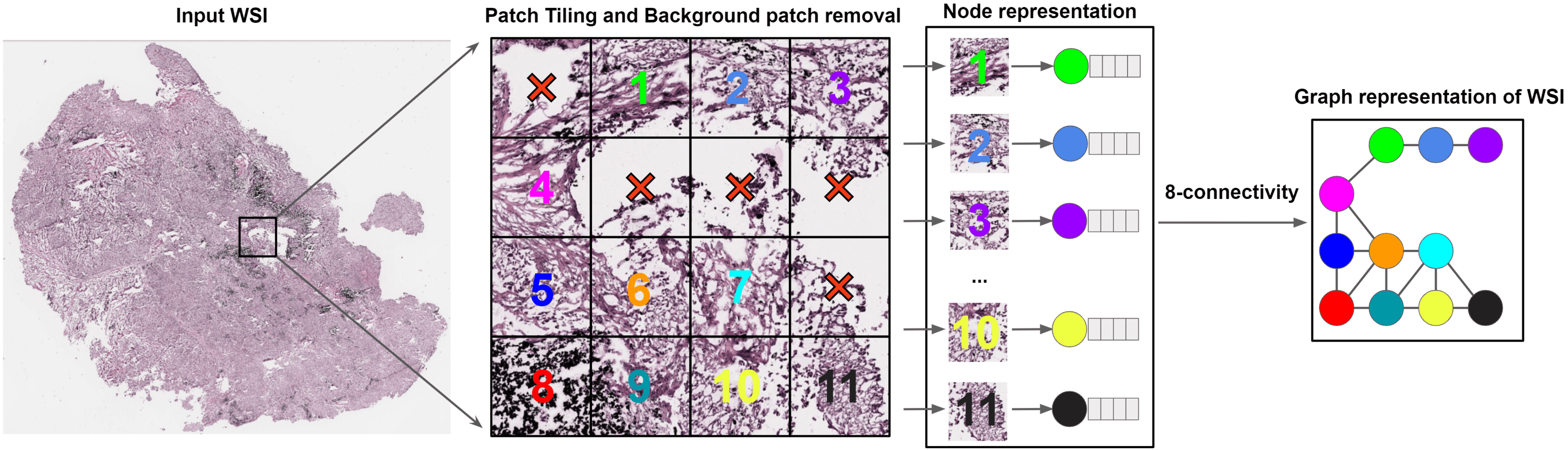
- Clinical Proteomic Tumor Analysis Consortium (CPTAC),
- National Lung Screening Trial (NLST),
- The Cancer Genome Atlas (TCGA)

Goal:

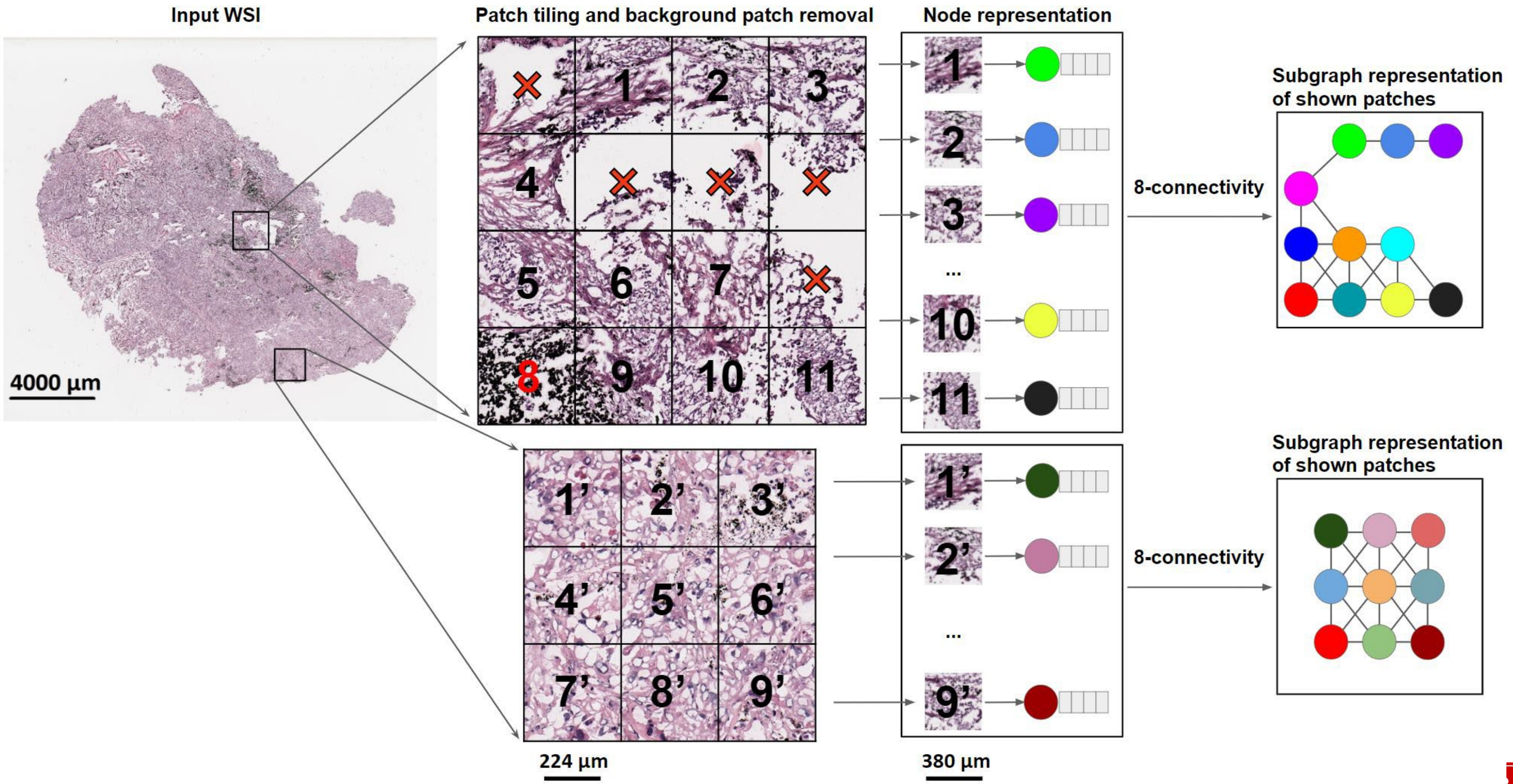
to distinguish

- adenocarcinoma (LUAD) and
- squamous cell carcinoma (LSCC)
- from adjacent non-cancerous tissue (normal)

Creating an Undirected Graph from Image Patches
Graph: V = Patches, E = Patch Adjacency

