AUTOMATIC CLASSIFICATION OF ARTERY/VEIN FROM SINGLE WAVELENGTH FUNDUS IMAGES

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Contents

Problem

- Vessels are regions of prominent interest in retinal fundus images.
- Classification of vessels into arteries and veins is required to assess the oxygen saturation level.
- It is also used to analyze various retinal pathologies, which alter the topography of blood vessels.[1]

Figure 1: A retinal fundus image.

[1] Ikram et al., *Investigative Ophthalmology & Visual Science*, 2004.

- In the case of central retinal venules and arterial occlusions, the oxygen saturation has been found to be lower[2].
- A deficit of oxygen in the retina as a result of blood supply deprivation is linked to diabetic retinopathy[3].
- Oxygen saturation level is generally measured using multi-wavelength fundus images.

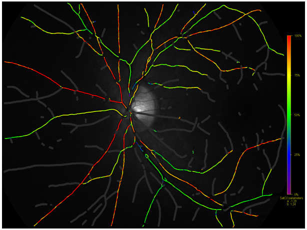


Figure 2: Retinal oximetry map.

[2] Eliasdottir et al., *Graefe's Archive for Clinical and Experimental Ophthalmology*, 2015.

[3] Hardarson et al., *British Journal of Ophthalmology*, 2012.

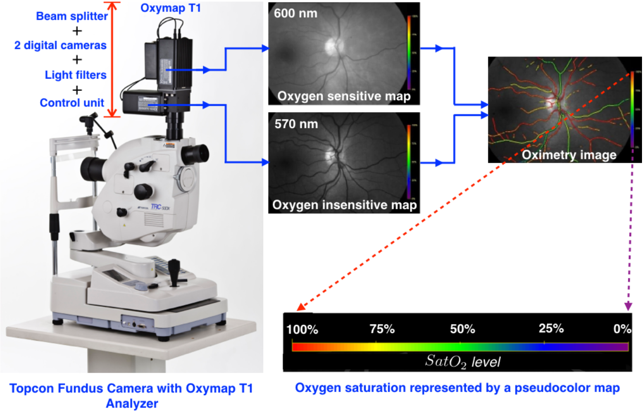
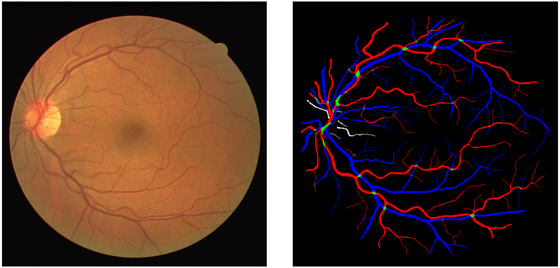


Figure 3: A dual-wavelength fundus imaging setup.

- Question: Could we perform artery-vein (A/V) classification using a single-wavelength fundus image?



(a) (b)

Figure 4: (a) A color fundus image; (b) Manual annotation: red indicates artery, blue indicates vein, green indicates crossing-over of arteries and veins, and white indicates neither artery nor vein.

Prior Art: Image Processing Techniques

- Dashtbozorg et al.[4] used intensity features for A/V classification by extracting the vasculature graph.
- Martinez-Perez et al.[5] improved the performance by combining topological and geometrical features with intensity features.

[4] Dashtbozorg et al., *IEEE Transactions on Image Processing*, 2013.
[5] Martinez-Perez et al., *IEEE Transactions on Biomedical Engineering*, 2002.

Prior Art: Deep Learning Techniques

- Meyer et al.[6] and Welikala et al.[7] used a fully-connected convolutional neural network for A/V classification.
- Galdran et al.[8] formulated the A/V classification task as a four-class segmentation problem to classify pixels into background, artery, vein, or uncertain classes.
- Zhang et al.[9] used dual-wavelength fundus images consisting of two monochromatic images captured at wavelengths 570 nm and 610 nm.

