Detection of Invasive Ductal Carcinoma

Binary classification of Breast Histopathology Images

Zeyu Fu, Yuanrong Liu, Yu Liu

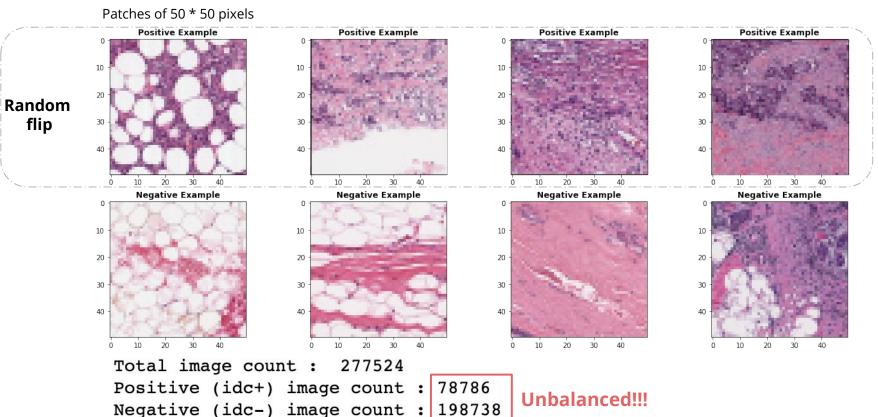
Background

Invasive Ductal Carcinoma (IDC) is the **most common** subtype of breast cancers. Accurately identifying and categorizing breast cancer subtypes is an important clinical task, and automated methods can be used to **save time** and **reduce error**.

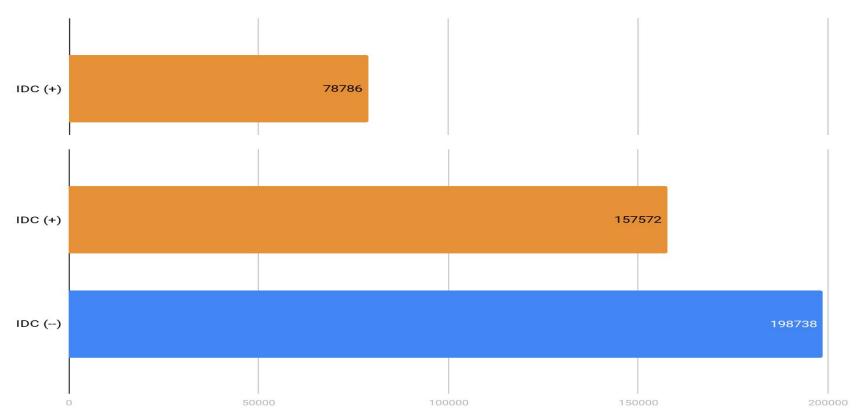
A common method for automatic aggressiveness grading is to **delineate the exact regions** of IDC inside of a whole slide images from patients.

We used **c**onvolutional **n**eural **n**etwork approaches to classify the positive or negative of IDC for more than **270,000** slide image patches with size **50x50** from 162 patients. This dataset is from Kaggle.

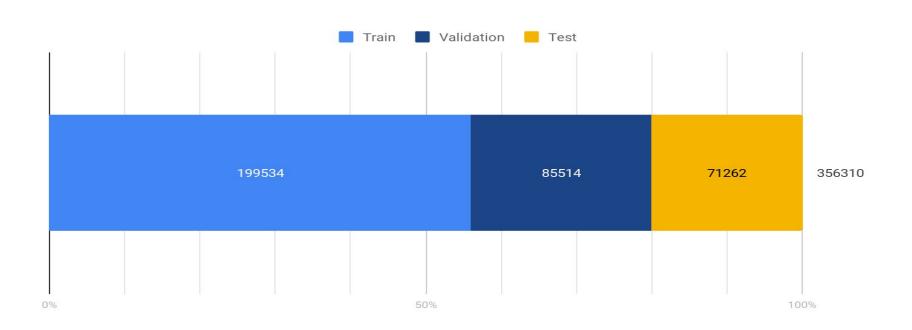
Image Data



Data Balancing



Data Split

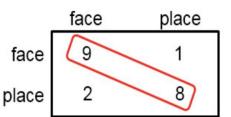


Evaluation

predicted labels

(made by the classifier)

true labels (given in the testing data)



