Comparison of image processing techniques on Retinal Blood Vessel Segmentation

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Introduction to problem

- Human eye is sensitive to vascular system pathologies
- 28.5% adults have diabetic retinopathy.[1]
- Fundus imaging, fluoresceine angiography, and OCT (optical coherence tomography) angiography are used for medical imaging

https://www.nysoa.org/page/eye-disease-anatomy-55.html

Datasets

- Drive
  - 40 images, 7 showing mild signs of early diabetic retinopathy
  - Radius of 540 pixels
  - Divided into training and testing with 20 images each

Related Works

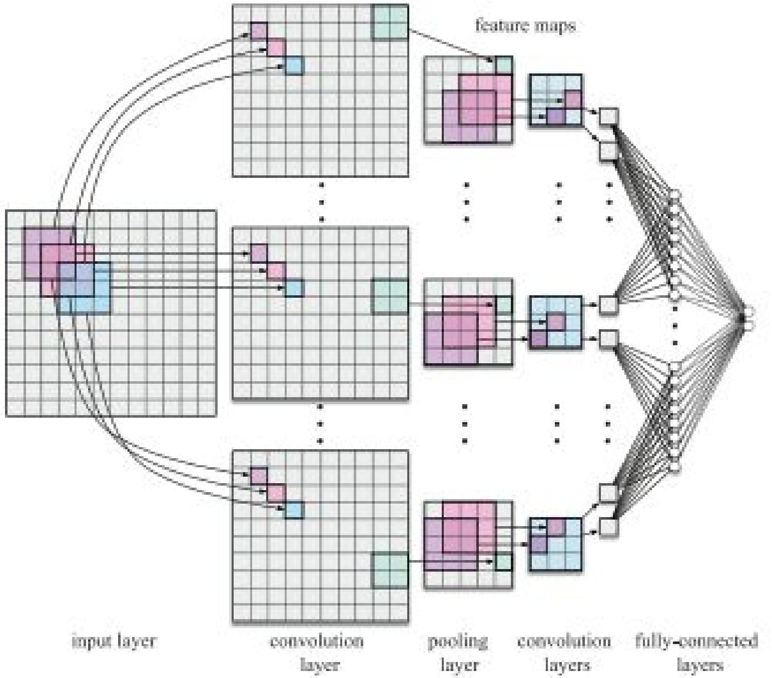
- Machine learning, matched filtering, morphological processing, vessel tracking, multi-scale and model-based approaches[3]
- Unsupervised :
  - Properties of structures manually hard-coded into algorithm.
- Supervised :
  - Learning through the features specified[4]
  - Learning through preprocessed image[2]
- Supervised methods usually less labor-intensive and perform better than the unsupervised ones.

Approach used

Neural Network based Approach

Features of Convolutional Neural Network used :

- Local Connectivity
- Parameter sharing
- Pooling
- Dropout



Liskowski et al., "Segmenting Retinal Blood Vessels with Deep Neural Networks", *IEEE Transactions on Medical Imaging*, vol. PP, no. 99, pp. 1-1, 2016.

Data Preparation

- Extraction of patches
  - decision on the class of a particular pixel is based on an m x m patch centered at that pixel.
  - Consider only patches that completely fit in the circular field of view (FOV).
- Image Preprocessing
  - RGB to Gray
  - Normalization and Standardization
  - CLAHE Equalization
  - Discrete Fourier Transform
  - Gabor Wavelet Transform

Data Preparation (contd.)

- Normalization: $X_{new} = (X - \mu)/\sigma$

  Standardization: $X_{new} = (x - x_{min})/(x_{max} - x_{min})$

- CLAHE (Contrast Limiting Adaptive histogram Equalization)
  - Adaptive method computes histograms in small blocks of image.
  - To avoid amplification of noise, contrast limiting is applied.

Data Preparation (contd.)

- If any histogram bin is above the specified contrast limit, those pixels are clipped and distributed uniformly to other bins.

❑ Fourier Transform of Image :

$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j)\, e^{-\iota 2\pi \left(\frac{ki}{N} + \frac{lj}{N}\right)}$$

- The real and imaginary frequency components at a location are given as input to the CNN model.
- Fast Fourier Transform(FFT) is used

Data Preparation (contd.)

