Microvasculature Segmentation of Arterioles Using Deep CNN

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Outline

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1. Vessel Segmentation
   - State-of-the-art
   - Motivation and challenges
2. Deep Learning Segmentation
   - CNN architecture
   - Training and Testing

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3. Experimental Results
   - Dataset and ground-truth
   - Comparison results

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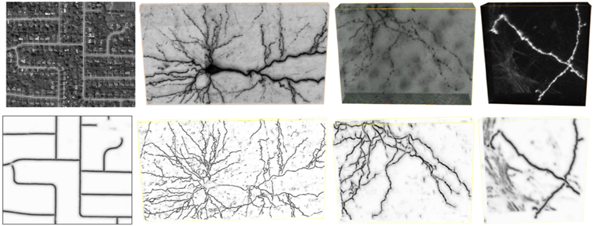
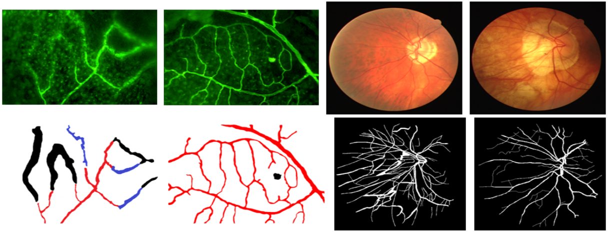
Segmentation of Curvilinear Structures



Sironi et al. Multiscale centerline detection. PAMI, 2015.



DRIVE - Digital Retinal Images for Vessel Extraction. http://www.isi.uu.nl/Research/Databases/DRIVE

Vessel segmentation - Literature

<table>
<tr><th>Paper</th><th>Method</th><th>Strength</th><th>Weaknesses</th></tr>
<tr><td>Frangi et al

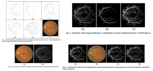
Hessian

(MICCAI, 1998)</td><td><table>
<tr><th colspan="2">2D</th><th colspan="3">3D</th><th>orientation pattern</th></tr>
<tr><td>λ_1</td><td>λ_2</td><td>λ_1</td><td>λ_2</td><td>λ_3</td><td></td></tr>
<tr><td>N</td><td>N</td><td>N</td><td>N</td><td>N</td><td>noisy, no preferred direction</td></tr>
<tr><td></td><td></td><td>L</td><td>L</td><td>H-</td><td>plate-like structure (bright)</td></tr>
<tr><td></td><td></td><td>L</td><td>L</td><td>H+</td><td>plate-like structure (dark)</td></tr>
<tr><td>L</td><td>H-</td><td>L</td><td>H-</td><td>H-</td><td>tubular structure (bright)</td></tr>
<tr><td>L</td><td>H+</td><td>L</td><td>H+</td><td>H+</td><td>tubular structure (dark)</td></tr>
<tr><td>H-</td><td>H-</td><td>H-</td><td>H-</td><td>H-</td><td>blob-like structure (bright)</td></tr>
<tr><td>H+</td><td>H+</td><td>H+</td><td>H+</td><td>H+</td><td>blob-like structure (dark)</td></tr>
</table></td><td>Analysis of the structures using Eigenvalues</td><td>Distinguishing between adjacent thin structures

Connecting broken structures

Handling noise, inhomogeneous background</td></tr>
<tr><td>Fraz et al

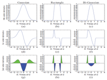
Bit plane

(CMBP, 2012)</td><td></td><td>For retinal imagery</td><td>Difficulty with complex network structure

Segmenting thin vessels

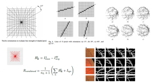
Restricted to Funduscopy images</td></tr>
<tr><td>Changyan Xiao

Bi Gaussian

(TIP, 2013)</td><td></td><td>Distinguishing between adjacent thin structures</td><td>Connecting broken structures

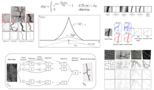
Handling irregular curvilinear structure</td></tr>
<tr><td>Nguyen et al

Line Detector

(PR, 2013)</td><td></td><td>For retinal imagery
Connects the gaps</td><td>One feature is not enough for

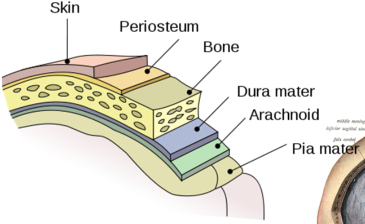
complicated structures</td></tr>
<tr><td>Sironi et al