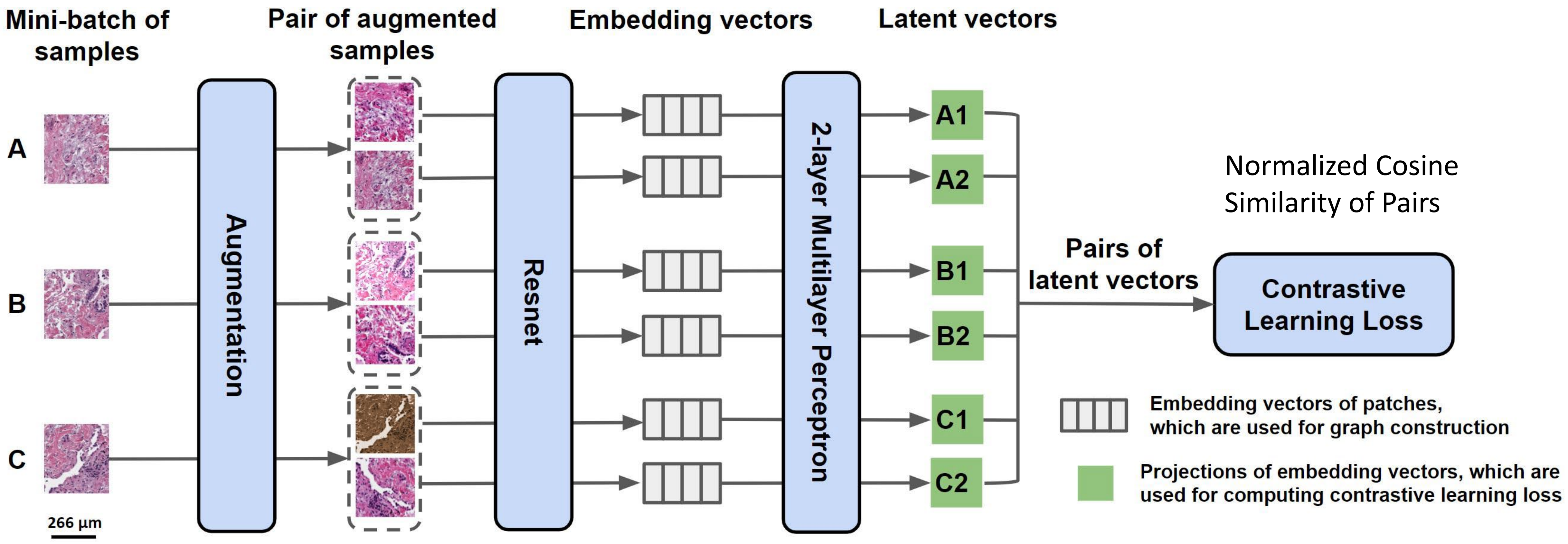


Two subgraphs

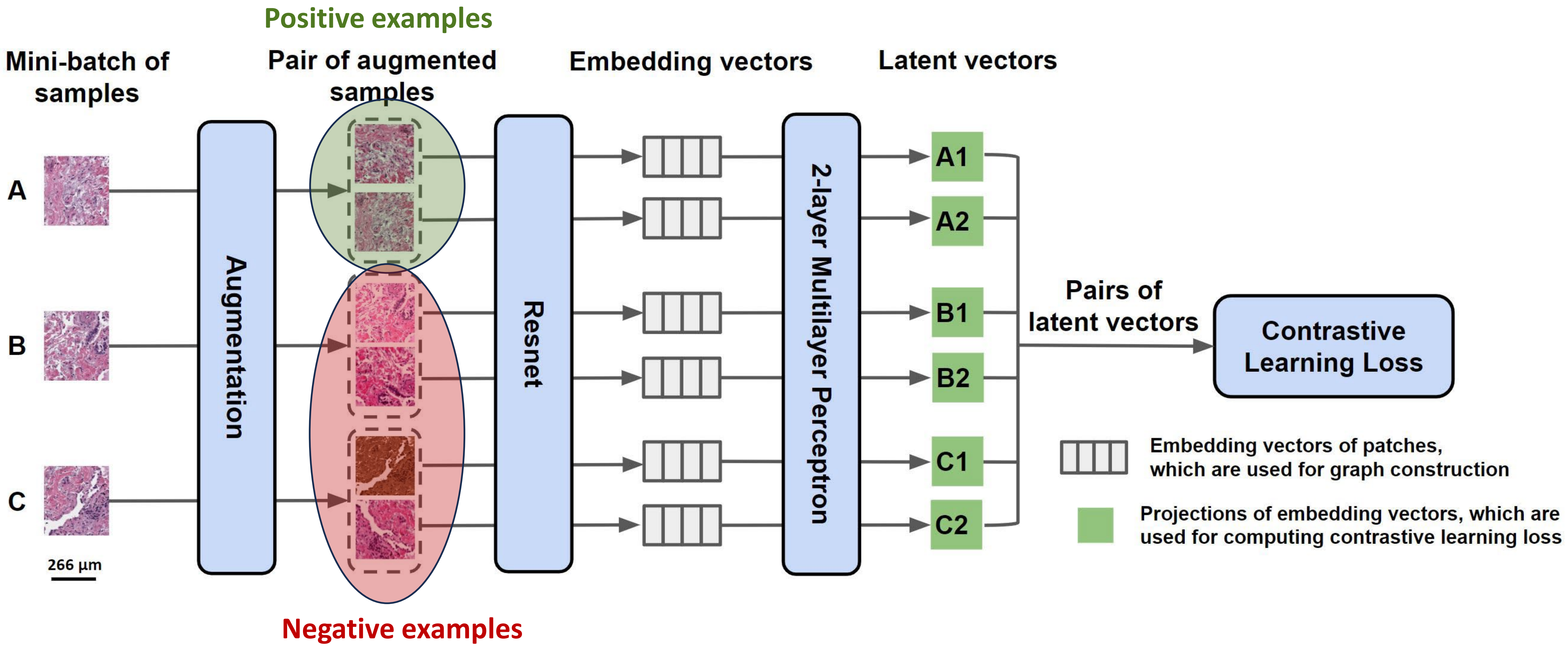


Contrastive Learning Loss for Feature Extraction