- 2D Gabor Wavelet Transform :
  - Poor localization of FFT in time domain.
  - Directional selectiveness capability of detecting oriented features and fine tuning to specific frequencies of 2D Gabor wavelet.
  - Two dimensional mother wavelet:

$$\psi(\vec{x}) = \frac{1}{\sigma^2} e^{-\frac{\vec{x}^2}{2\sigma^2}} e^{i \vec{e}_h^T \vec{x}}$$

2D Gabor Wavelet Transform(contd.)

- first part is a Gaussian with standard deviation σ.
- second part is the complex-valued even wave $\exp(ie^T_h x)$ with spatial frequency $e_h = (1, 0)^T$ pointing along the horizontal axis.
- The continuous Gabor wavelet family in spatial domain:

$$\psi_{k,\vartheta,\vec{t}}(\vec{x}) = k^2\, \psi\left(k\, Q(\vartheta)^{\mathrm{T}}\, (\vec{x} - \vec{t})\right)$$

$$= \frac{k^2}{\sigma^2}\, \mathrm{e}^{-\frac{k^2 (\vec{x}-\vec{t})^2}{2\sigma^2}}\, \mathrm{e}^{i\, \vec{e}_h^{\mathrm{T}} \left(k\, Q(\vartheta)^{\mathrm{T}} (\vec{x}-\vec{t})\right)}$$

2D Gabor Wavelet Transform (contd.)

$$\vec{k} = \begin{pmatrix} k_h \\ k_v \end{pmatrix} = k\, Q(\vartheta)\ \vec{e}_h = \begin{pmatrix} k\ \cos(\vartheta) \\ k\ \sin(\vartheta) \end{pmatrix}$$

- Q(ϑ) is the rotation matrix of the wavelet and ϑ is the rotation angle.
- Input real and imaginary components of Wavelet Transform to neural network.

Previous Results

State of the art results (below mentioned architecture):
AUC - 0.979
Accuracy - 95.35%

ARCHITECTURE OF THE EVALUATED CNNS. LAYER NAMES ARE FOLLOWED BY NUMBERS OF FEATURE MAPS. SQUARE BRACKETS SPECIFY RF SIZE, STRIDE AND PADDING

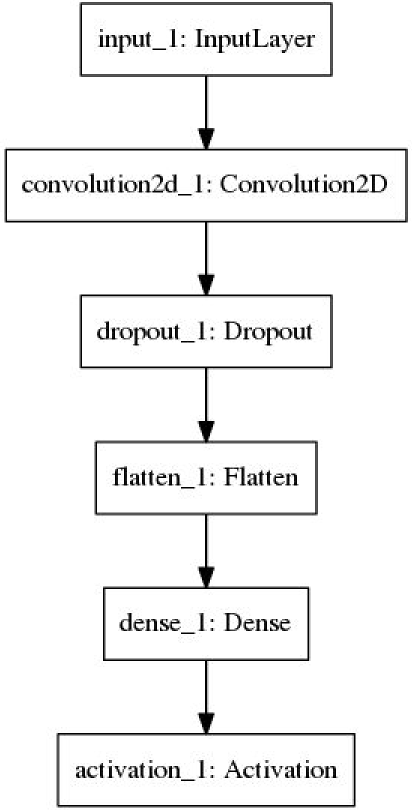
PLAIN	$\underset{[4\times4\times1\times0]}{conv64} \rightarrow \underset{[3\times3\times1\times1]}{conv64} \rightarrow \underset{[2\times2\times2\times0]}{maxpool} \rightarrow \underset{[3\times3\times1\times1]}{conv128} \rightarrow \underset{[3\times3\times1\times1]}{conv128} \rightarrow \underset{[2\times2\times2\times0]}{maxpool} \rightarrow fc512 \rightarrow fc512 \rightarrow fc2$
NO-POOL	$\underset{[3\times3\times1\times1]}{conv64} \rightarrow \underset{[3\times3\times1\times1]}{conv64} \rightarrow \underset{[3\times3\times1\times1]}{conv128} \rightarrow \underset{[3\times3\times1\times1]}{conv128} \rightarrow fc512 \rightarrow fc512 \rightarrow fc2$

Liskowski et al., "Segmenting Retinal Blood Vessels with Deep Neural Networks", *IEEE Transactions on Medical Imaging*, vol. PP, no. 99, pp. 1-1, 2016.