Multiscale

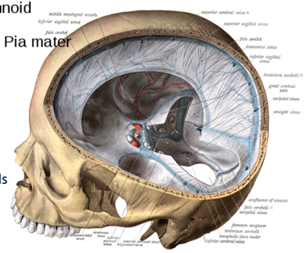
(PAMI, 2016)</td><td></td><td>General framework
Centerline detection</td><td>Time and computational complexity

Connecting broken vessel structures</td></tr>
</table>

Motivation - Effect of estrogen receptors on angiogenesis and vascular remodeling

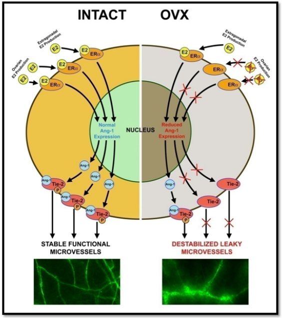


Meninges of the CNS



Dura mater extends into skull cavity

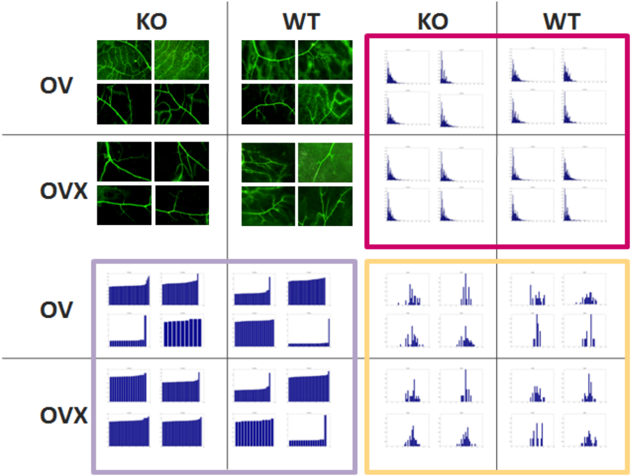
Estrogen Controls Angiopoietin-1 (Ang-1) Expression via ER-alpha



Courtesy: Wikipedia

Microvasculature structure extraction and quantitative analysis using mice dura mater

Motivation - OV vs OVX quantification

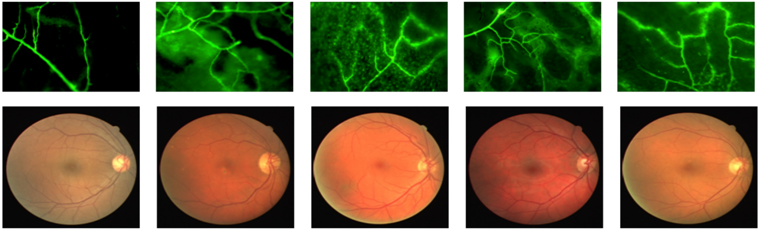


Quantitative parameters

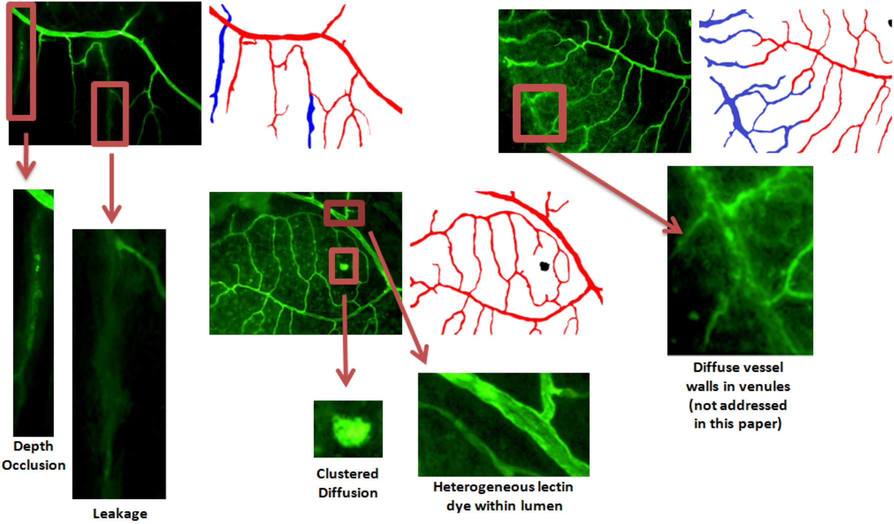
- Midline and vessel wall
- Branching angles
- Diameter ratios
- Tortuosity
- Segment lengths
- Permeability
- Curvature
- Vessel diameter
- Surface Area