regular ("overall") accuracy

$$\frac{9+8}{9+1+2+8} = 0.85$$

$$\frac{TP + TN}{TP + FN + FP + TN}$$

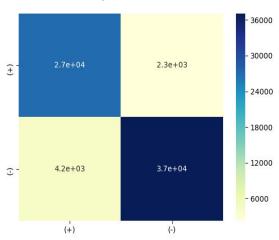
balanced accuracy

$$\left[\frac{9}{9+1} + \frac{8}{2+8} \right] / 2 = 0.8$$

$$\left[\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right] / 2$$

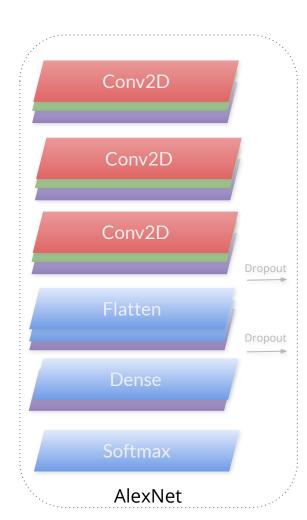
Predicted Labels Made by the classifier

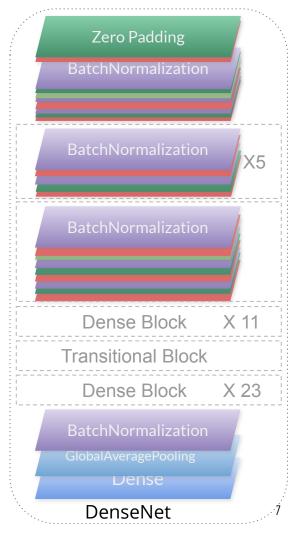
True Labels Given in the testing data



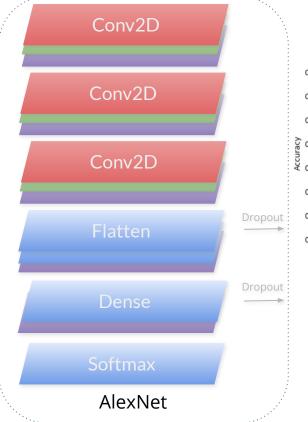
Models

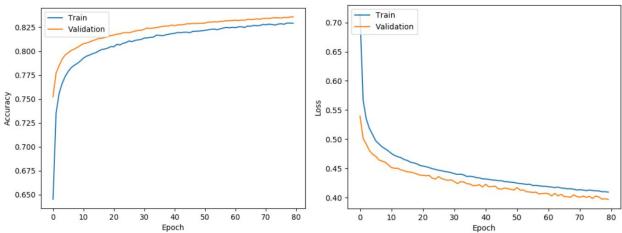






AlexNet





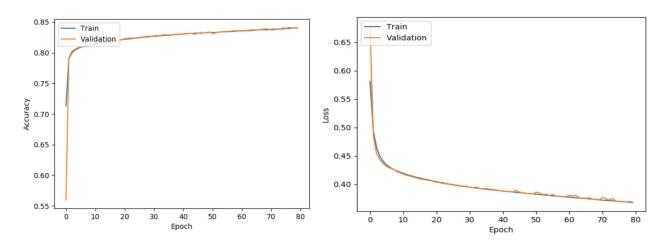
Regular accuracy is 83.37%

Balanced accuracy is 83.10%

testing on **70,765** test examples

Zero Padding BatchNormalization X5 Dense Block Transitional Block Dense Block X 23 GlobalAveragePooling DenseNet

DenseNet



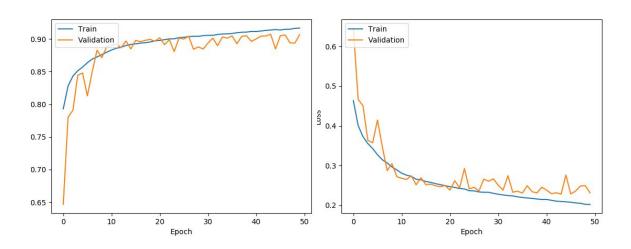
Regular accuracy is **85.28%**

Balanced accuracy is **85.39%**

testing on **70,765** test examples

Conv2D Max pooling Dropout Conv2D Max pooling Dropout Conv2D Max pooling Dropout Dense VGG

VGG



Regular accuracy is **90.90%**

Balanced accuracy is **90.50%**

over **70,765** test examples

Conclusion

| | Pr | Rc/Sen | Spc | F1 | BAC |
|--------|--------|--------|--------|--------|--------|
| CNN | 0.6540 | 0.7960 | 0.8886 | 0.7180 | 0.8423 |
| FCH | 0.7086 | 0.6450 | 0.9298 | 0.6753 | 0.7874 |
| RGBH | 0.7564 | 0.5956 | 0.9493 | 0.6664 | 0.7724 |
| GH | 0.7102 | 0.5240 | 0.9434 | 0.6031 | 0.7337 |
| JPEGCH | 0.7570 | 0.4646 | 0.9605 | 0.5758 | 0.7126 |
| M7Edge | 0.7360 | 0.4372 | 0.9585 | 0.5485 | 0.6979 |
| NT | 0.6246 | 0.2851 | 0.9547 | 0.3915 | 0.6199 |
| LBP | 0.7575 | 0.2291 | 0.9806 | 0.3518 | 0.6048 |
| NA | 0.6184 | 0.2413 | 0.9606 | 0.3472 | 0.6009 |
| HSVCH | 0.7662 | 0.2223 | 0.9821 | 0.3446 | 0.6022 |

Cruz-Roa, A., Basavanhally, A., González, F., Gilmore, H., Feldman, M., Ganesan, S., ... & Madabhushi, A. (2014, March). Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks. In *Medical Imaging 2014: Digital Pathology* (Vol. 9041, p. 904103). International Society for Optics and Photonics.

| Method | F-score | Balance accuracy |
|--------------------------------|---------|------------------|
| Alexnet, Resize | 0.7648 | 0.8468 |
| Alexnet, Resize + Dropout | 0.757 | 0.8423 |
| Alexnet, Cropping | 0.7533 | 0.8415 |
| Alexnet, Cropping + Additional | 0.7558 | 0.8368 |
| Rotations | | |

Janowczyk, A., & Madabhushi, A. (2016). Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases. *Journal of pathology informatics*, 7.

Our best is 90.50%!!!

Thank you