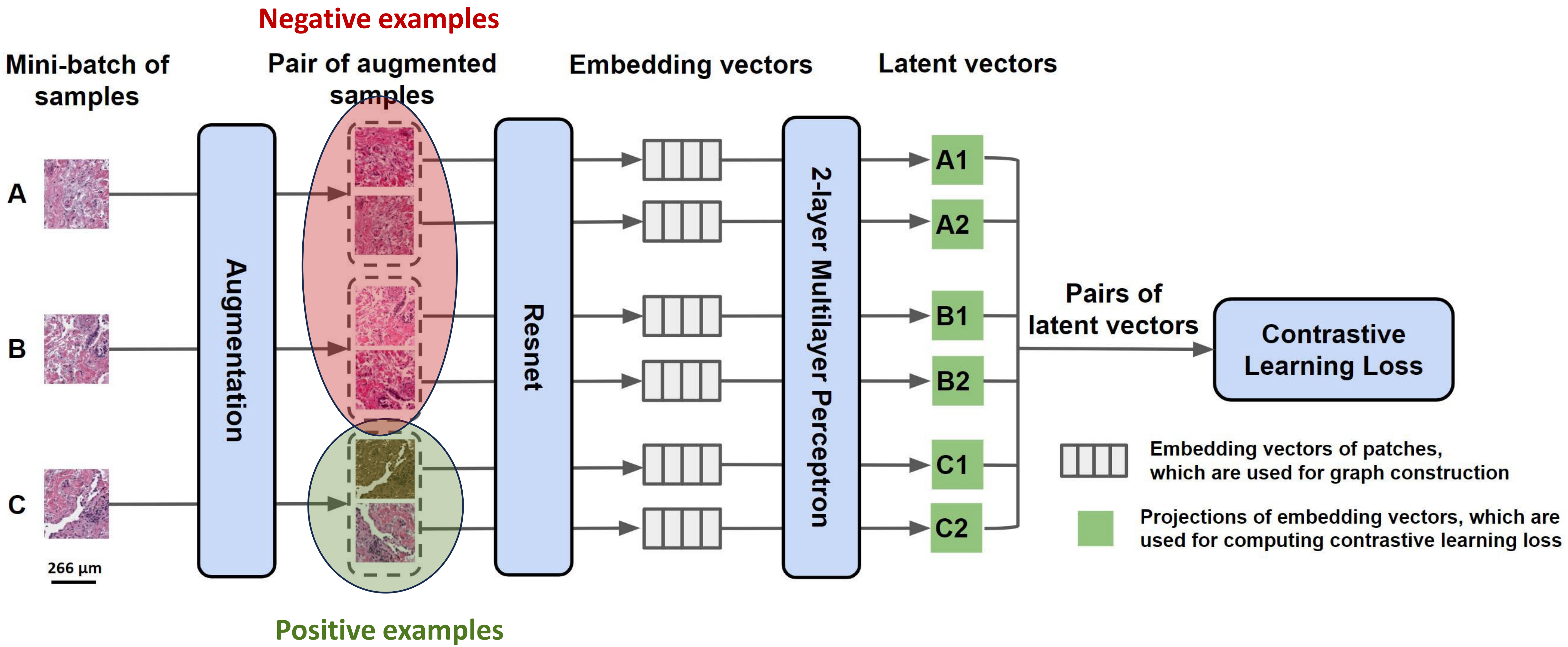
Normalized Cosine Similarity of Pairs



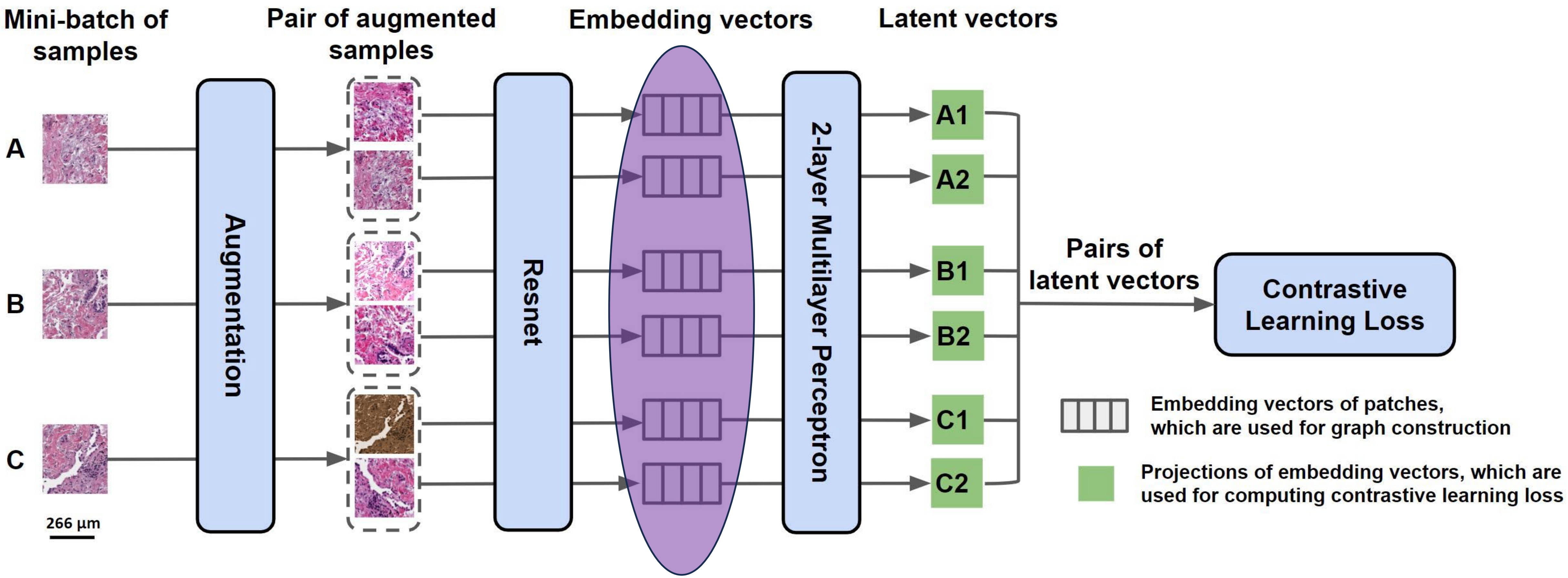
Contrastive Learning Loss for Feature Extraction

