

# H2G-Net: A multi-resolution refinement approach for semantic segmentation of gigapixel histopathological images

André Pedersen<sup>1,2</sup>, Erik Smistad<sup>3,4</sup>, Tor V. Rise<sup>1,5</sup>, Vibeke G. Dale<sup>1,5</sup>, Henrik S. Pettersen<sup>1,5</sup>,  
Tor-Arne S. Nordmo<sup>6</sup>, David Bouget<sup>4</sup>, Ingerid Reinertsen<sup>3,4</sup>, and Marit Valla<sup>1,2,5,7</sup>

<sup>1</sup> IKOM, NTNU, <sup>2</sup> Clinic of Surgery, St. Olavs hospital, <sup>3</sup> ISB, NTNU <sup>4</sup> SINTEF, NTNU, <sup>5</sup> Dept. of Pathology, St. Olavs hospital, <sup>6</sup> IFI, UiT,

<sup>7</sup> Clinic of Laboratory Medicine, St. Olavs hospital

## Objectives and contributions

**Goal:** Accurate and rapid segmentation of breast cancer in histopathological images.

### Clinical motivation

Existing solutions are:

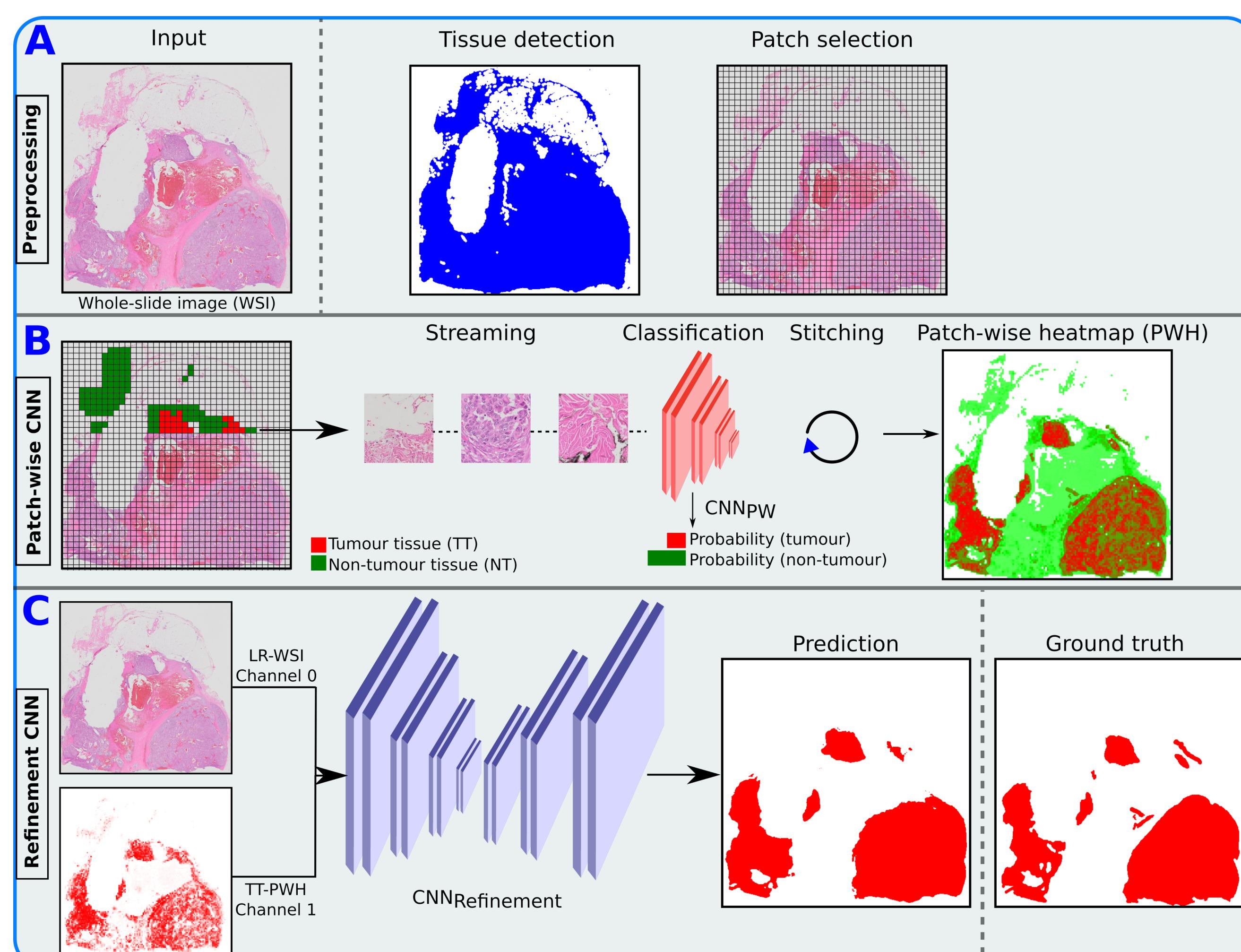
- Too computationally expensive or slow for routine usage.
- Not open-access or user-friendly.
- Do not efficiently use high and low-resolution information.

