

Cancer Metastasis Detection via Spatially Structured Deep Network

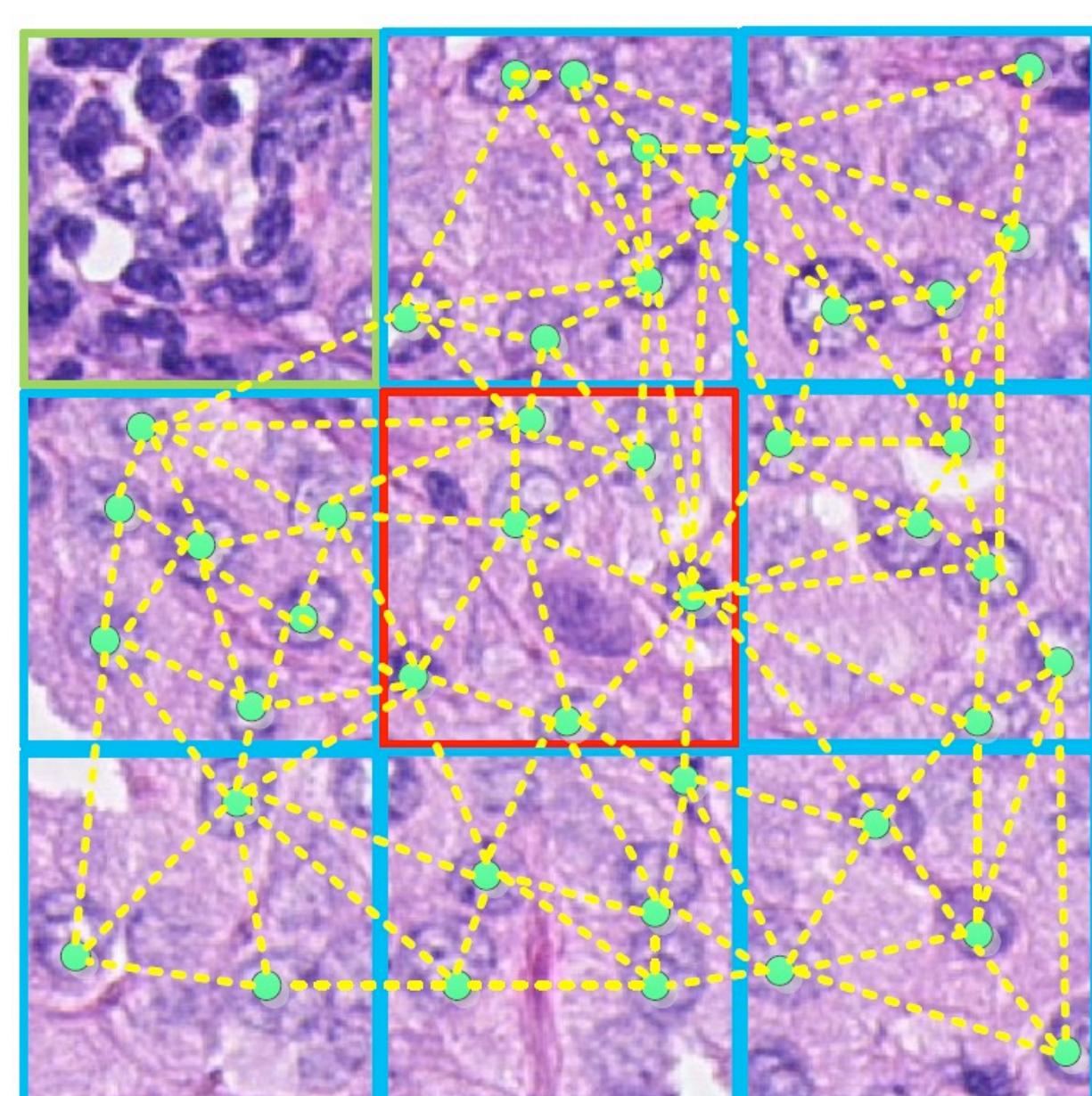
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Background

