Invasive Cancer Detection Utilizing Compressed Convolutional Neural Network and Transfer Learning

Bin Kong[1], Shanhui Sun[2], Xin Wang[2], Qi Song[2], and Shaoting Zhang[1]

1. Department of Computer Science, UNC Charlotte, Charlotte, NC, USA
2. CuraCloud Corporation, Seattle, WA, USA

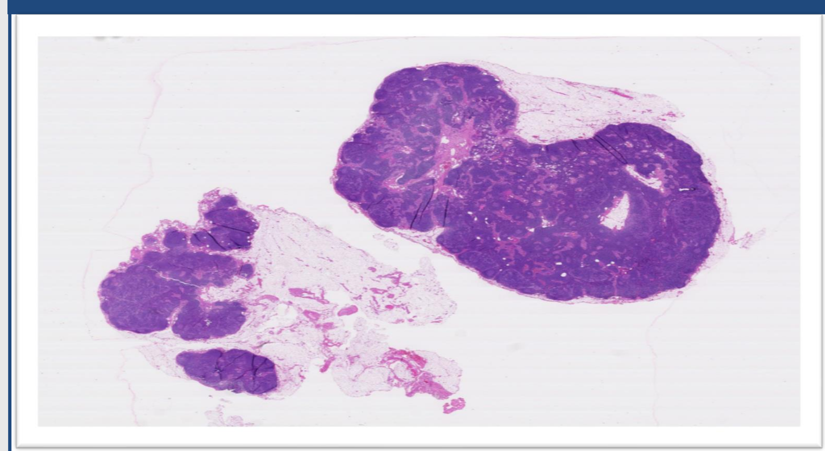
UNC CHARLOTTE

CuraCloud

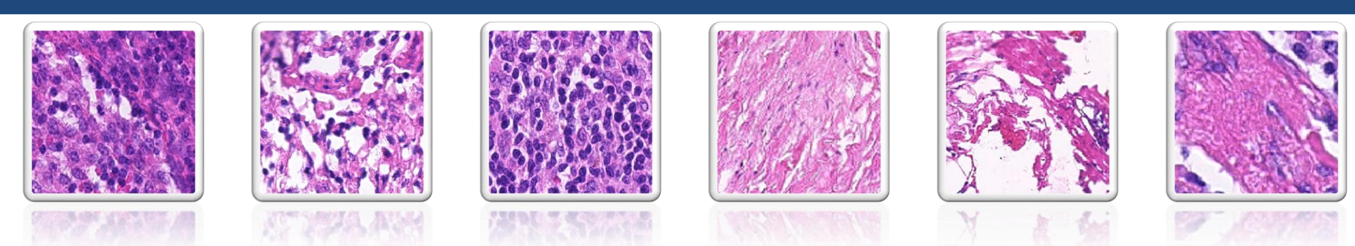
Background

- **Background:** Identification of invasive cancer in whole slide images (WSIs) is crucial for tumor staging as well as treatment planning. CNN based approaches have greatly advanced the detection accuracy. However, computational burdens become barriers in clinical applications due to Gigantic size image.
- **Motivation:** (1) A large model (e.g., Inception V3) consumes a lot computation resources and runs slow. (2) High performance computing resources are not always available due to high cost. (3) Existed model compressing methods scarify accuracy. (4) Our method handles both accuracy and efficiency problems using compressed CNN and transfer learning.