[6] Meyer et al., *Proc. Int. Conf. on Image Analysis and Recognition*, 2018.
[7] Welikala et al., *Computers in Biology and Medicine*, 2017.
[8] Galdran et al., *Proc. IEEE Int. Symp. on Biomed. Imag.*, 2019.
[9] Zhang et al., *IEEE Access*, 2019.

Challenges

- Visually hard to distinguish between arteries and veins given a single wavelength retinal fundus image.
- Lack of large, publicly available datasets with A/V annotations for training a deep neural network.
- Requires complex pre-processing and post-processing steps to achieve higher classification accuracy.

Proposed Method

- We use ResNet-50 trained on ImageNet[10] as the backbone network to perform feature extraction.
- We concatenate the features extracted from the residual blocks having the same filter dimensions.
- The extracted features are upsampled and passed through *squeeze-and-excite* blocks.

[10] Deng et al., *Proc. IEEE Int. Conf. on CVPR*. 2009.

AV-Net

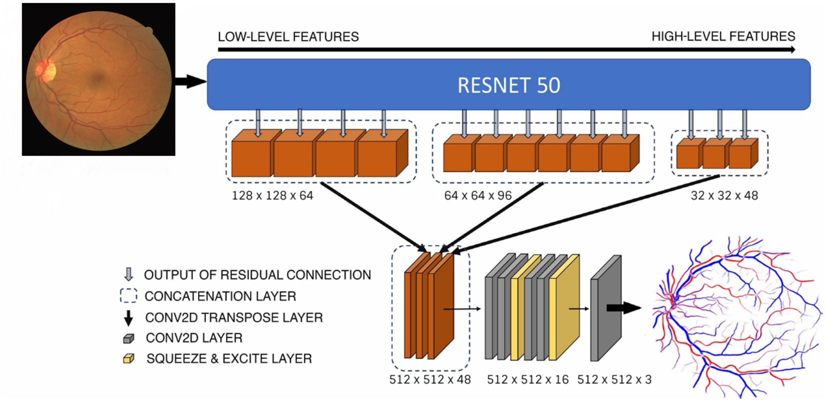


Figure 5: Proposed Artery/Vein Net.

Training the AV-Net

- Three classes: artery, vein, neither.
- Minimize the three-class categorical cross-entropy ($\mathcal{CCE}$) loss:

$$\mathcal{CCE} = -\sum_{c=0}^{2} y_c \log\left(\frac{e^{\hat{y}_c}}{\sum_{i=0}^{2} e^{\hat{y}_i}}\right), \tag{1}$$

where y_c indicates the correct label and $\hat{y}_c$ indicates the predicted probability of a pixel ($c = 0, 1, 2$).

- The loss function is optimized by using rectified Adam[11], which uses warm-up.
- The learning rate $7e - 3$ for the optimizer was obtained using a grid search.

[11] Liu et al., *arXiv preprint arXiv:1908.03265*, 2019.

Experimental Validation

- The AV-Net is trained on three publicly available datasets namely RITE[12], IOSTAR[13], LES-AV[14], and cross-validated on HRF[15].
- These datasets contain images of different contrast, brightness, and illumination.

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[12] Hu et al., *Proc. Int. Conf. on MICCAI*. 2013.
[13] Sureshjani et al., *Proc. Int. Conf. on Image Analysis and Recognition*, 2015.
[14] Orlando et al., *Proc. Int. Conf. on MICCAI*. 2018.
[15] Odstrcilik et al., *IET Image Processing*, 2013.

Datasets Used for A/V Classification

Dataset	# images	Resolution
RITE	40	565×584
LES-AV	22	1444×1620
IOSTAR	30	1024×1024
HRF	45	3504×2336

- Crossings between vessels are labelled as neither an artery nor a vein as shown below.

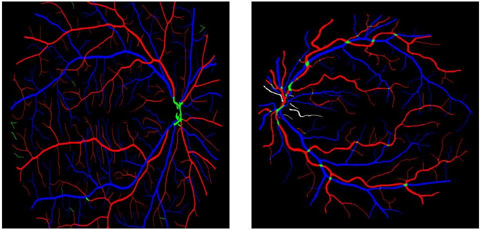

Figure 6: Ground-truth from HRF (left) and RITE (right) datasets. Green: crossing of vessels; and white: uncertainty of vessels being an artery or a vein.