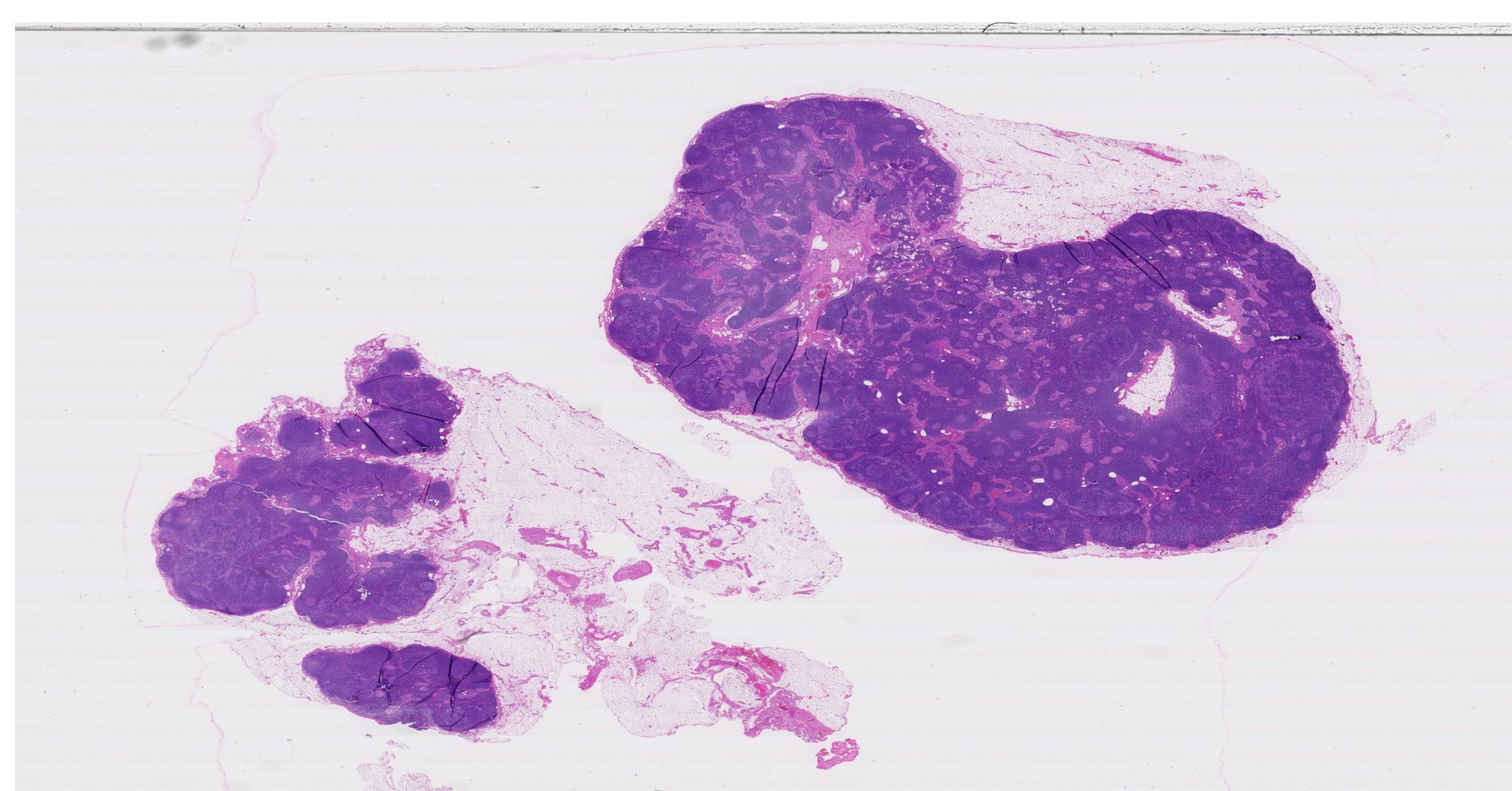
- Our goal: Develop a Computer-aided diagnosis (CAD) platform for metastasis detection of lymph nodes in Whole-slide Images (WSIs).
- Motivations: Current state-of-the-art methods divide WSIs into small patches and tackle them individually. However, the spatially structured information, which is vital for the inference, is ignored.