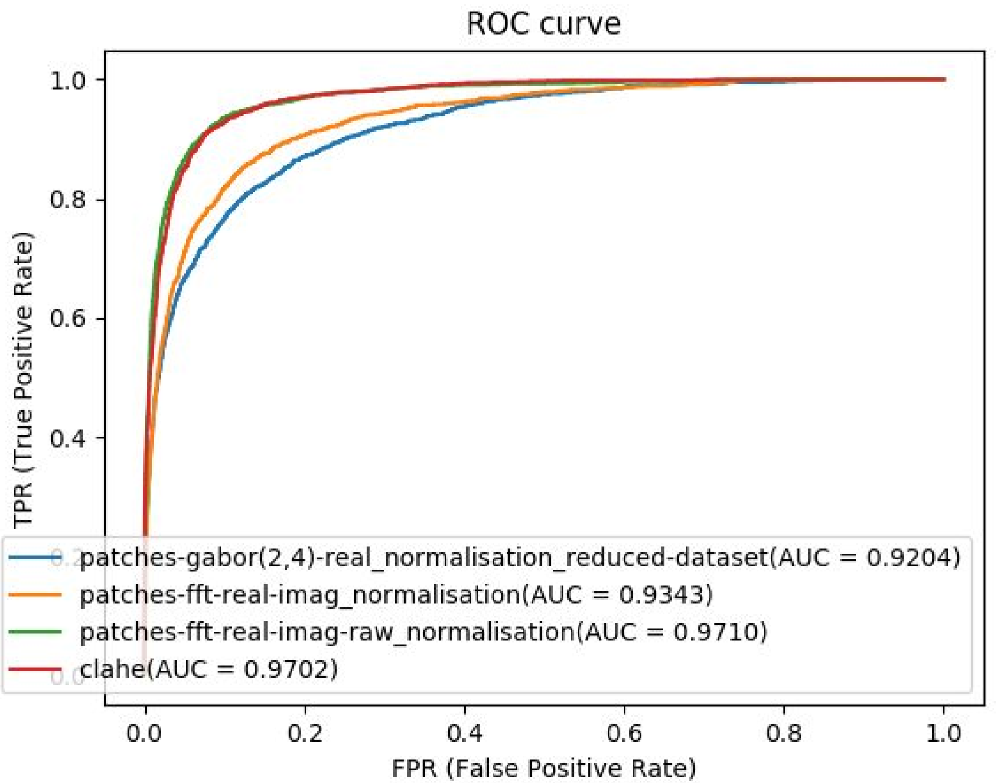
Experiment

Preprocessing techniques used:

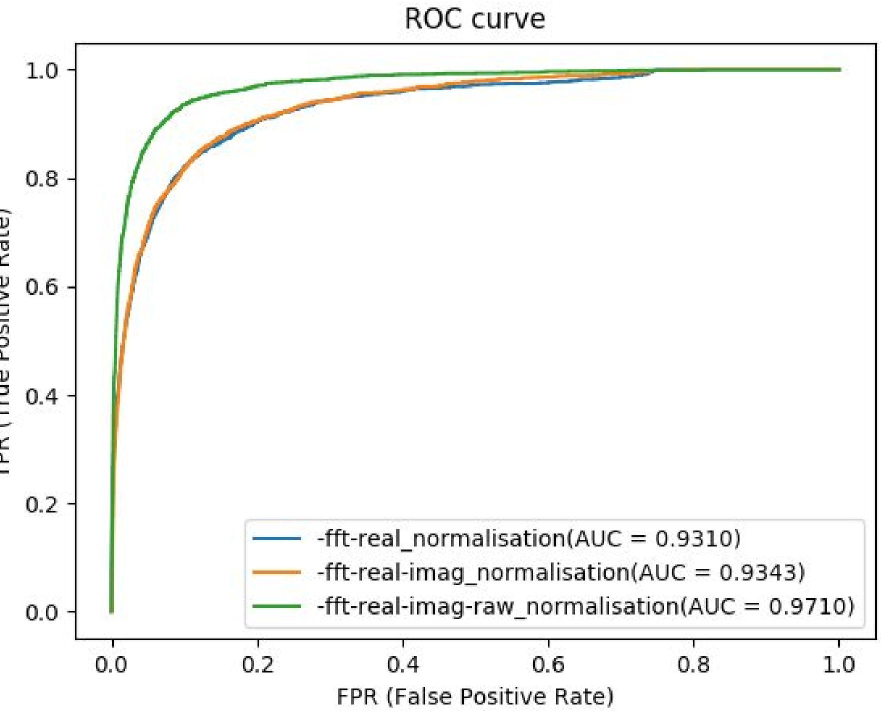
- No processing
- CLAHE
- FFT
- Gabor

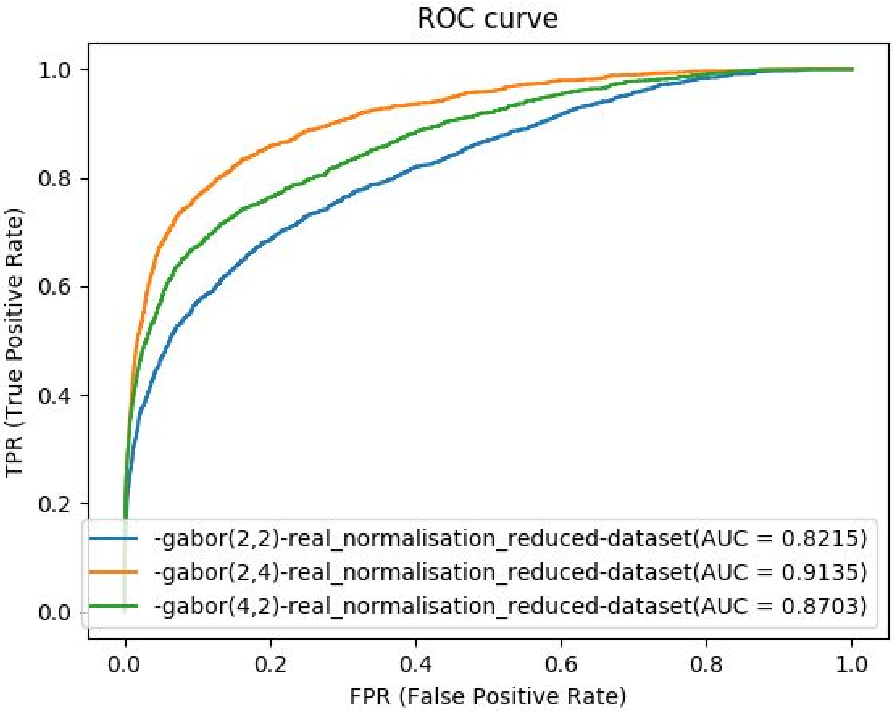


Results

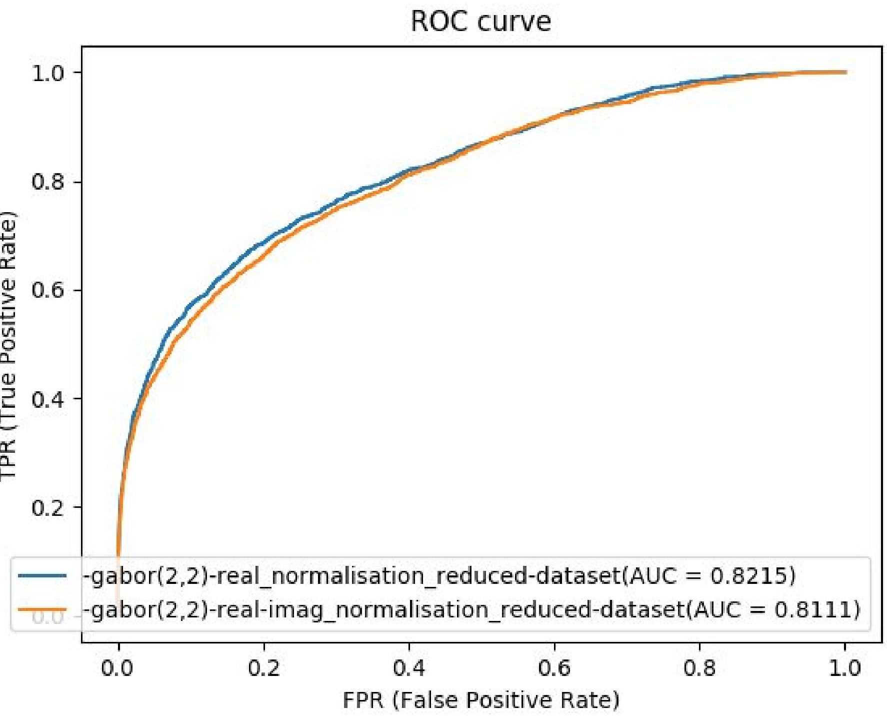

ROC curve
TPR (True Positive Rate)
FPR (False Positive Rate)
1.0
0.8
0.6
0.4
0.0
0.2
0.4
0.6
0.8
1.0
patches-gabor(2,4)-real_normalisation_reduced-dataset(AUC = 0.9204)
patches-fft-real-imag_normalisation(AUC = 0.9343)
patches-fft-real-imag-raw_normalisation(AUC = 0.9710)
clahe(AUC = 0.9702)

