Automated Optic Disc (OD) Localization in The Neonatal Fundus Image

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Purpose

Retinal image analysis relies on accurate OD localization, yet we know of no robust OD localization algorithms for the neonatal fundus image.

OD localization is difficult in the neonatal fundus because of poor, variable imaging quality and morphological variation.

Main issues:
- Motion and lens blur
- Fading
- Inter-image color variation
- Inter-image illumination changes
- Inconsistent OD appearance

Method

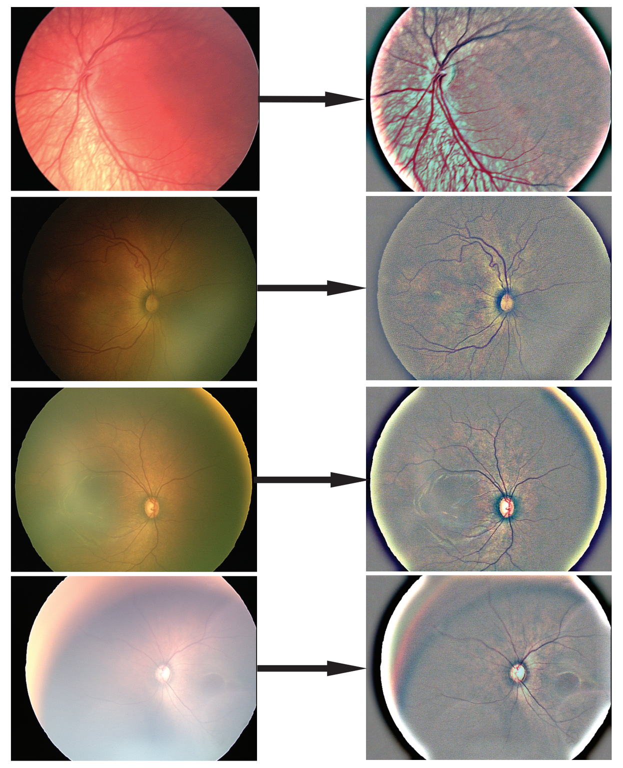
Use a machine learning perspective to learning OD location, invariant to appearance changes.

Input → Preprocess → Feature Extraction → Hough Forest

1) Preprocessing

Preprocessing minimizes photometric variations in the input images. We use a *high pass filter*, to remove global color information.

Removes inter-image color and illumination variation. Homogenizes intra-image color and illumination variation.



Training & Validation set: 300 images from St. Mary's Hospital, London, UK of 294 patients screened for ROP

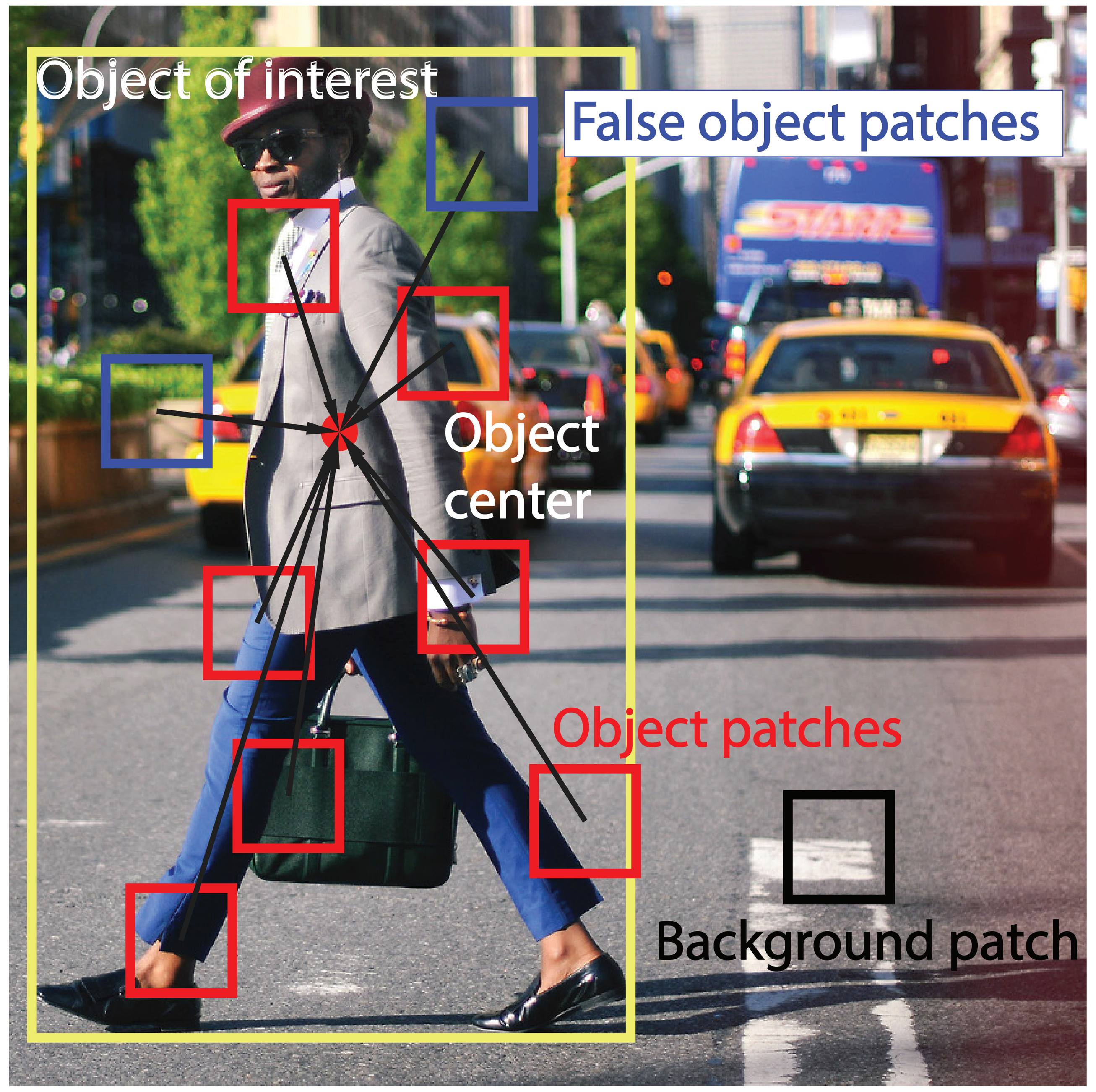
Test set: 1464 images from 35 patients screened for ROP over 347 examinations, collected in Alberta Children's Hospital, Calgary, Canada.