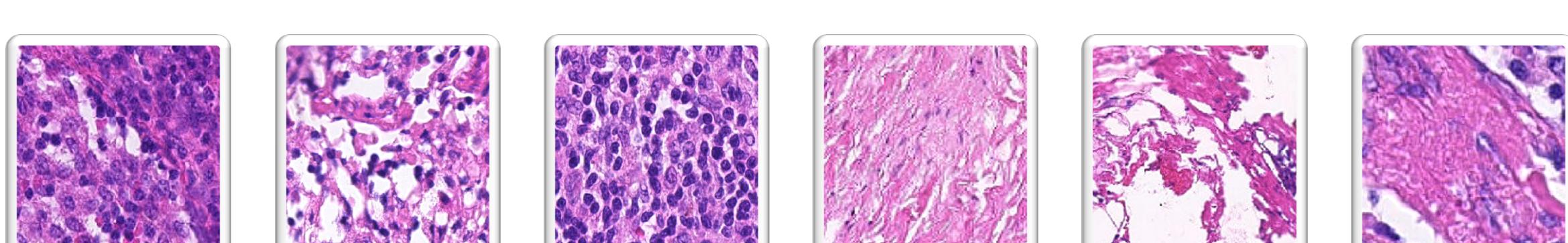
- Observation 1:** Nuclei follow certain patterns
Observation 2: When a patch is in the tumor region, its neighbors also have a high prob. to be labeled a tumor, and vice versa.

Challenges

- Gigantic Size: WSIs are very large (e.g., 100k by 200k).

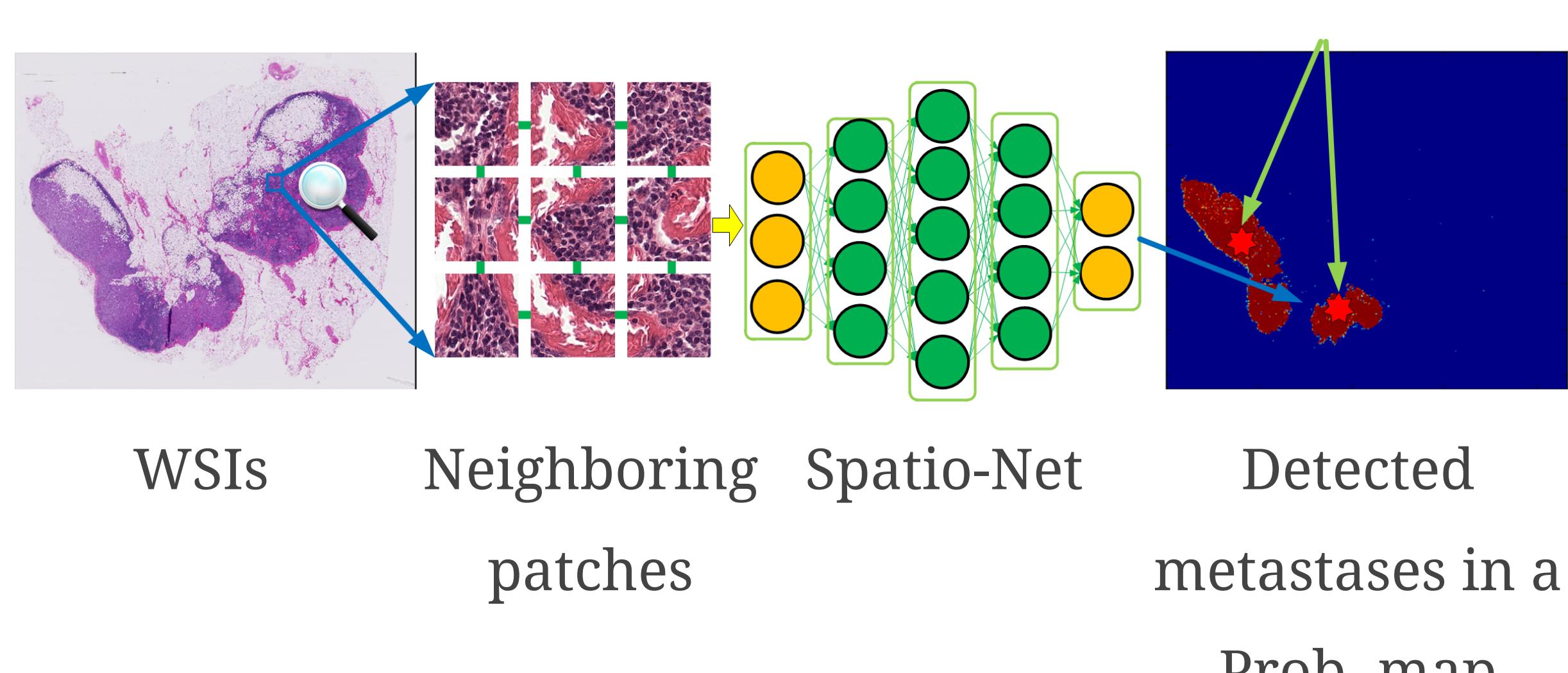


- Large Variances: Even regions from the same WSI seem visually dissimilar.