Challenges

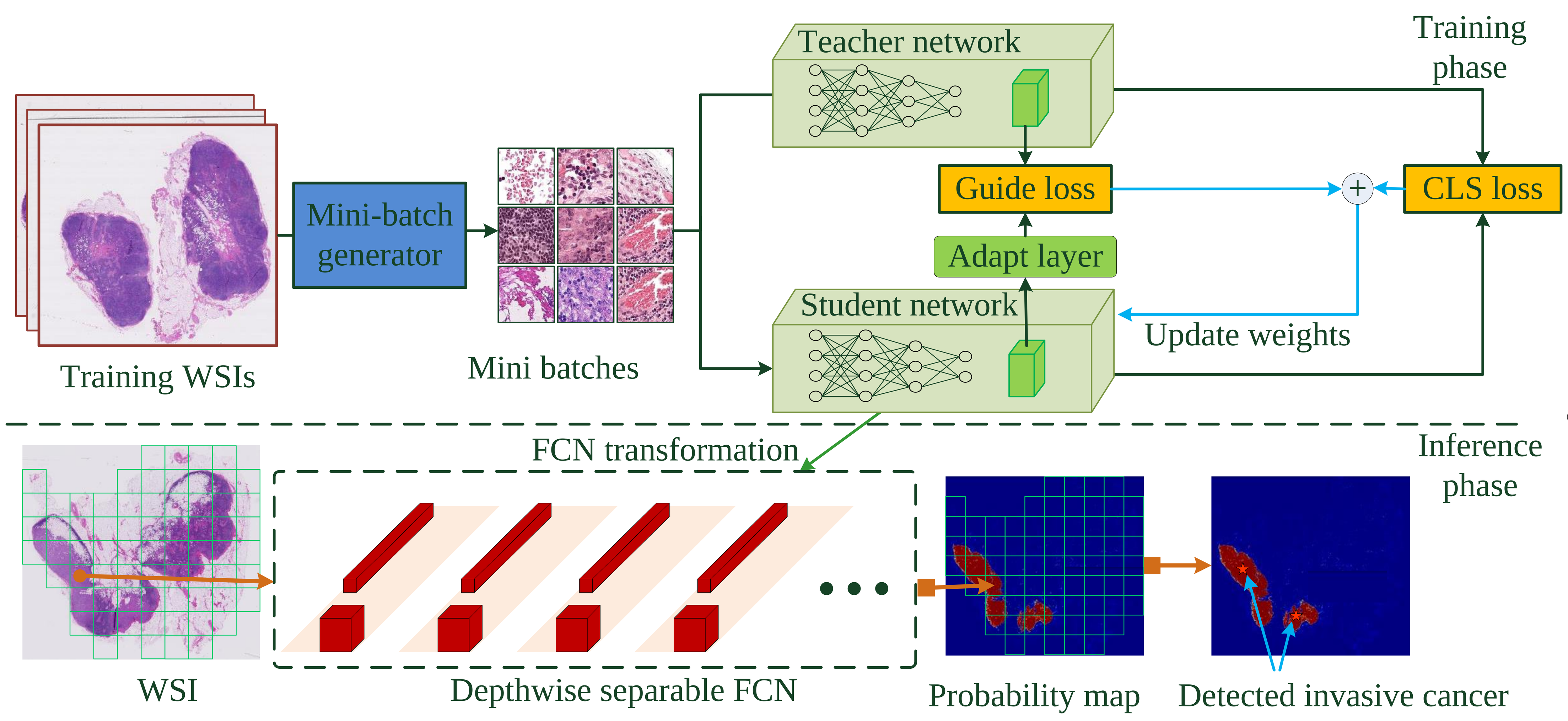


- **Gigantic Size:** high resolution e.g. 100k×200k.
- **Computing resource**: Cloud computing or HPC can mitigate the problem, but it either has a data traffic problem or is not always available due to the high cost.



- **Large Variances:** : (1) color variations induced in slide preparation, stain and scanner (2) cell shape variation

Our Method



- **Training:** The objective function is a combination of three terms: classification loss (hard classification + distillation loss), guide loss, and a regularization loss.

