Semi-Supervised Learning for Cancer Detection of Lymph Node Metastases

Amit Kumar Jaiswal*[1] Ivan Panshin*[2] Dimitrij Shulkin*[3] Nagender Aneja[4] Samuel Abramov[5]

[1]University of Bedfordshire [2]Perm State University

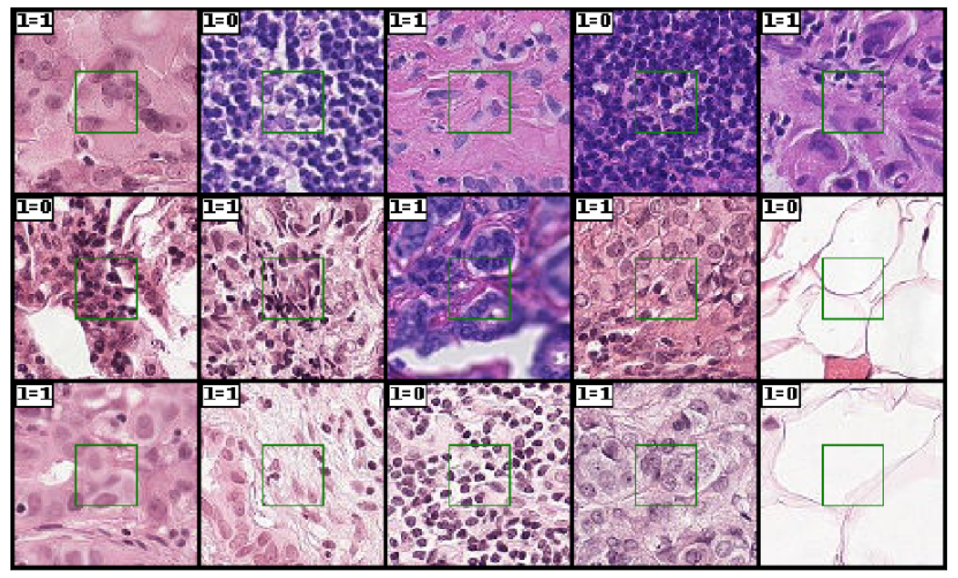
[3]Schaeffler Group [4]Universiti Brunei Darussalam [5]Abramov Software GmbH & Co. KG

CVPR LONG BEACH CALIFORNIA June 16-20, 2019

Problem Formulation and Contribution

Goal: Identifying metastatic cancer in tiny image patches extracted from large pathological scans of sentinel lymph node sections.

Cancer Detection Task: Consider a binary classification task of small histopathologic images (96 x 96px) which determine the tumor labels $l \in \{0, 1\}$ delineating the absence or presence of tumor tissues.

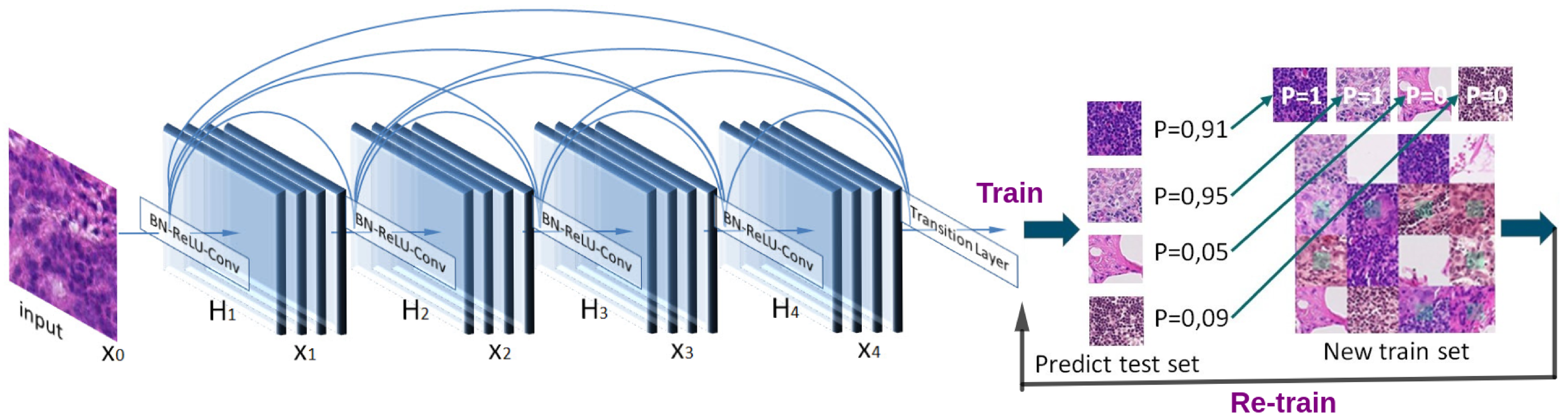


Contributions: A semi-supervised learning approach that

- magnifies differentiation between low-density classes for incremental training of labeled and unlabeled data simultaneously.
- performs better generalization by enlarging the training set for the proposed model using pseudo labeling [4].
- significantly improves our proposed DenseNet201 based model over the existing baseline published in [1].