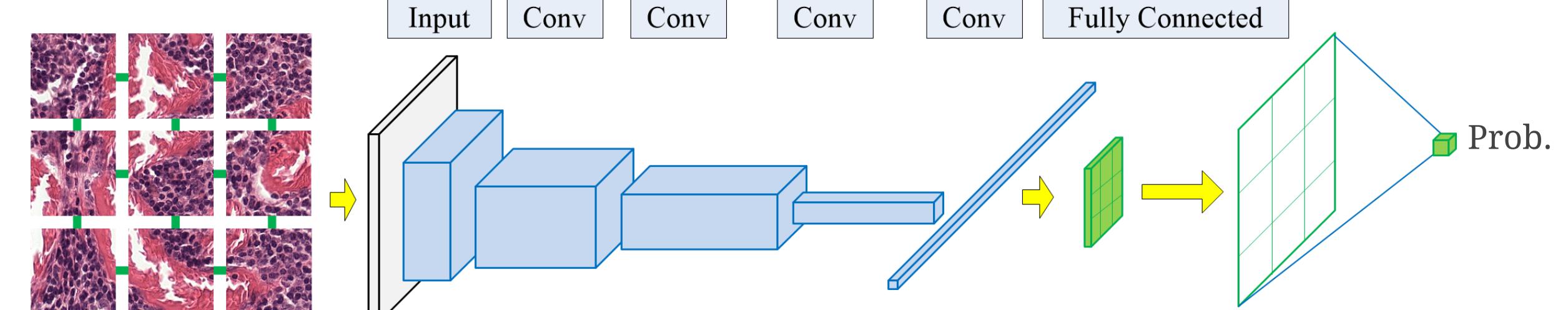
Our Method (1)

- Overview of the framework



Our Method (2)

- Details of Spatio-Net



Neighboring patches → CNN → Fixed-lengthed features → 2D-LSTM

- We optimize the following loss function

$$\lambda = \arg \min_{\lambda} \{L_{cls} + \alpha L_{reg}(\lambda) + \beta L_{spatio}\}$$

Cross entropy loss

Regularization term

$$L_{spatio} = \frac{1}{2}(L_{ind} - L_{dif})$$

Same Category

$$L_{ind} = \frac{1}{N} \sum_{x_* \in \mathbb{D}} \sum_l \{\mathbb{1}(y_* = y_l) \cdot [\eta(x_*) - \eta(x_l)]^2\}$$

$$L_{dif} = \frac{1}{N} \sum_{x_* \in \mathbb{D}} \sum_l \{\mathbb{1}(y_* \neq y_l) \cdot [\eta(x_*) - \eta(x_l)]^2\}$$

Different Categories

Experimental Results

- CAMELYON16: 160 normal and 110 tumor WSIs.
- Five-fold cross validation is performed on this dataset.

Methods	Baseline	Baseline+PostPro	Spatio-Net
Ave. FROC	0.7012	0.7104	0.7539
STD	0.012	0.015	0.008

- Different CNNs are used (with or without Spatially Structured (SS) constraint).
- Demonstrating that our method can benefit generic CNNs.

Methods	ZFNet	ZFNet (with SS)	GoogleNet	GoogleNet (with SS)	ResNet-101	ResNet-101 (with SS)
Ave. FROC	0.6832	0.7249	0.6932	0.7438	0.7012	0.7539
STD	0.018	0.013	0.011	0.014	0.012	0.008

Take Home Messages

- By integrating CNN and 2D LSTM, our framework not only learns representative features from each patch, but also considers the spatial dependencies.
- By enforcing the spatially structured constraint, the accuracy is greatly improved.
- The Ave. FROC of our system outperforms the baseline models by more than 5%.