ARTERY/VEIN CLASSIFICATION IN FUNDUS IMAGES USING CNN AND LIKELIHOOD SCORE PROPAGATION

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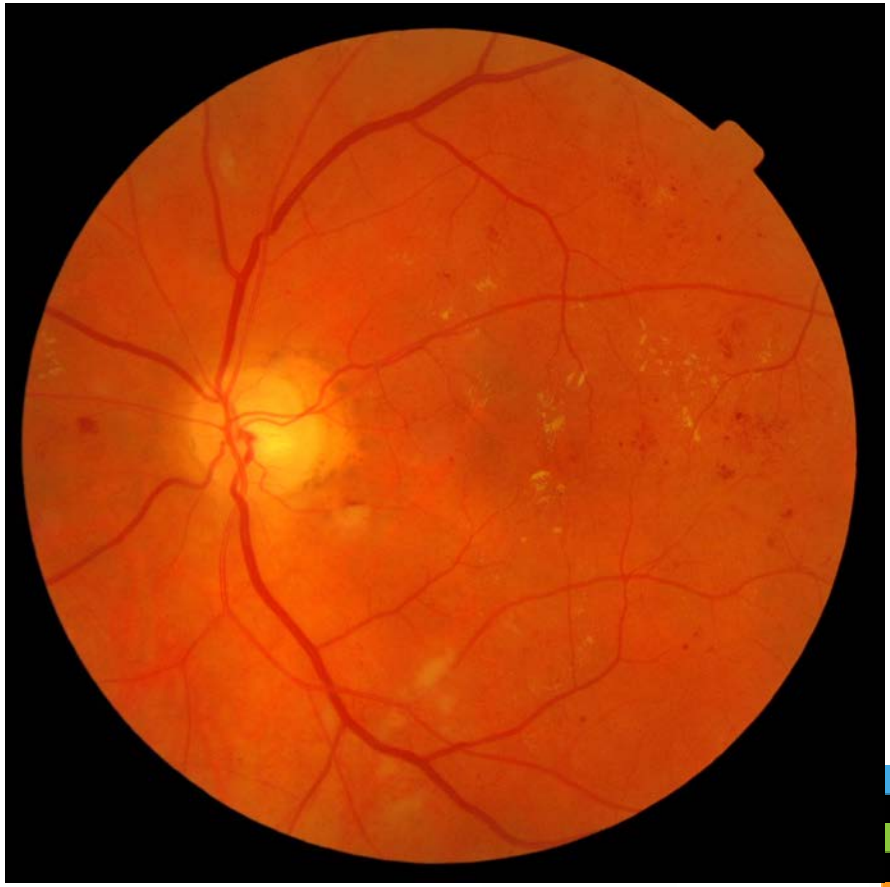
MOTIVATION

- Changes in blood vessels occur with many pathologies

- Retina imaging through digital fundus camera allow a non-invasive access to the vessels

- Changes on the arteries are different from those on the veins according to the pathologies