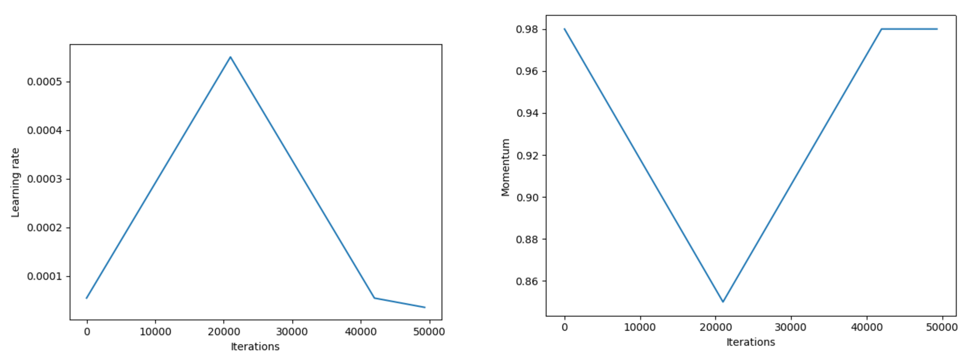
Methodology

Network Architecture:



Semi-Supervised Learning:

One Cycle Policy [3]



- One Cycle Policy - Learning rate with the step size (left)
- Cyclical Momentum (right)

Supervised Loss Function:

$$\sum_{i=1}^{C} \mathcal{L}(y_i, f_i(x))$$

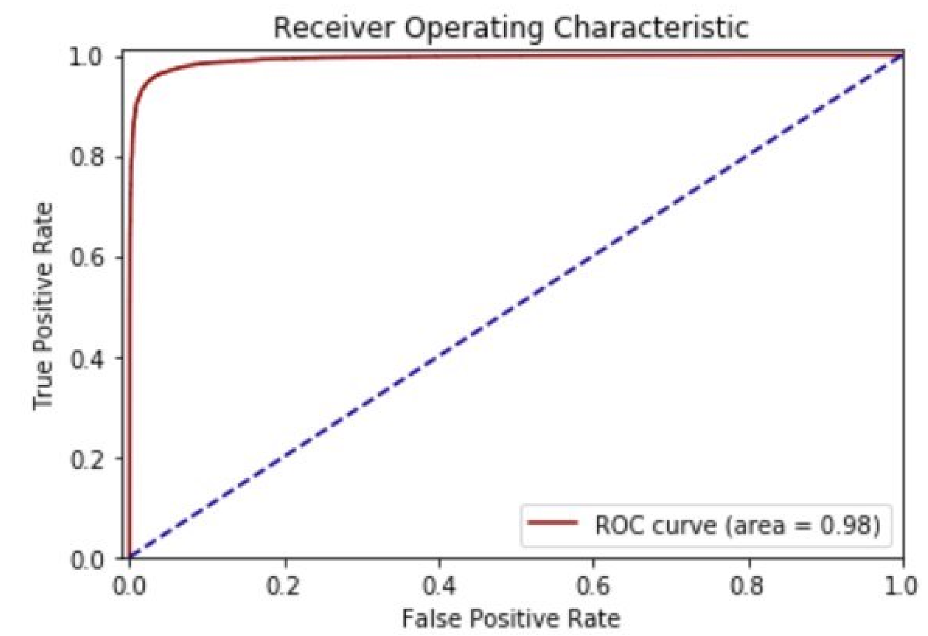
The Joint Loss Function:

$$\mathcal{L} = \frac{1}{n} \sum_{m=1}^{n} \sum_{i=1}^{C} \mathcal{L}(y_i^m, f_i^m) + \alpha(t) \frac{1}{n'} \sum_{m=1}^{n'} \sum_{i=1}^{C} \mathcal{L}(y_i'^m, f_i'^m)$$