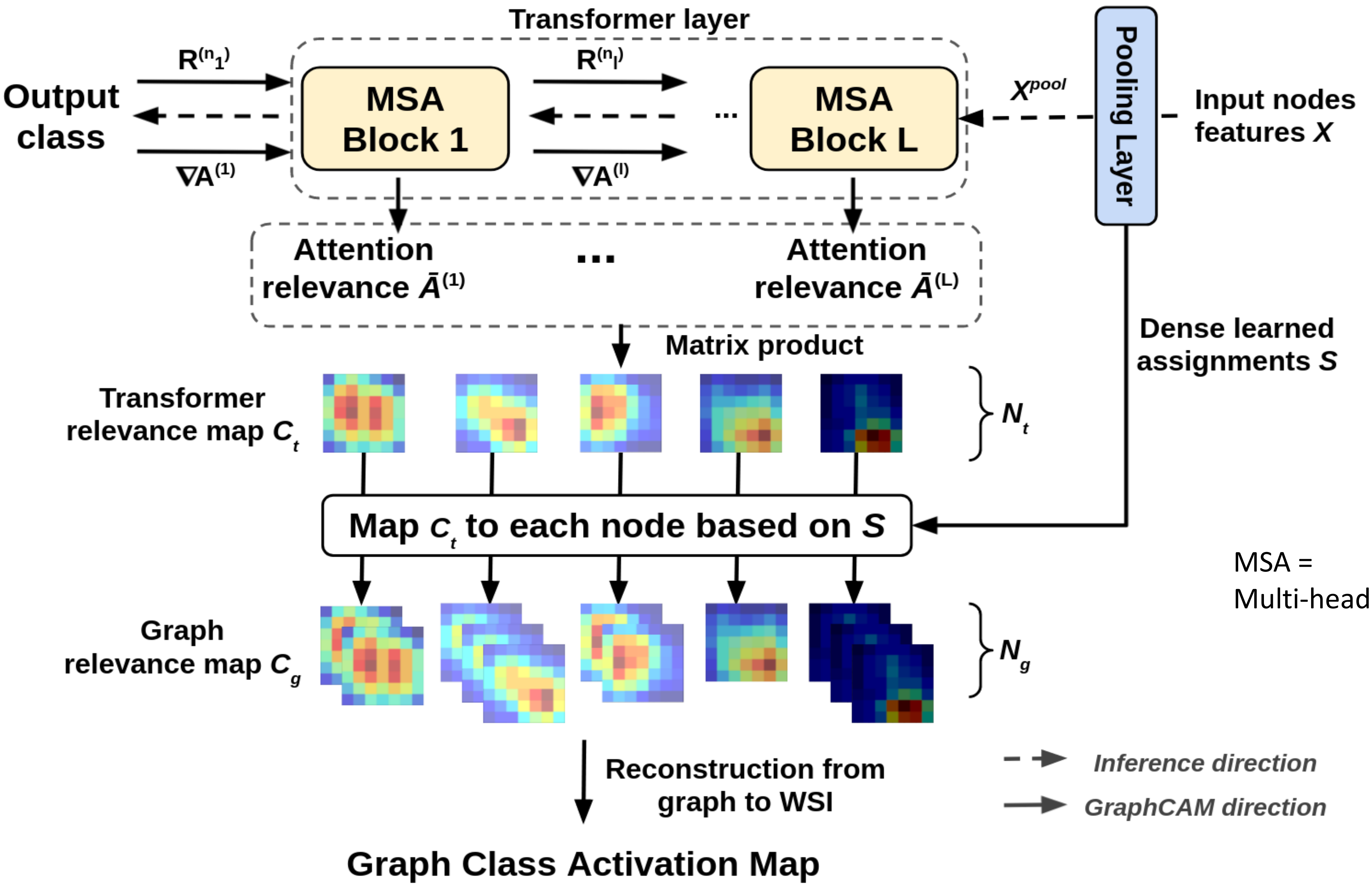


Contrastive Learning Loss for Feature Extraction



After Training: Use Embeddings for Patch Analysis





Graph nodes
~ tokens
Adjacency matrix
~ positional information of tokens

MSA =
Multi-headed Self Attention

BOSTON UNIVERSITY

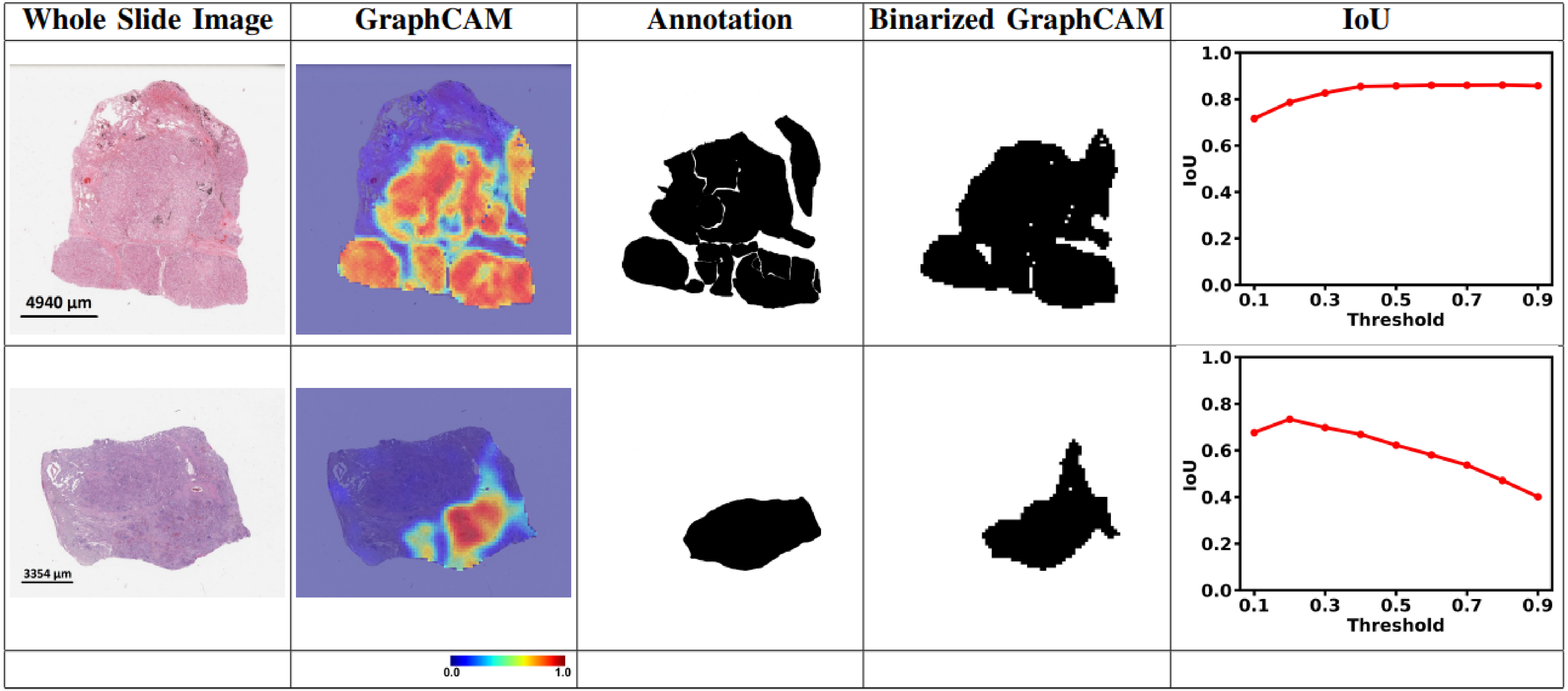


Fig. 4: **GraphCAMs and their comparison with the expert annotations.** For each WSI, we generated GraphCAMs and compared them with annotations from the pathologist. The first column contains the original WSIs, the second and third columns contain GraphCAMs and pathologist's annotations, respectively and the fourth column contains the binarized GraphCAMs based on the threshold from the Intersection of Union (IoU) plot in the last column. The first row shows an LUAD case and the second row denotes an LSCC case.