Birth weight 470-1680 g, born 24-33 weeks GA, examined 30-48 weeks PMA, 1-11 exams per subject.

This project is Ethics Board approved.

3) Hough Forests

A simple algorithm to locate the centers of objects[3].



Offset patches with corresponding offsets for storing. To locate image center, add offset to each patch position.

Training

1) Store object patch offset from object center.
2) Build *random forest**, mapping patches to offsets.

Testing

1) Looking up patches in random forest.
2) Add offsets to patch locations.
3) Estimate object center from mode of votes.

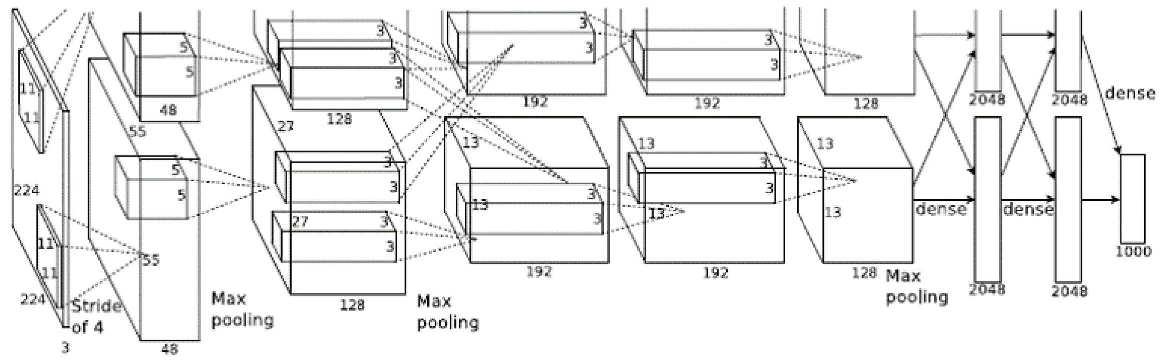
*Random forests[4] return the offset of the 'closest looking' patch for unseen patches at test time. They can be retrained for any dataset, so are highly generalizable.

2) Feature Extraction

- Use convolutional neural network features.

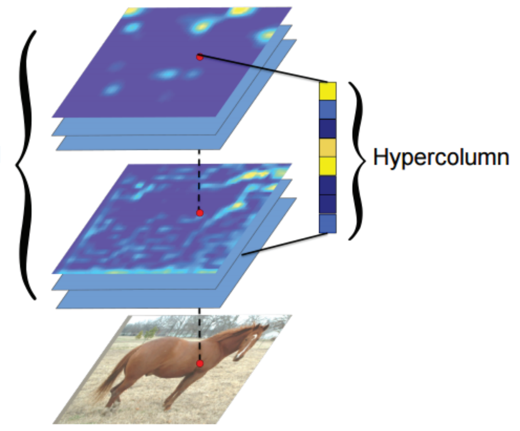
- Resize hidden feature maps into stack and extract *hyperpatches* for multiscale discriminative features.