### Key Contributions:

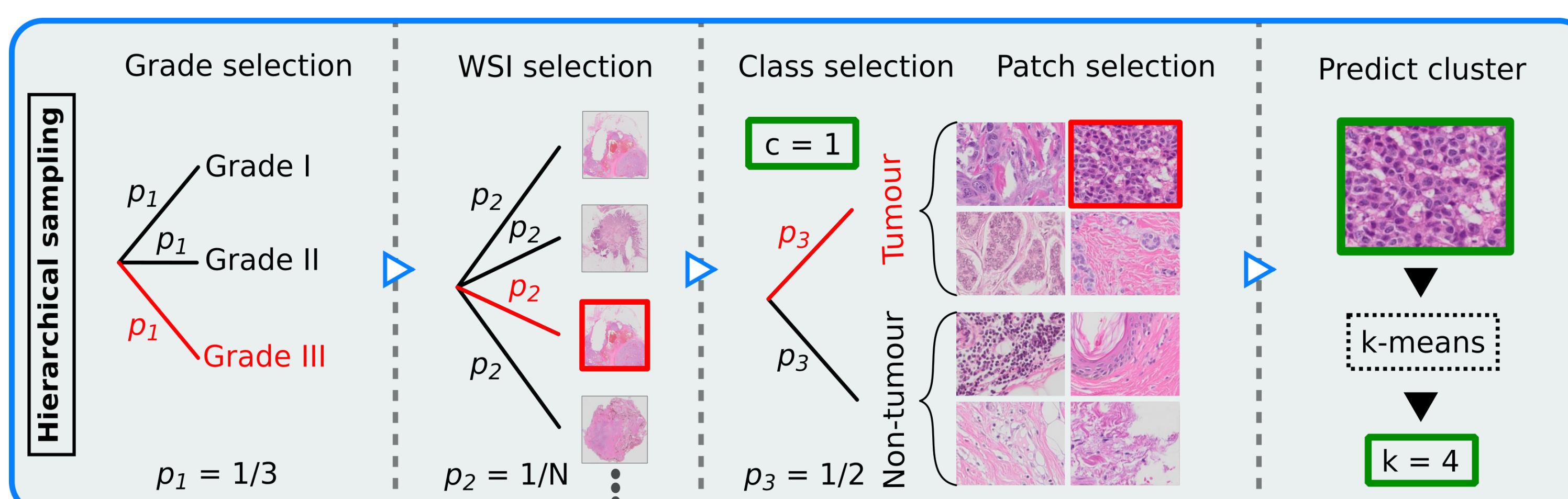
- A simple, rapid, and efficient model for automatic breast cancer segmentation.
- A two-stage, multi-scale convolutional neural network, H2G-Net.
- A novel framework for memory efficient, hierarchical-balanced, random patch sampling.

## Methodology

### Inference pipeline of H2G-Net:



### Hierarchical sampling scheme:



### Loss function for detection stage:

$$\mathcal{L}_{CWCE} = -\frac{1}{K_b} \sum_{k=1}^{K_b} \sum_{c=1}^C \sum_{i=1}^B \mathbb{1}(q_{i,k} = k) y_{i,c} \log(p_{i,c})$$

- $\mathcal{L}_{CWCE}$ : Cluster-weighted categorical cross-entropy loss
- $K_b$ : Cluster frequency for a given mini batch of size  $B$
- $y$ : Current ground truth class of a total number of classes  $C$
- $p, q$ : Class and cluster prediction for a given class  $c$  and cluster  $k$

## Experiments & Results

### Quantitative Results on BCS-1 test set:

Designs	Recall	Precision	DSC
(1) Otsu	$0.990 \pm 0.027$	$0.534 \pm 0.200$	$0.669 \pm 0.179$
(2) UNet-LR	$0.931 \pm 0.113$	$0.851 \pm 0.165$	$0.874 \pm 0.128$
(3) Inc-PW	$0.881 \pm 0.118$	$0.909 \pm 0.099$	$0.887 \pm 0.089$
(4) Mob-PW	$0.879 \pm 0.123$	$0.907 \pm 0.100$	$0.885 \pm 0.094$
(5) Mob-KM-PW	$0.853 \pm 0.124$	$0.909 \pm 0.097$	$0.872 \pm 0.092$
(6) Mob-PW-AGUNet	<b><math>0.954 \pm 0.066</math></b>	$0.909 \pm 0.097$	$0.927 \pm 0.072$
(7) Mob-PW-DAGUNet	$0.942 \pm 0.075$	$0.922 \pm 0.091$	$0.928 \pm 0.072$
(8) Mob-PW-DoubleUNet	$0.949 \pm 0.073$	$0.919 \pm 0.093$	$0.929 \pm 0.074$
(9) H2G-Net	$0.944 \pm 0.074$	<b><math>0.929 \pm 0.088</math></b>	<b><math>0.933 \pm 0.069</math></b>