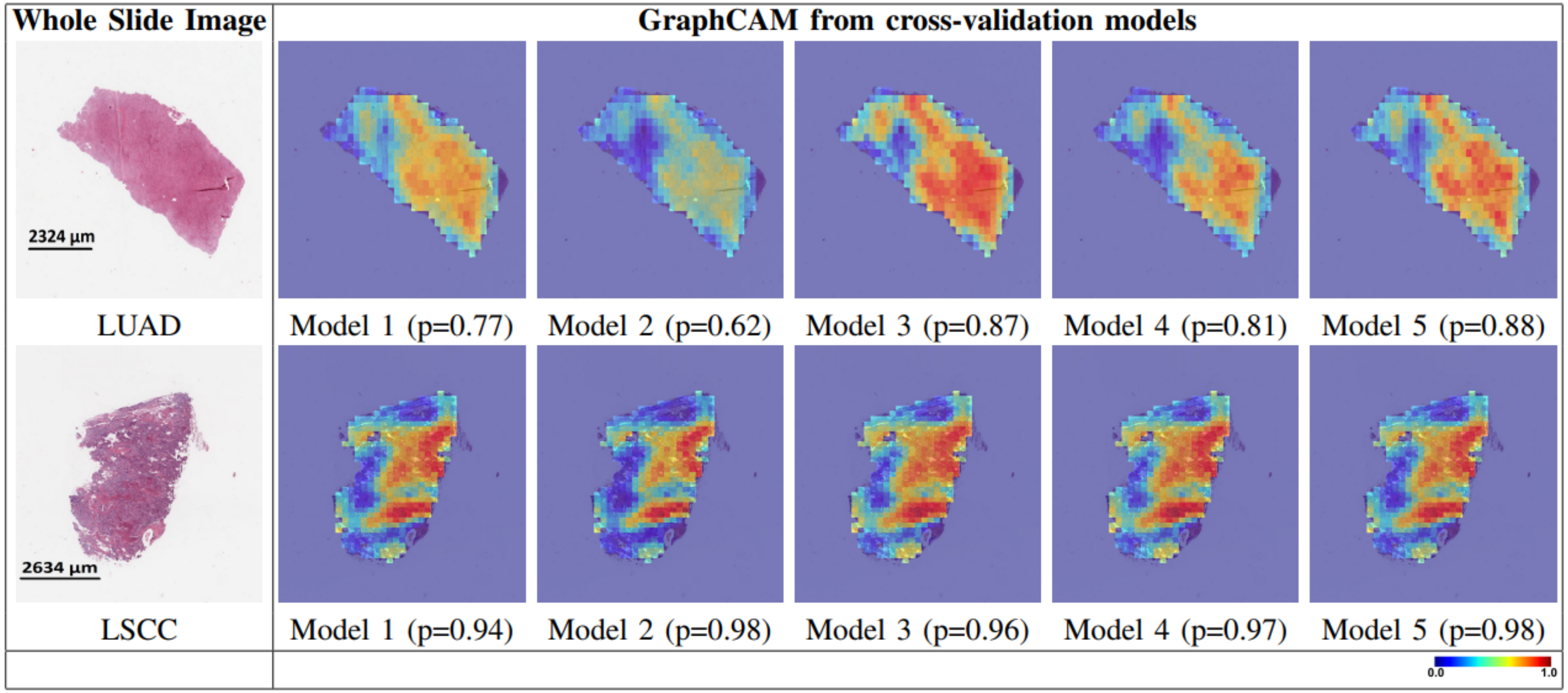
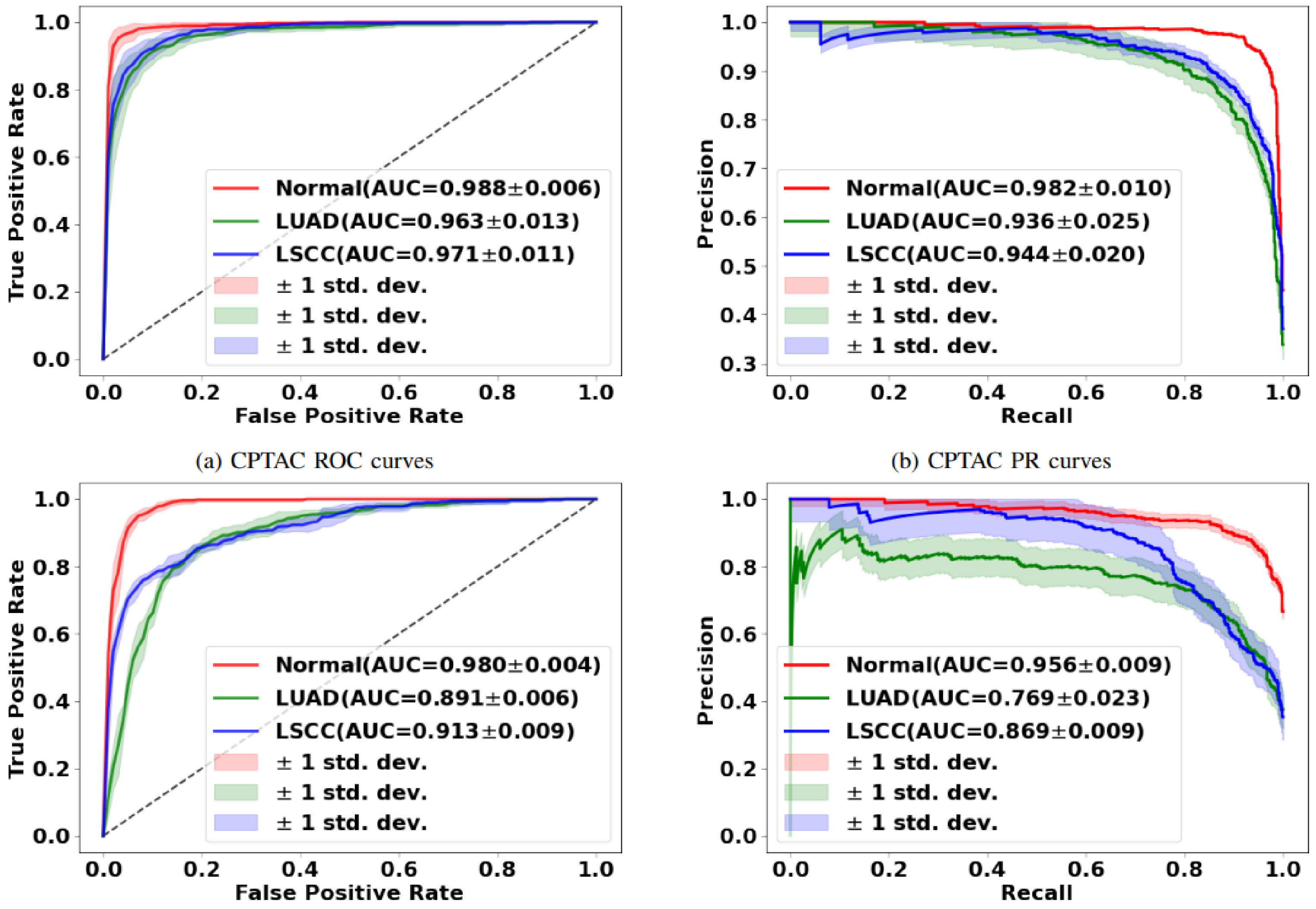