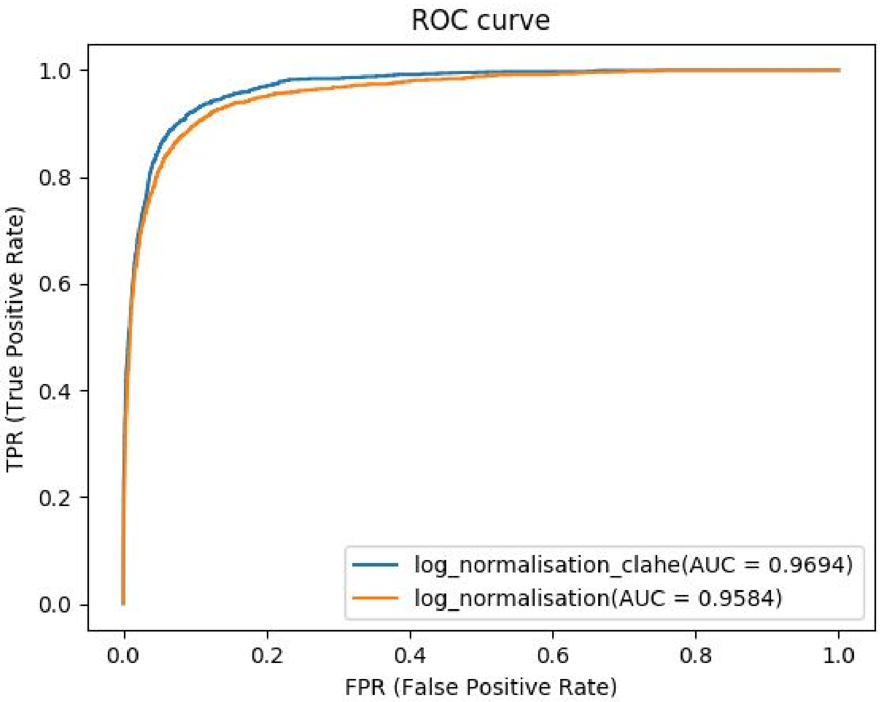
Results (contd.)



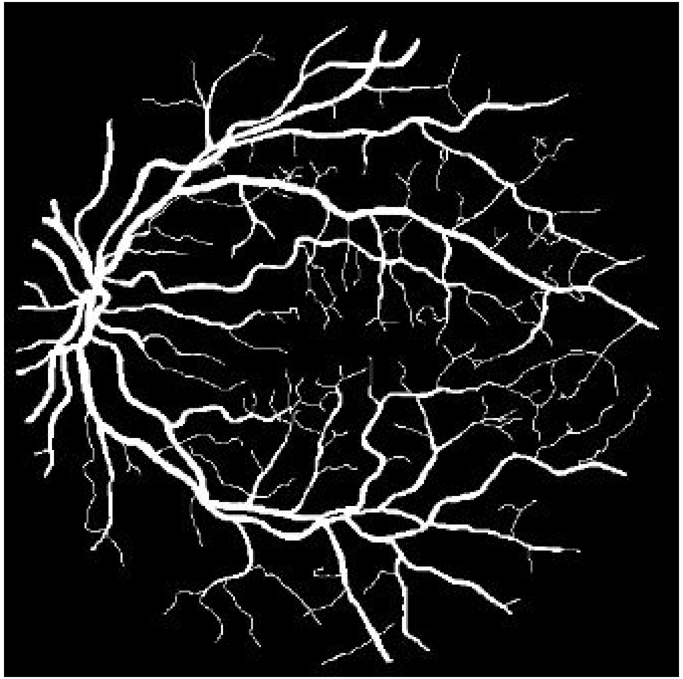


Results (contd.)