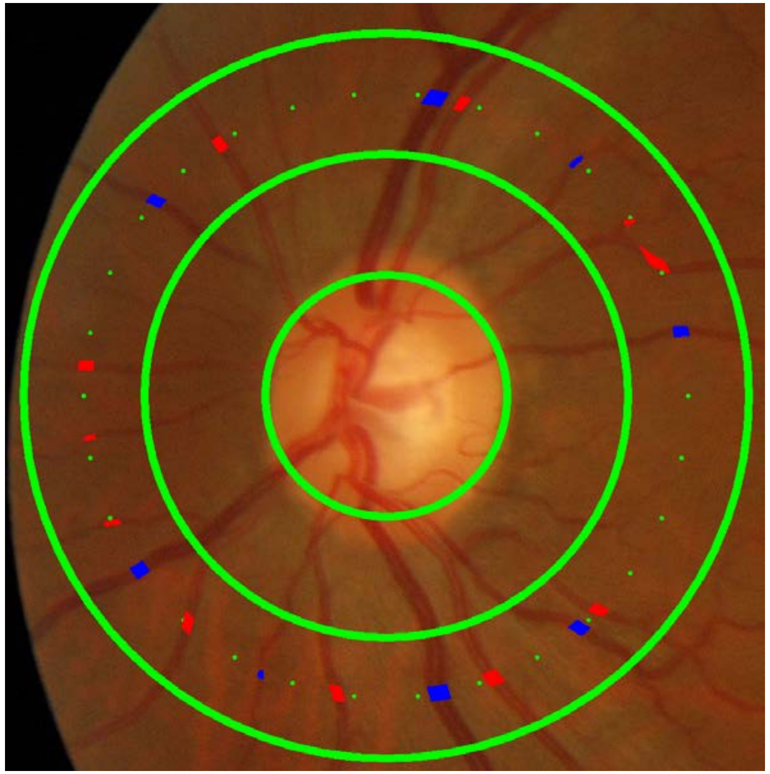
MOTIVATION

- One measure used to track these vessel changes is the arterio-venous diameter ratio.

- Calculated only around the optic disc

- It is correlated with risk of coronary artery disease, hypertension, cholesterol level, progression of retinopathy and smoking [1].

→Could a global measure be more indicative of vessel changes?



[1] R.Klein, B.K.Klein, and S.E.Moss, “The relation of retinal vessel caliber to the incidence and progression of diabetic retinopathy: Xix: the Wisconsin epidemiologic study of diabetic retinopathy,” Archives of Ophthalmology, vol. 122, no. 1, pp. 76–83, 2004.

STATE OF THE ART

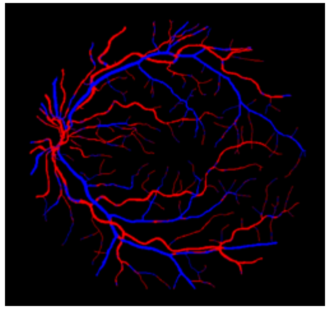
- Mainly machine learning techniques with color, intensity features locally classify pixels into arteries/veins
- ... followed by a graph-based method that improve pixel classification using global topology rules of the vascular tree [1,2]

→ no deep learning methods to date

[1] B. Dashtbozorg, A. M. Mendona, and A. Campilho, “An automatic graph-based approach for artery/vein classification in retinal images,” IEEE Transactions on Image Processing, vol. 23, no. 3, pp. 1073–1083, 2014.
[2] R. Estrada, M. J. Allingham, P. S. Mettu, S. W. Cousins, C. Tomasi, and S. Farsiu, “Retinal artery-vein classification via topology estimation,” IEEE Transactions on Medical Imaging, vol. 34, no. 12, pp. 2518–2534, Dec 2015.