Epifluorescence-based microvasculature network versus retinal imagery (DRIVE)

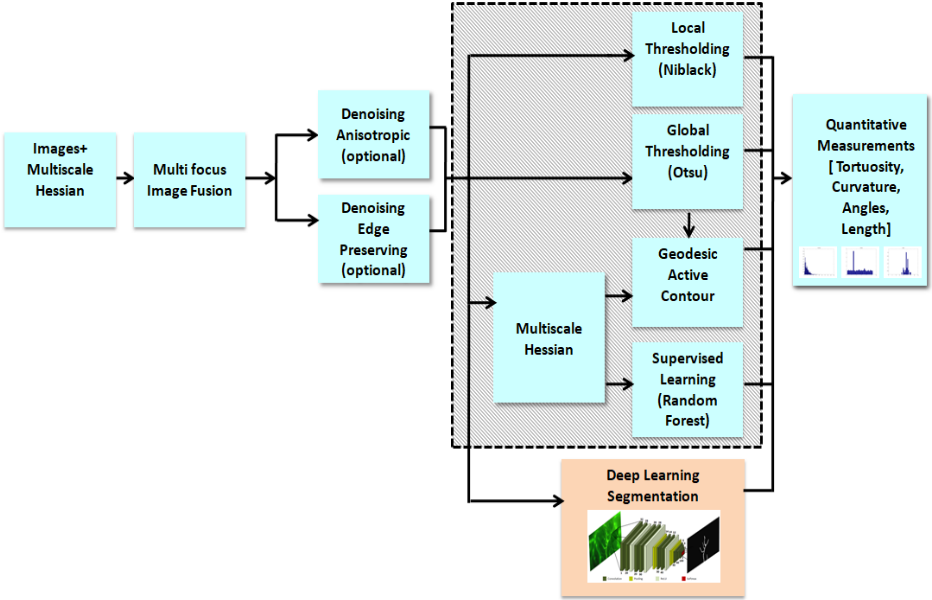
1. Graph Network vs Tree Structure
2. Greater texture variability in both fg and bg
3. Inhomogeneous staining of the microvasculature
4. Different binding properties between arterioles and capillaries
5. Uneven contrast, low texture content
6. Nonlinear binding of the fluorescence dye



Challenging cases for fluorescence-based microvasculature network segmentation

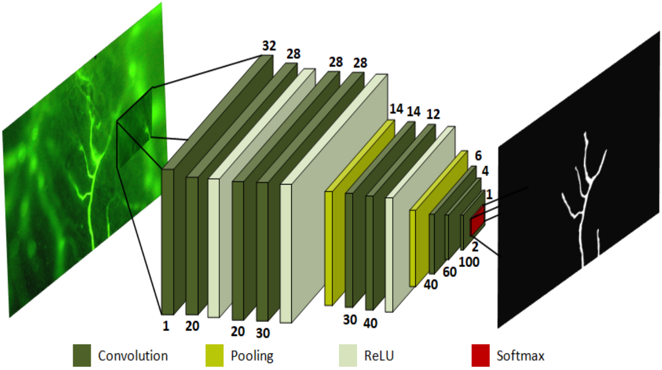


Microvasculature segmentation and analysis



Outline

Proposed Deep Learning Network

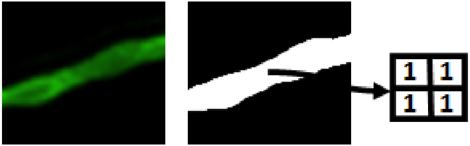


CNN architecture

Layer Type	Input	Filter size	Output	Padding
Conv	32*32*1	5*5*1*20	28*28*20	0
Conv	28*28*20	5*5*20*20	28*28*20	2
Relu				
Conv	28*28*20	5*5*20*30	28*28*30	2
Conv	28*28*30	5*5*30*30	28*28*30	2
Relu				
Pooling	28*28*30	[2 2]	14*14*30	0
Conv	14*14*30	3*3*30*40	14*14*40	1
Conv	14*14*40	3*3*40*60	12*12*60	0
Relu				
Pooling	12*12*60	[2 2]	6*6*60	0
Conv	6*6*60	3*3*60*80	4*4*80	0
Fully connected	4*4*80	4*4*80*100	1*1*100	0
Fully connected	1*1*100	1*1*100*2	1*1*2	0
Softmaxloss			F or B	