- Use a pre-trained AlexNet[1] trained on ImageNet[2] competition data.



Dimensionality Reduction

8x8x1376 ⟶ 8x8x400



Other details

Hough forest accumulation

Patch votes posed as marginalization.

Image

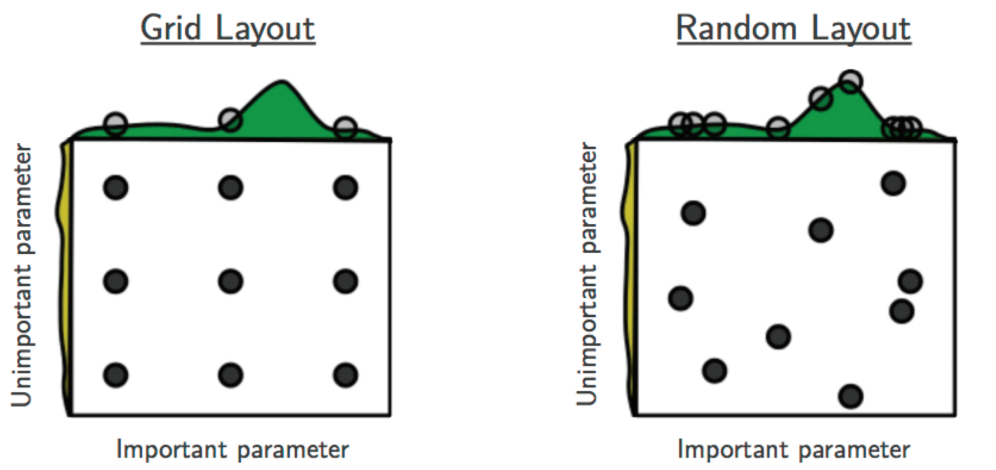
$$p(\mathbf{c}|\mathbf{I}) = \sum_{p\in\mathcal{P}(\mathbf{I})} p(\mathbf{c}|\mathbf{f}(p), p\cap\mathcal{O})\,p(p, p\cap\mathcal{O}|\mathbf{I})$$

$$= \sum_{p\in\mathcal{P}(\mathbf{I})} \underbrace{p(\mathbf{c}|\mathbf{f}(p), p\cap\mathcal{O})}_{\text{location term}}\,\underbrace{p(p\cap\mathcal{O}|p)}_{\text{weighting}}\,\underbrace{p(p|\mathbf{I})}_{\text{patch sampling}}$$

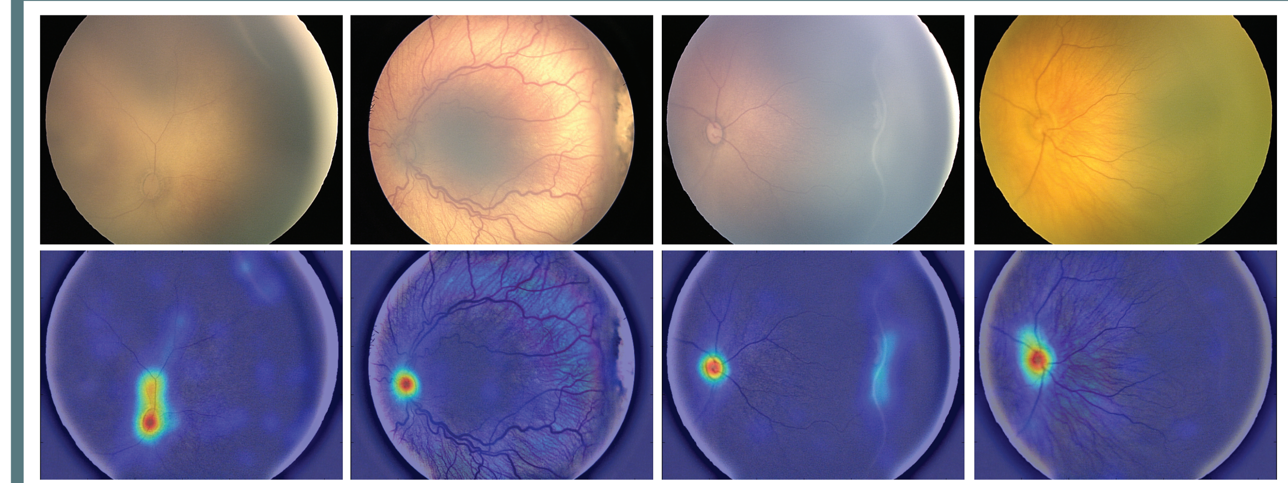
Object center
CNN features
Patch belongs to object

Hyperparameter Optimization

Used Hyperopt[5] tree of parzen estimators to optimize all hyper- and metaparameters for the pipeline.