SUMMARY OF THE METHODOLOGY

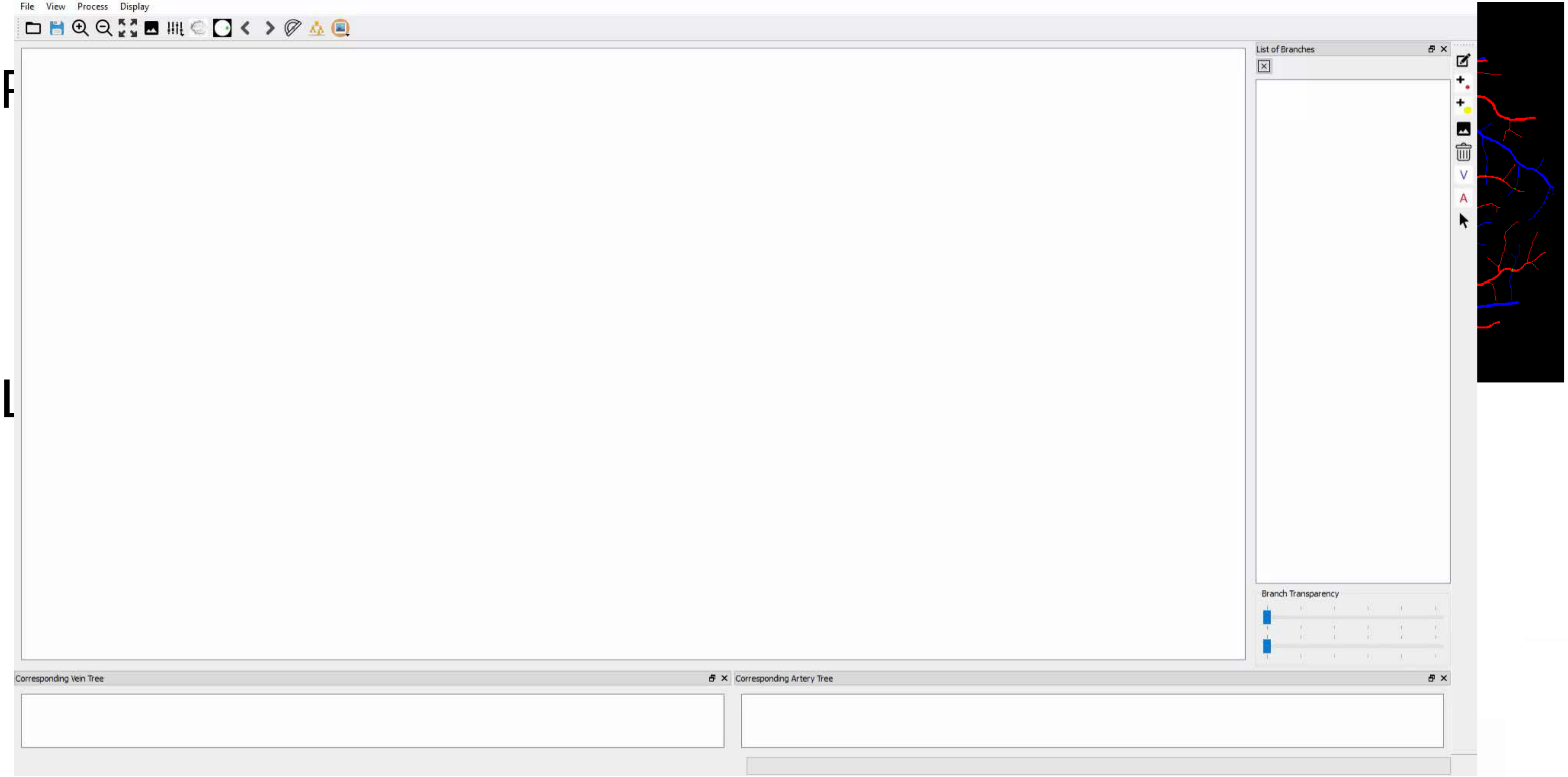
Dataset Annotation → CNN training → (CNN model) → CNN inference → (Initial labeling) → Likelihood Score Propagation



Large datasets
but not annotated

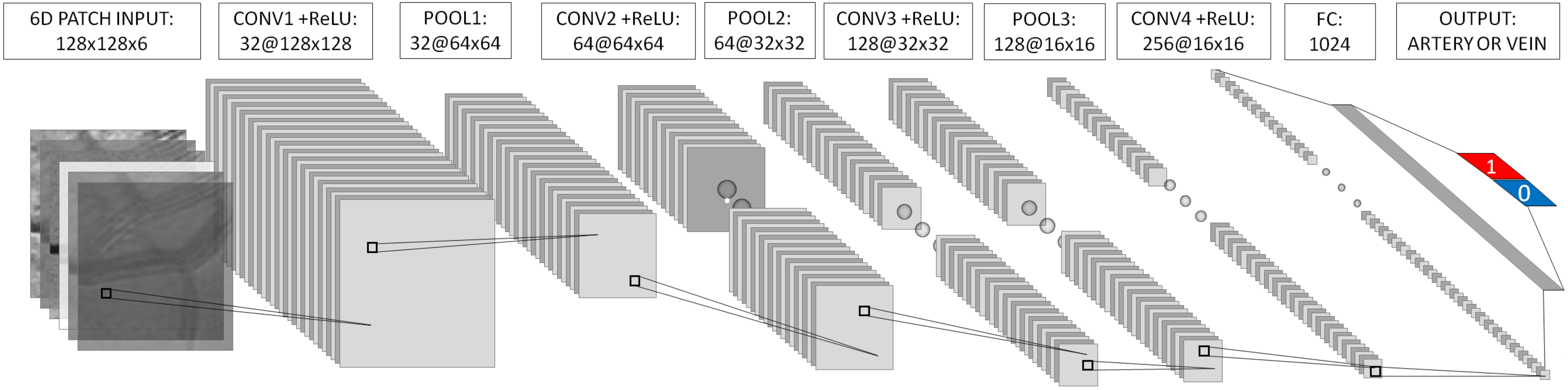
DATASET ANNOTATION

- F
- L



CNN MODEL

- Central pre-segmented vessels pixel in the patch is classified as artery or vein
- 4 Convolutional Layers
- ADAM stochastic gradient descent