Training and Testing

1. Our DBNet uses $32 * 32$ microscopy image patches.
2. Output two classes for microvasculature network as foreground, and other regions as background.
3. 880600 Training patches from 10 different epifluorescence microscopy images with stride equal to 4 .
4. Border patches not used: FG vessel if the corresponding ground truth

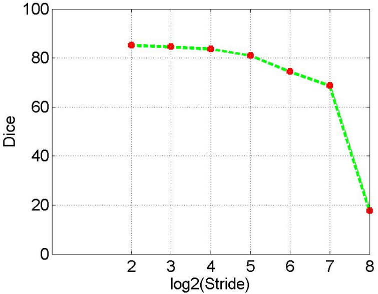


has all 1's.

5. Testing phase uses overlapping patches through the network to obtain smooth binary segmentations.

Trained patches VS. Dice values

Stride	patches number	Dice value
256	300	17.73
128	990	68.68
64	3740	74.47
32	14190	81.04
16	55250	83.68
8	221000	84.77
4	880600	85.26



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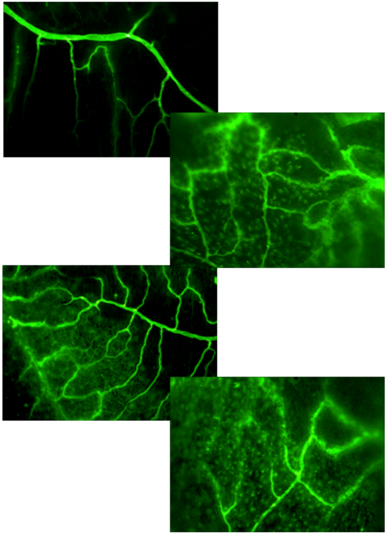
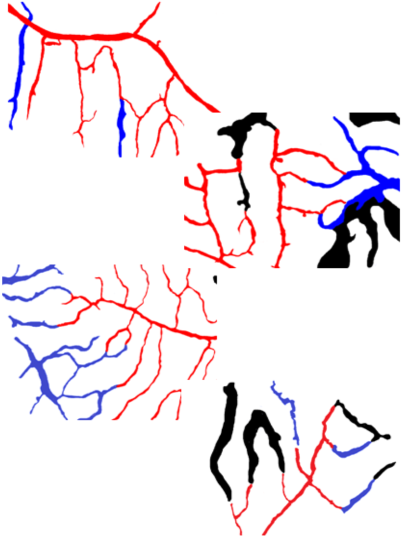
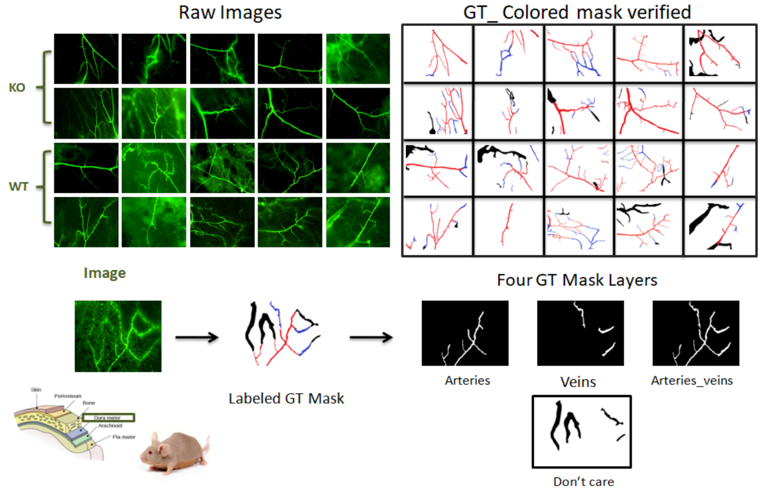
Ground-truth masks - arterioles, venules, no-care