Experiments & Results

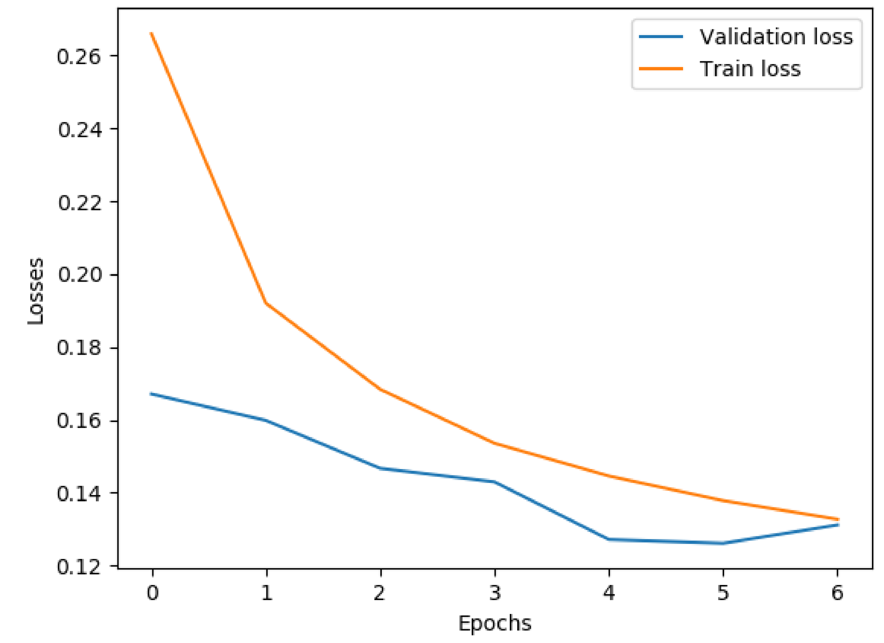
Results on modified PatchCamelyon Benchmark [2]:

Model	51% Test Data	49% Test Data	100% Test Data
VGG16	0.9768	0.9721	0.9745
InceptionResNetV2	0.9764	0.9769	0.9766
Xception	0.9748	0.9756	0.9752
InceptionV3	0.9758	0.9790	0.9774
SE-ResNet101	0.9784	0.9781	0.9783
DenseNet201	**0.9786**	**0.9802**	**0.9794**
GDenseNet [1]			0.9630

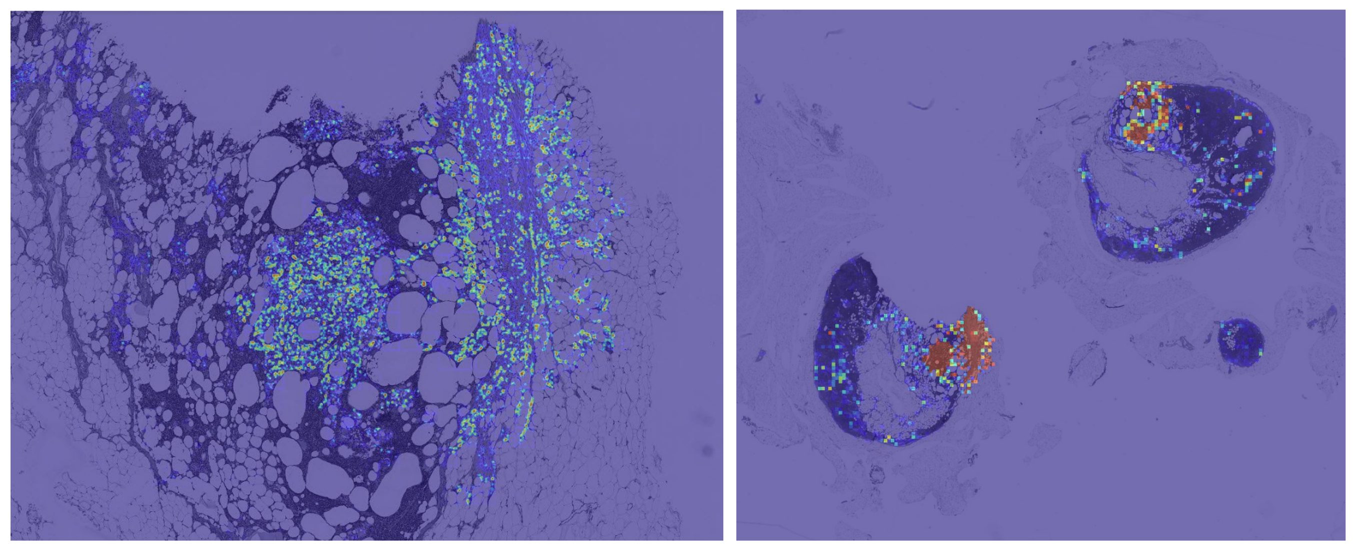


Ensembles:

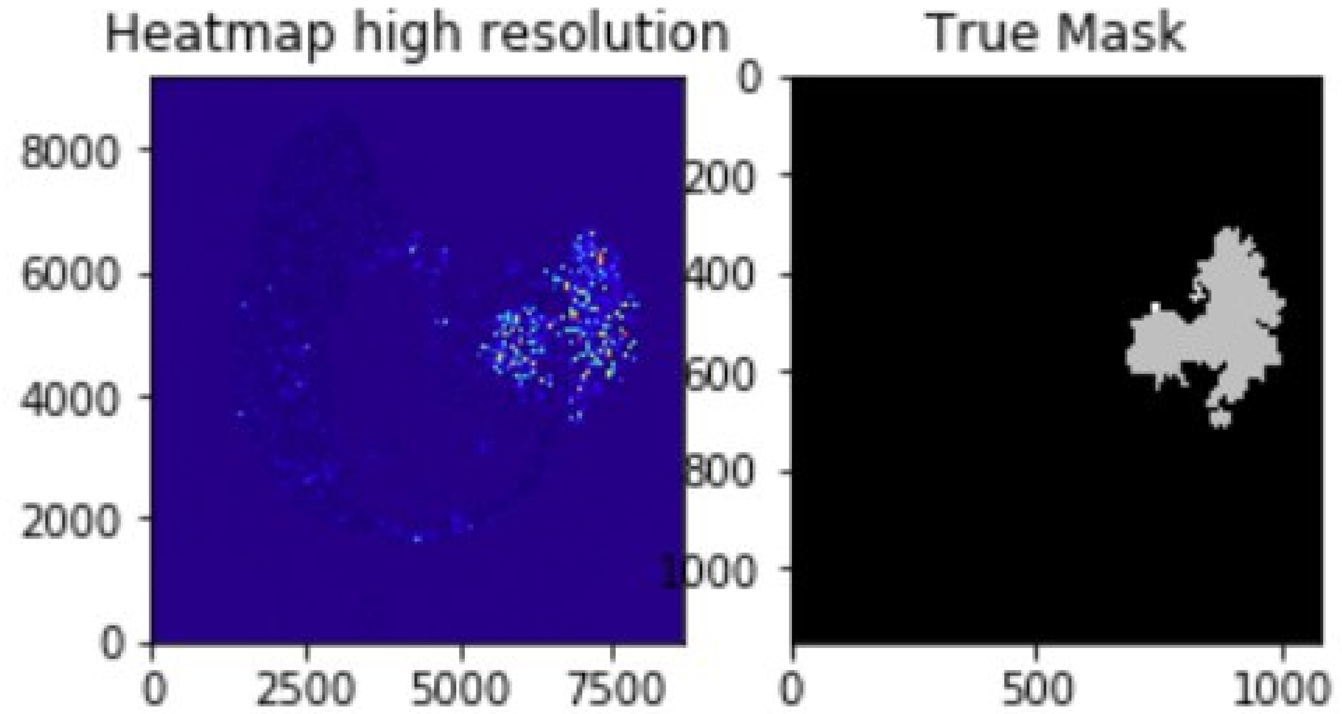
Model	51% Test Data	49% Test Data	100% Test Data
Ensemble (7 SE-ResNet101)	0.9810	0.9822	0.9816
Best single model (DenseNet201)	0.9786	0.9802	0.9794
GDenseNet [1]			0.9630



Predicted TUMOR Tissues:



(a) Whole Slide Image (b) Tissue Mask



Conclusion:

Our proposed model is a learning-based, but semi-supervised approach to detect metastatic cancer.

- Outperforms strong CNN baseline [1] evaluated on 100% of test data.
- Our model can detect cancerous cells in histopathologic images with better performance than human pathologists.

References:

[1] Veeling *et al.* Rotation equivariant CNNs for digital pathology. In International Conference on Medical image computing and computer-assisted intervention (pp. 210-218). Springer, Cham.

[2] `https://www.kaggle.com/c/histopathologic-cancer-detection/data`

[3] Smith *et al.* (2018). Super-convergence: Very fast training of residual networks using large learning rates.

[4] Lee, D. H. (2013, June). Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In Workshop on Challenges in Representation Learning, ICML (Vol. 3, p. 2).