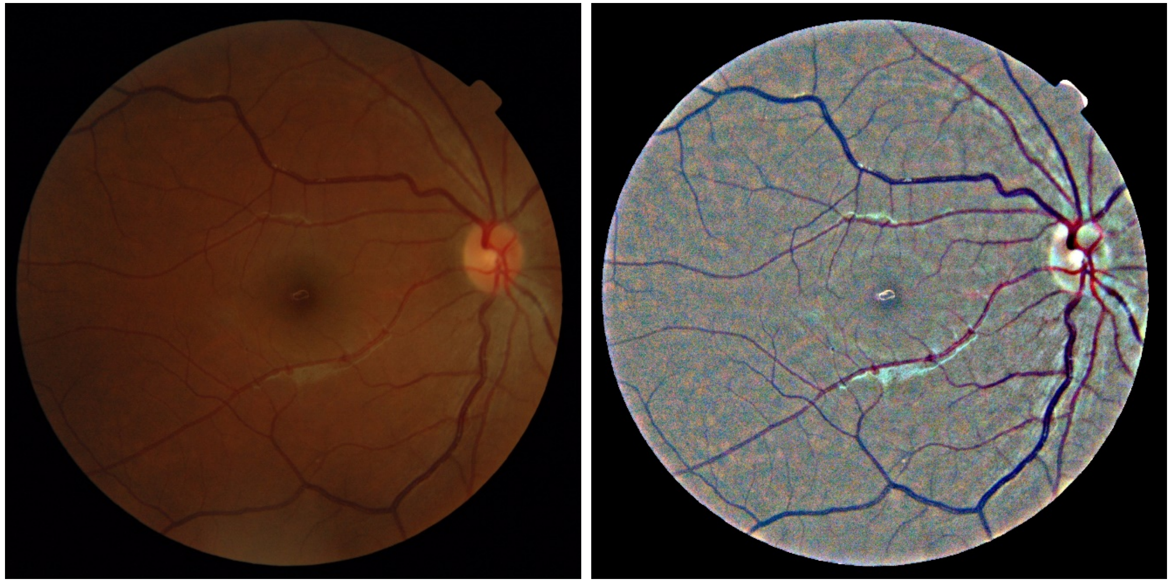


- Six channels input (3 RGB channels + 3 RGB normalized channels)

TRAINING STRATEGIES

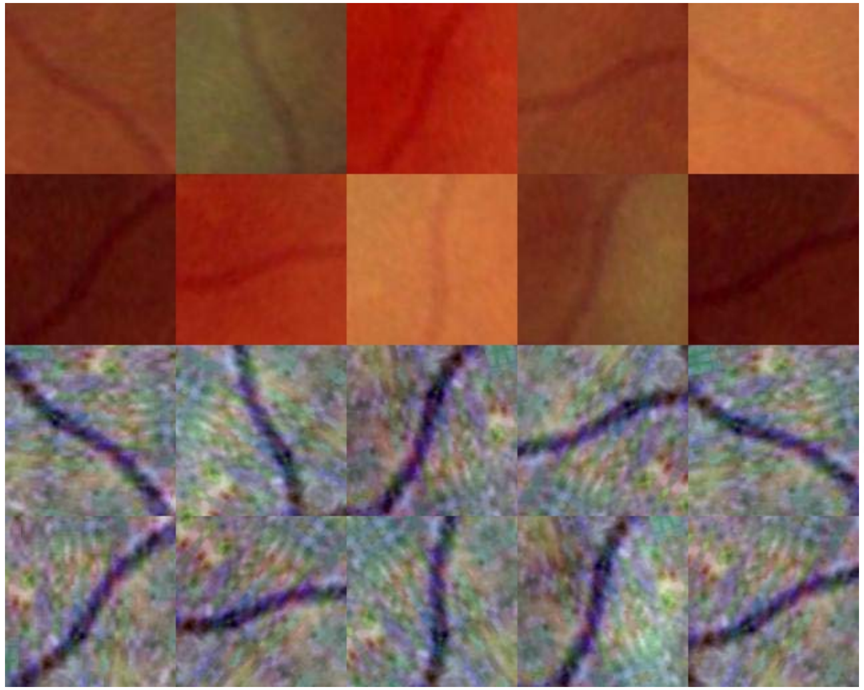
- 6 channels input : Normalized channels