Results

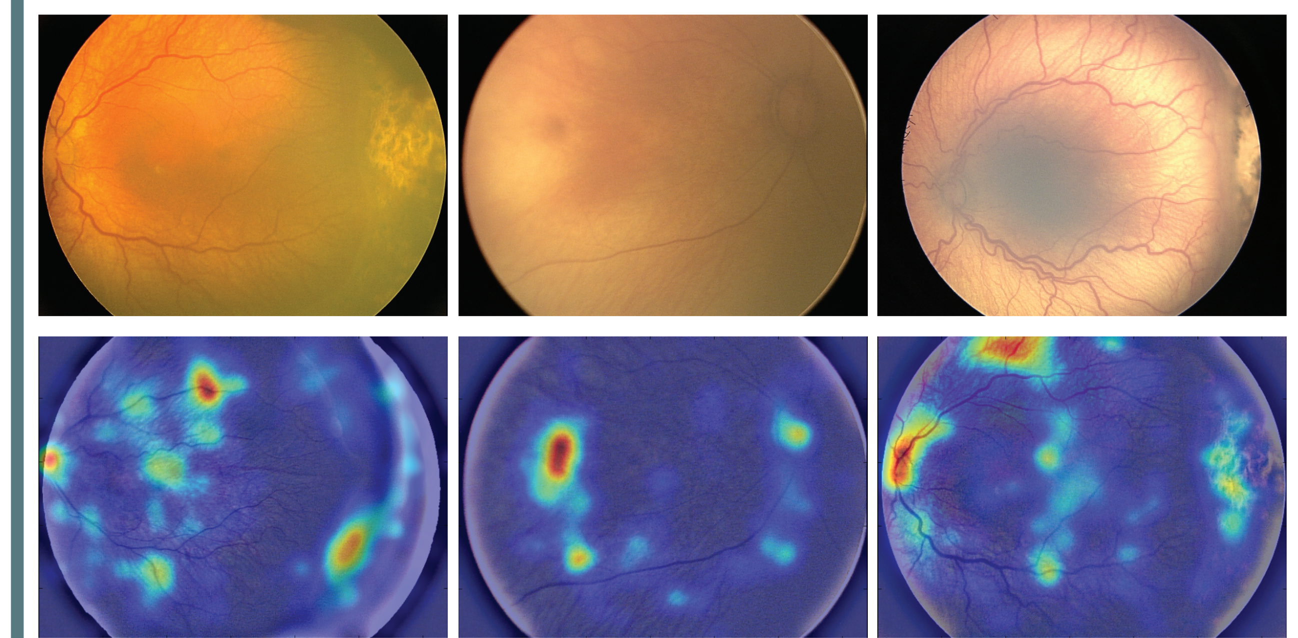


Accumulation

Above: Successful* OD localization.

Below: Failure cases---difficult to predict, easy to detect. Could be rectified using hard negative mining (future research).

*Success defined as localization to within OD perimeter



Training set: 100 images

Validation set: 200 images

Testing: 1464 images

Success/failures: 1417/47 (96.8%/3.2%)

Run time: ~10 secs per image in python, can easily optimize under 1 sec.

Conclusion

- **Successful** OD localization in the neontal fundus
- **Stage 1** in vessel analysis for vascular retinopathies.
- **Easily extended**/improved e.g., hard negative mining, latest convolutional neural network features.
- **Adaptive**: can easily be retrained on new datasets (not just retinas)
- **Data efficient**

With thanks to Dr Anna Ells for permitting the use of her ROP dataset.

References:
[1] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.
[2] Deng, Jia, et al. "Imagenet: A large-scale hierarchical image database." Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. IEEE, 2009.
[3] Gall, Juergen, and Victor Lempitsky. "Class-specific hough forests for object detection." Decision forests for computer vision and medical image analysis. Springer London, 2013. 143-157.
[4] Breiman, Leo. "Random forests." Machine learning 45.1 (2001): 5-32.
[5] Bergstra, James, Dan Yamins, and David D. Cox. "Hyperopt: A python library for optimizing the hyperparameters of machine learning algorithms." Proceedings of the 12th Python in Science Conference. 2013.