$$L = \frac{1}{|\mathbb{S}|}\sum_{x \in \mathbb{S}}(L_{cls}(x) + \lambda L_{guide}(x)) + \gamma L_{reg}$$

$$L_{cls} = L_{hard} + \beta L_{soft}$$

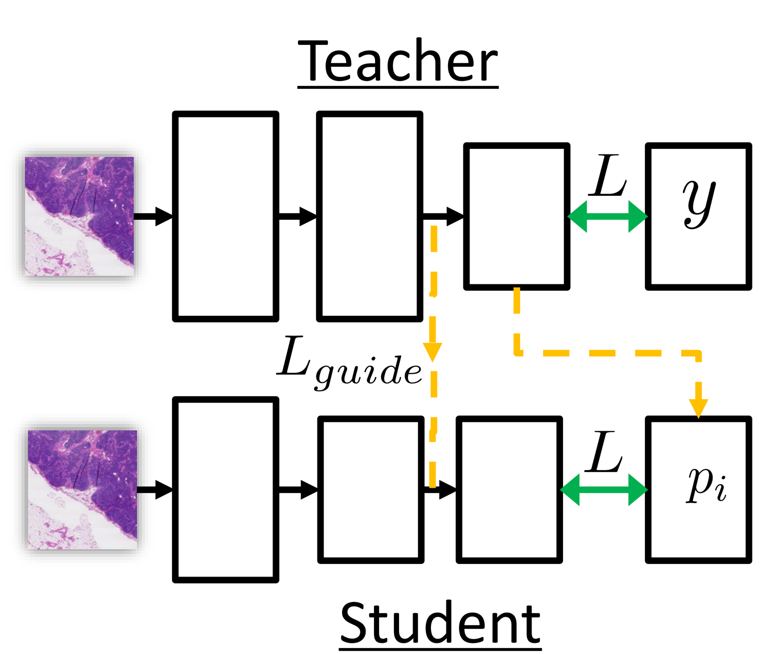
- **Our Network (Student):** a small capacity network using 3 × 3 depthwise separable convolutions. It enables efficient computation and less memory.

$$\frac{1}{N} + \frac{1}{D_K^2}$$

N: # of channels of feature map

D_K: kernel size

- **Transfer Learning:** A trained Inception V3 network (teacher) is used to supervise the student:



$$p_i = \frac{\exp(z_i/T)}{\sum_{j \in \{0,1\}} \exp(z_j/T)}$$

Distillation

- **Efficient Inference:** FCN allows feeding in large image patch in the inference. Compressed FCN makes the inference fast.

Experimental Results

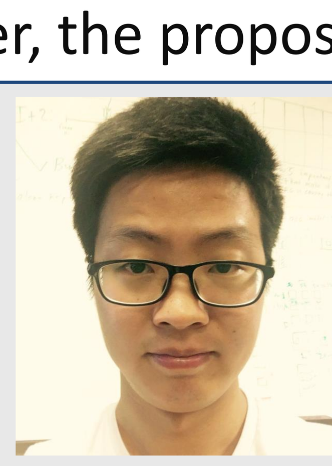
- Dataset: Gastric cancer dataset (204 training and 68 testing WSIs) and CAMELYON16 (270 training and 120 testing WSIs).
- Small capacity network significantly reduce the computational cost but accuracy drops.
- FCN further improve the efficiency.
- Once the student gained knowledge from the teacher, the accuracy recovered.

Methods		I	IF	S	SF	DSF	DSFG
Gastric Cancer	Time (mins.)	3.8	2.3	1.5	0.6	0.6	**0.6**
	Ave. FROC	0.806	0.813	0.768	0.773	0.801	**0.811**
CAMELYON16	Time (mins.)	17.0	9.1	7.8	3.6	3.6	**3.6**
	Ave. FROC	0.857	0.859	0.809	0.815	0.847	**0.856**

Summary

- Computational Cost & memory consumption are two major issues for clinical deployment of invasive cancer detection system (e.g., IVD devices).
- Our fully convolutional student network can significantly reduce the computational cost and thus applicable in clinical practice.
- Reducing the capacity of CNN reduces the accuracy. However, the proposed transfer learning can recover the accuracy.

UNC CHARLOTTE



Contact Email:
bkong@uncc.edu
sunshanhui@gmail.com
szhang16@uncc.edu