$$I_{norm} = \frac{I - median(I)}{\sigma_I} * \sigma_0 + 128$$



- Data augmentation: Rotation and PCA augmentation

  → For medical application: have to be the most realistic

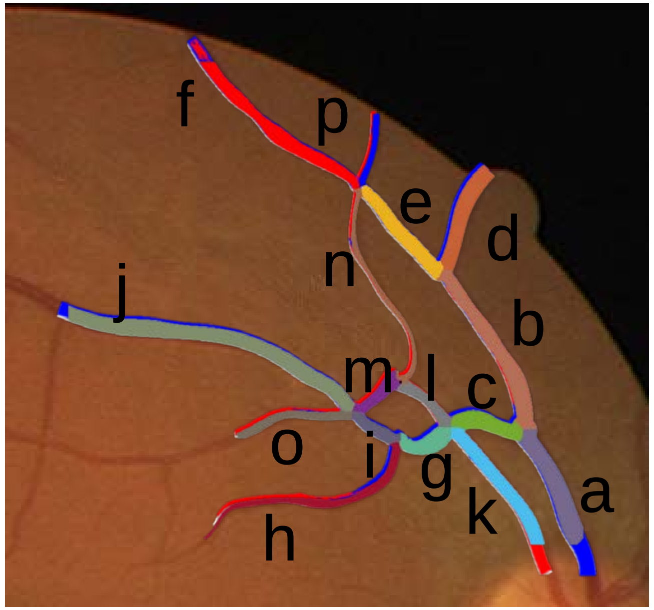


LIKELIHOOD SCORE PROPAGATION

- Graph-based method that propagates initial CNN labeling through the vasculature

→ use of global topology of the retinal vessels network

- Every branch (nodes) is connected to all the branches. the edge is connected to the cost (position and label cost)



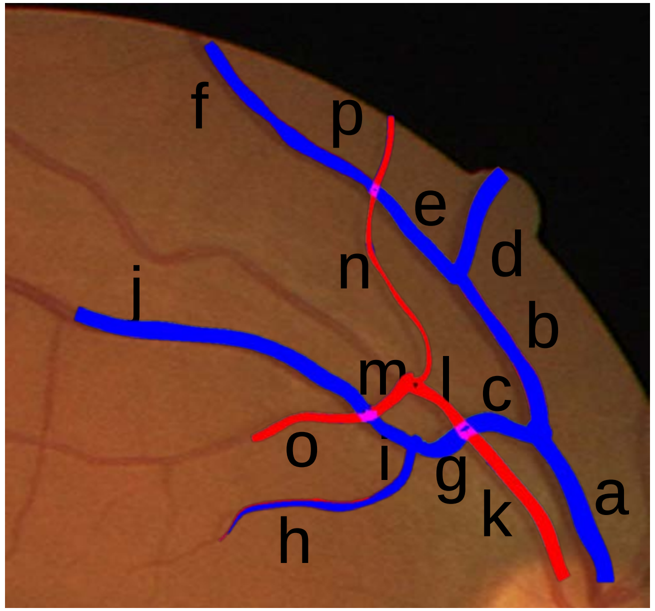
LIKELIHOOD SCORE PROPAGATION

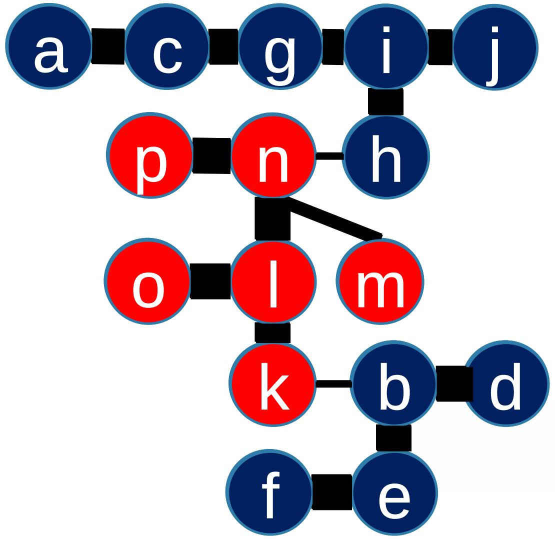
- For efficiency, the graph is simplified into its minimal spanning tree
- Traversing the tree twice to propagate the scores
  - First each child give its label attenuated by the position cost

$$s_i = s_i + \sum_{b_i \setminus \mathrm{P}(b_j) = b_i} \exp \frac{c_{pos}(b_i, b_j)}{\sigma_{prop}} s_j$$

