Pathological Lymph Node Classification on Gigapixel Images

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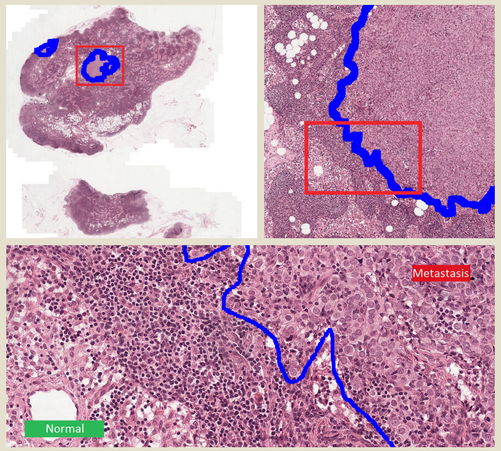
Motivation

Metastases in lymph nodes are one of the most important prognostic factors in breast cancer. This is because the lymph nodes are the first place the cancer is likely to spread. The current manual diagnostic procedure is time consuming and prone to error.

We present multiple models and feature selection algorithms and compare their results at a difficult multi-class classification task.

Data

- Data from the CAMELYON challenge 2017
- 500 images from 100 patients with ground truths for 4 classes
- Giga-pixel slide images in a multi-level format



Feature Extraction Methods

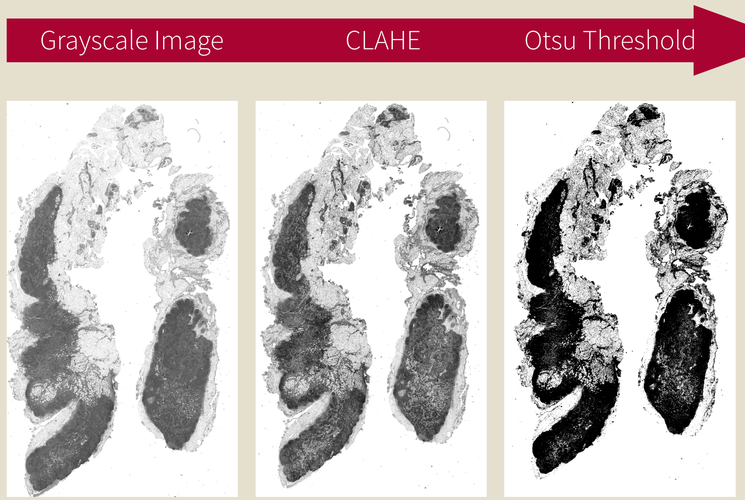
Color Buckets:
- Histogram of pixel colors
- Metastases tend to be darker

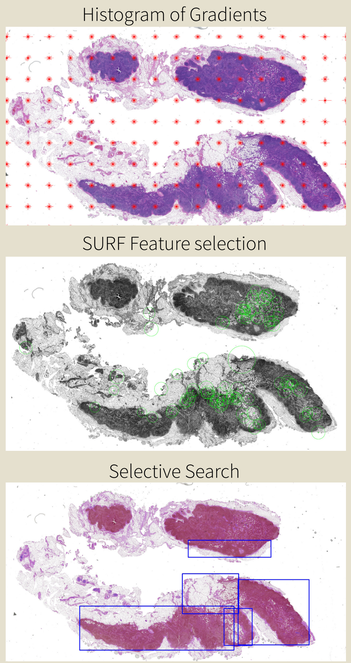
Histogram of Gradients
- Histogram of pixel-wise gradients in 8x8 blocks

SURF with Bag of Words
- Extract features with SURF
- Cluster features (kNN) to get bag of words
- Encode each image using the bag

Selective Search
- Propose bounding boxes
- Isolate smaller regions of interest

Preprocessing





Results

Training on 400 examples. Test on 100 examples.

Algorithm	Feature Extraction	Train/Test Accuracy (%)
SVM (polynomial)	Color Buckets	62/63***
SVM (polynomial)	Bag of Words	55/24
RUSBoost	HOG	86/24
Residual Network	Selective Search	80/46

Discussion

- Imbalance of classes and size of the images poses a unique problem
  - Feature selection made more important
- Generalization appears to be a problem

RUSBoost HoG				Residual Network				SVM Color Buckets			
13	20	20	11	26	3	21	20	63	0	0	0
0	2	3	1	2	0	0	0	6	0	0	0
4	4	5	0	3	0	4	3	13	0	0	0
2	8	3	4	2	0	0	16	18	0	0	0

Future Work

- Experiment with randomly balanced training sets to address class imbalance
- Train two classifiers, one binary and one to discriminate types of metastases
- Experiment with better feature selection/region proposal algorithms
  - R-CNN[2]

Models: SVM

Fits 4 planes used for binary 'one-vs-all' classification among all the classes

- Polynomial Kernel

$$K(x,y) = (x^T+c)^d$$

- Hinge loss

$$l = \max(\ 0\ ,\ 1\text{-}yx)$$

Models: Ensemble Learning

Uses multiple 'weak learners' which cast weighted votes during classification.

New learners focus on misclassifications

- AdaBoost: Decision trees as weak learners
- Subspace: kNN as weak learners
- RUSBoost: Decision trees as weak learners

Models: Residual Network[3]

A convolutional NN with a skip connection

- Each example is comprised of stacked bounding boxes from selective search
- Forward Prop

$$z^{[i]} = W^{[i]}\ a^{[i-1]} + b^{[i-1]} + \underline{Wx}$$

$$a^{[i]} = g(\ z^{[i]}\ )$$

References

[1] Uijlings, J.R.R., van de Sande, K.E.A., Gevers, T. et al. Int J Comput Vis (2013) 104: 154.

[2] S.Ren,K.He,R.Girshick,andJ.Sun,"Faster r-cnn:Towardsrealtime object detection with region proposal networks," in NIPS, 2015.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," arXiv:1512.03385, 2015.