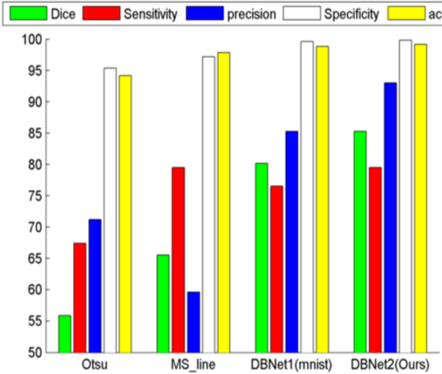


Data Set: Epifluorescence Imgaes OVX

1. Dataset - 20 images, 10 Wild-type (WT) + 10 Knock-out (KO, ERβ)
2. Ground-truth (GT) - manually marked by expert Physiologists
3. Separate masks for arterioles, venules, no-care



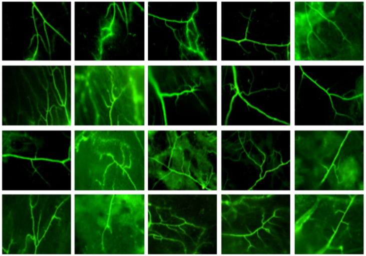
Quantitative comparison results - Dice values



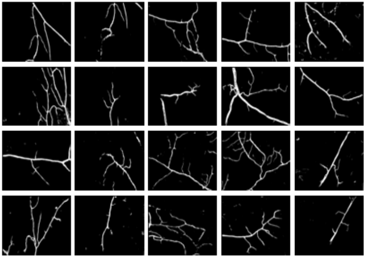
Method	Otsu Thresh.	Multiscale Line det.	MNIST (MCT)	DBNet (ours)
Dice	55.91	65.56	80.16	85.26
Sensitivity	67.41	79.48	76.51	79.52
Precision	71.22	59.66	85.24	93.00
Specificity	95.33	97.13	99.54	99.79
Accuracy	94.16	97.80	98.79	99.11

- MNIST(MCT) MatConvNet applied to vessel images
- DBNet: Discriminative bimodal networks

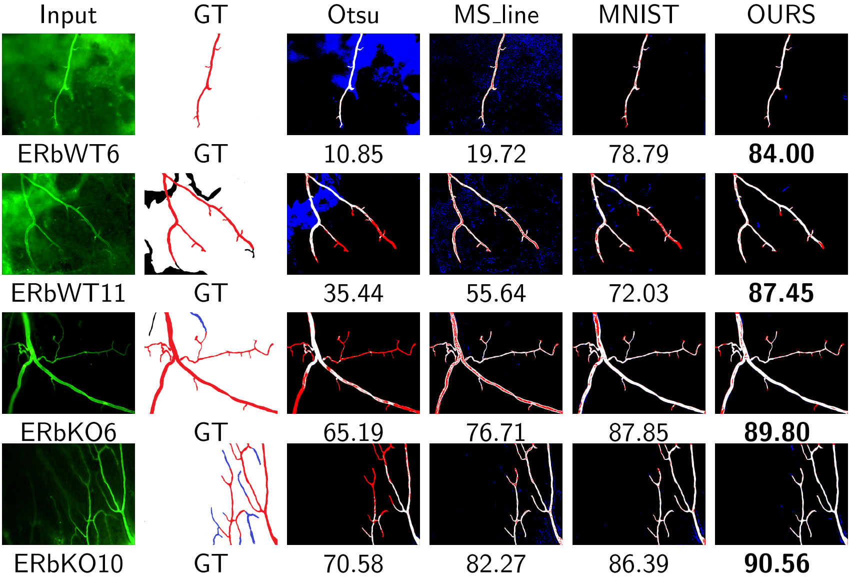
Input



Our Deep Learning Results



Arteriole results (Otsu, MS_line, Mnist vs Ours)



MS_line: Nguyen et al. multi-scale line detection. PR, 2013.

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Conclusions

Work done:

- ✓ Our deep learning segmentation outperforms other methods in terms of five evaluation metrics.
- ✓ Experimental results for both WT and KO animal models achieves an overall accuracy of 99%
- ✓ General pipeline that can be adapted in biomedical (retinal,neuronal) and curvilinear structures (road network).

Future work:

- New approach for segmenting the diffused venule regions
- Quantitative analysis of segmented microvasculature structures for statistical evaluation of vessel remodeling between WT and KO
- Apply semantic segmentation

Appendix: MNIST Configuration in MatConvNet framework applied to our vessels images