  - Then each parent gives the remaining label propagation to its children

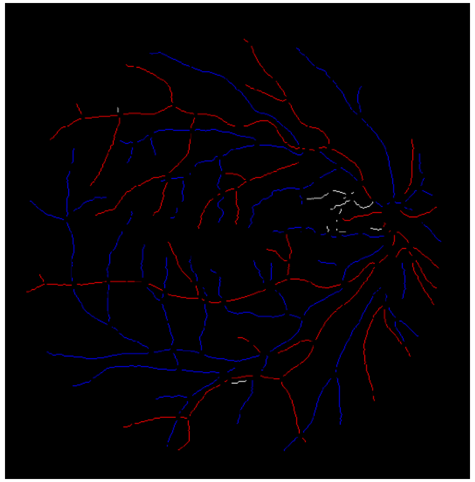
$$s_j = s_j + \exp \frac{c_{pos}(b_i, b_j)}{\sigma_{prop}} \left[s_i - s_j \exp \frac{c_{pos}(b_i, b_j)}{\sigma_{prop}} \right]$$

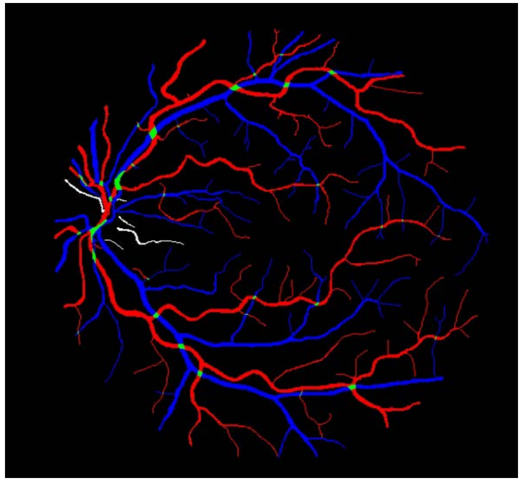




DATA AND PARAMETERS

- Training data
  - 20 images from DRIVE
  - 70 images from MESSIDOR
  - = 1 500 000 128x128 patches
  - 10% training data as validation set





- Test data
  - 2 ground truth set for the 20 test images of DRIVE (centerline CT-DRIVE and all pixels ALL-DRIVE)
  - 30 images from MESSIDOR

- Each training stopped after 50 epochs
- Empirical strategy to select the model

RESULTS

- Better results than the state of the art
- Still need a graph propagation as CNN labeling remains local
- LSP improve the most on smallest vessels

Dataset	Method	Sensitivity	Specificity
CT-DRIVE	CNN + LSP	93.6% ± 5%	93.1% ± 6%
	TE*[1]	91.7% ± 7%	91.7% ± 7%
	LDA+GTR*[2]	90.0%	84.0%
	CNN	86.0% ± 4%	83.8% ± 9%
	kNN[3]	80.0%	80.0%
ALL-DRIVE	CNN + LSP	92.3%	93.1%
	CNN	90.9%	87.6%
MESSIDOR	CNN + LSP	90.6%	97.6%
	CNN	88.8%	91.8%

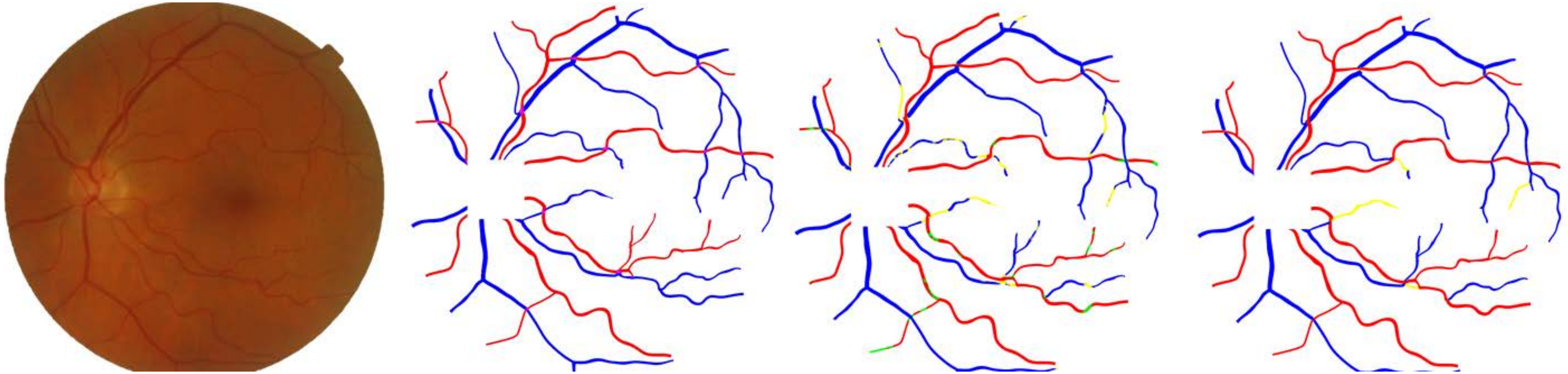
*TE = Topology Estimation [1]; *GTR = Graph Topology Rules [2]