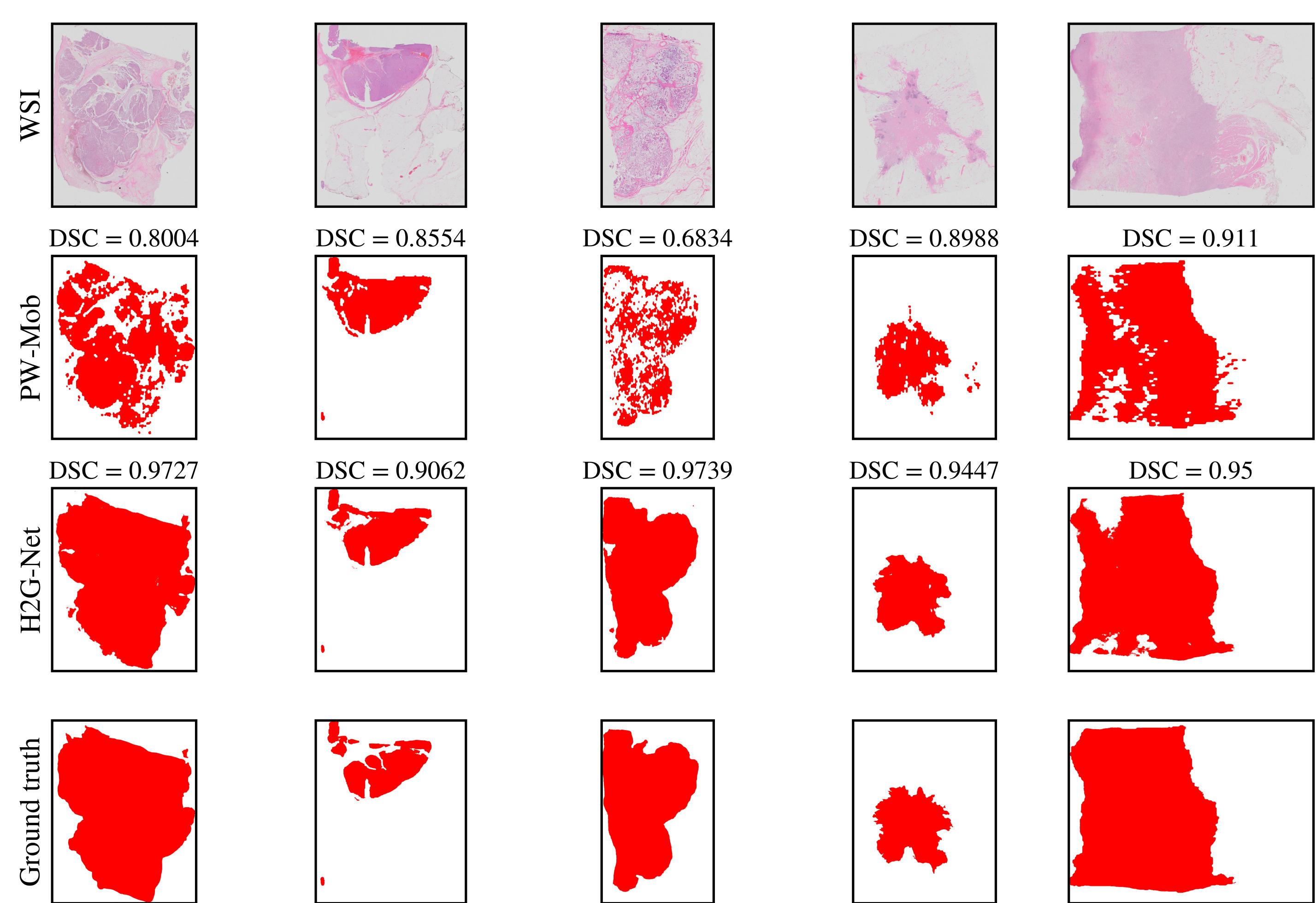
- An ablation study was conducted to find the most impactful components of the pipeline. The numbers represent performance metrics (the higher the better).
- LR: low-resolution, PW: patch-wise, Inc: InceptionV3, Mob: MobileNetV2, DSC: dice similarity coefficient

### Runtime measurements (in seconds) using H2G-Net:

	Patch-wise	Refinement	Total
OpenVINO	$57.32 \pm 0.20$	$0.75 \pm 0.01$	$58.07 \pm 0.20$
TensorRT	$39.88 \pm 0.62$	$0.38 \pm 0.00$	$40.26 \pm 0.62$

- Runtime measurements were conducted on a representative  $\times 400$  WSI, using both the OpenVINO (CPU) and TensorRT (GPU) inference engines.

### Qualitative Results on BCS-1 test set:



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