Fig. 5: **Graph class activation map performance.** GraphCAMs generated on WSIs across the runs performed via 5-fold cross validation are shown. The first column shows the original WSIs and the other columns show the GraphCAMs with prediction probabilities on the cross-validated model runs. The first row shows a sample WSI from the LUAD class and the second row shows an WSI from the LSCC class. The colormap represents the probability by which an WSI region is associated with the output label of interest.



(a) CPTAC ROC curves

(b) CPTAC PR curves

(c) TCGA ROC curves

(d) TCGA PR curves

Fig. 3: **Model performance on the CPTAC and TCGA datasets**. Mean ROC and PR curves along with standard deviations for the classification tasks (normal vs. tumor; LUAD vs. others; LSCC vs. others) are shown.

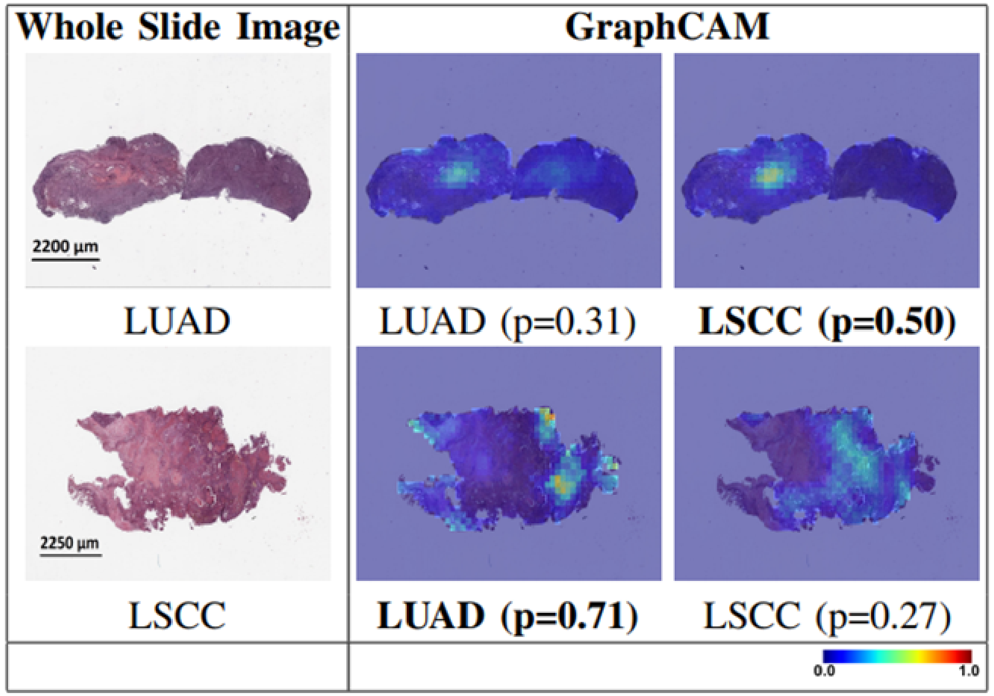


Fig. 6: **GraphCAMs for failure cases.** The first row shows a sample WSI from the LUAD class where the model prediction was LSCC, and the second row shows an WSI from the LSCC class where the model prediction was LUAD. The first column shows the original WSI, and the second and third columns show the generated GraphCAMs along with prediction probabilities. The bold font underneath certain GraphCAMs was used to indicate the model predicted class label for the respective cases. Since this is a 3-label classification task (normal vs. LUAD vs. LSCC), the LUAD and LSCC probability values do not add up to 1.

Learning Outcomes

- Learn about Whole Slide Images
- Learn about pathologists' difficulty in establishing "ground truth"
- Learn about two AI models that interpret pathology images
    1. Feature Pyramid Network with Global/Local Feature Exchange
    2. Transformer with graph input and "activation map" output

Both AI models are available for you to use for your course project