Dataset	Method	Accuracy for diameter (in pixels)			
		1	2 to 4	5 to 10	> 10
ALL-DRIVE	CNN + LSP	75.2%	78.9%	94.0%	99.3%
	CNN	55.0%	73.4%	91.9%	97.3%

[1] R. Estrada et al., "Retinal artery-vein classification via topology estimation," IEEE Transactions on Medical Imaging, 2015.
[2] B. Dashtbozorg et al., "An automatic graph-based approach for artery/vein classification in retinal images," IEEE Transactions on Image Processing, 2014.
[3] M. Niemeijer et al., "Automated measurement of the arteriolar-to-venular width ratio in digital color fundus photographs," IEEE Trans Med Imaging, 2011

RESULTS

- Results



- ROC curves
  - 6D input > 3D input
  - LSP can propagate errors as well

→ best improvement near the error equal rate

CONCLUSION

- Deep learning techniques demonstrate really good accuracy for artery/vein classification

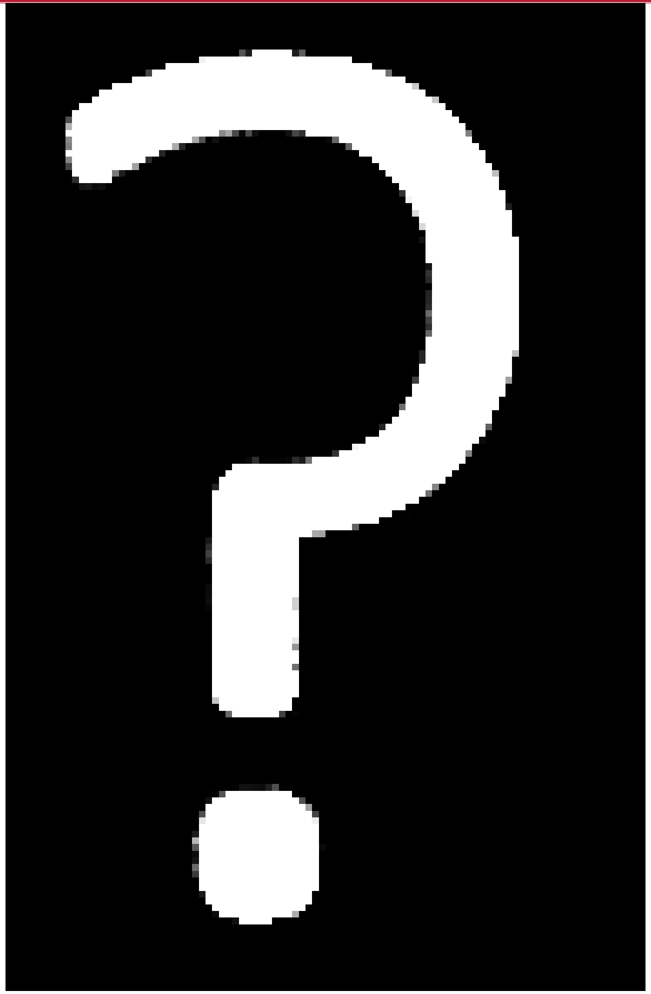
- Where local information is poor, a global graph-based method still improve the CNN labeling (here our fast LSP method)

- Future works:
  - get rid of the graph-based method → need for more labeled data

  → using our CNN pretrained model, learn with more data with semi-supervised CNN variant like adversarial networks

  → feed the CNN with a larger patch

QUESTIONS



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