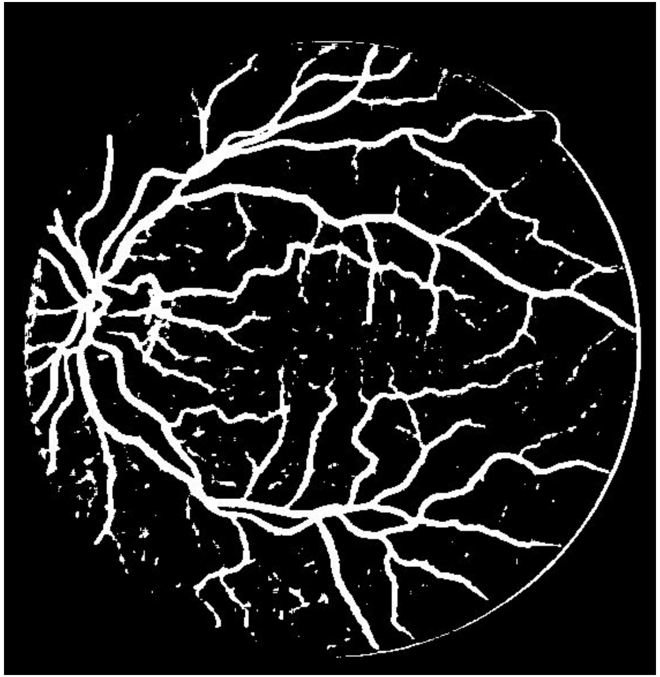


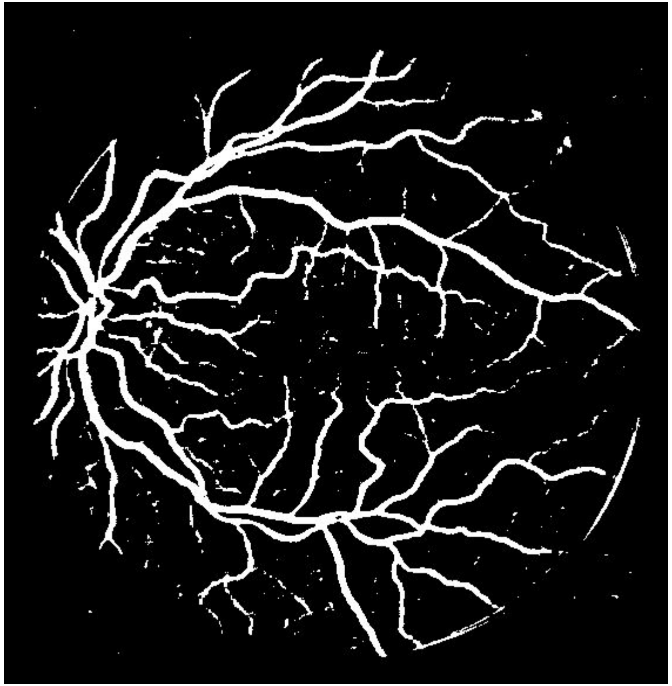
Results (contd.)



Original test Image 1(on left) and corresponding ground truth image(on right).

Results (contd.)





The predicted output using CLAHE equalization (on left) and predicted output using real and imaginary components of FFT along with original image patches (on right).

Future Work

- Processing the output image:
  - Connected Components
  - Erosion
- Exploring Gabor Wavelet, by varying
  - Rotation angle,
  - Scaling factor

References

1. http://www.diabetes.org/diabetes-basics/statistics/
2. Liskowski et al., "Segmenting Retinal Blood Vessels with Deep Neural Networks", *IEEE Transactions on Medical Imaging*, vol. PP, no. 99, pp. 1-1, 2016.
3. M. Fraz et al., “Blood vessel segmentation methodologies in retinal images—A survey,” Comput. Methods Prog. Biomed., vol. 108, no. 1, pp. 407–433, Oct. 2012.
4. A. Krizhevsky and G. Hinton, “Learning multiple layers of features from tiny images”, Computer Sci. Dept., Univ. Toronto, Tech. Rep., 2009, vol. 1, p. 7.
5. Soares et al., “Retinal vessel segmentation using the 2-d Gabor wavelet and supervised classification,” *Medical Imaging, IEEE Transactions on*, vol. 25, no. 9, pp. 1214–1222, 2006.

References (contd.)

6. Martina Melinscak , Pavle Prentasic and Sven Loncaric, “Retinal Vessel Segmentation Using Deep Neural Networks”, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 35, NO. 11, November 2016.
7. Manuel Guenther. “Statistical Gabor graph based techniques for the detection, recognition, classification and visualization of human faces”, PhD thesis, Technical University of Ilmenau, June 2011.
8. A. Anjos et al., "Bob: a free signal processing and machine learning toolbox for researchers," in 20th ACM Conference on Multimedia Systems (ACMMM), Nara, Japan. ACM Press, Oct. 2012.

Thank You

Questions/Suggestions