- We have not considered vessel crossings and vessel uncertainty cases to enable a fair comparison with the previously proposed methods.

Training and Validation Data

- A total of 92 images obtained from RITE, IOSTAR, and LES-AV datasets were sorted randomly into training and validation sets (70% & 30%, respectively).
- Data augmentation[16] techniques involving
  1. rotation,
  2. shearing,
  3. horizontal flip, and
  4. vertical flip

  have been employed.

[16] Shorten et al., *Journal of Big Data*, 2019.

A/V Classification Results

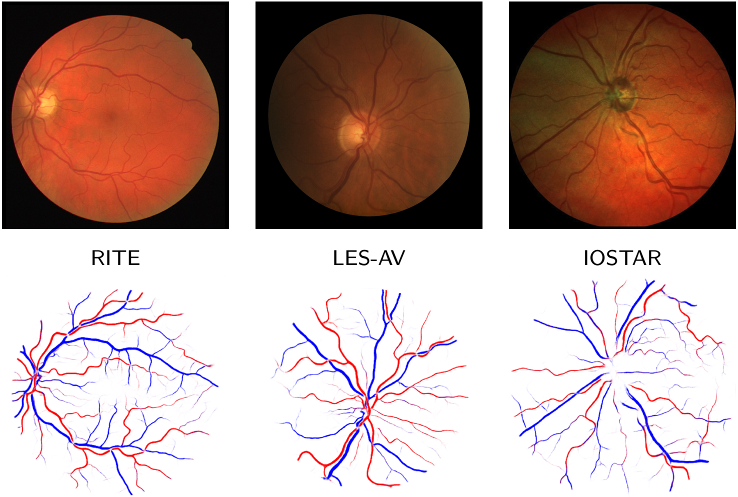

Figure 7: Artery-vein vasculature using AV-Net. (blue: vein; red: artery).

A/V Classification Results

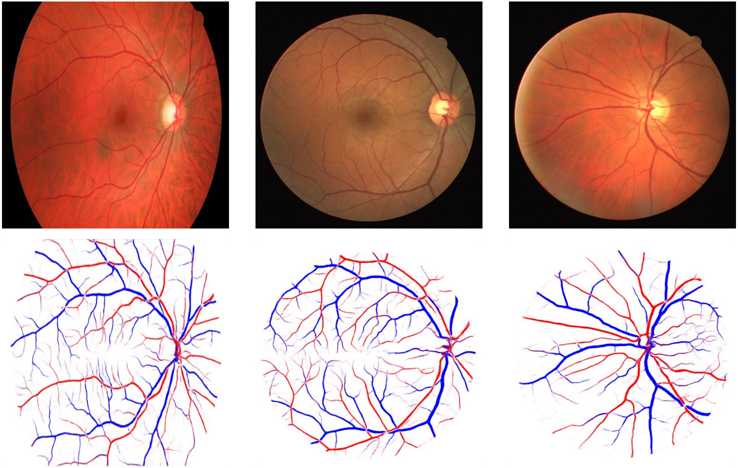

Figure 8: Artery-vein vasculature using AV-Net. (blue: vein; red: artery).

Performance Metrics

We employ the standard metrics for performance comparison:

- *Sensitivity* $(S_n) = \frac{TP}{TP+FN}$
- *Specificity* $(S_p) = \frac{TN}{TN+FP}$
- *Accuracy* $(A_c) = \frac{TP+TN}{TP+TN+FP+FN}$

TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

Performance Comparison

Dataset	Method	Vessel map required as input	S_n	S_p	A_c	AUC
HRF	FCN[17]	✓	-	-	**0.965**	-
	AV-NET	✗	**0.907**	**0.915**	0.915	**0.965**
IOSTAR	**AV-NET**	✗	**0.925**	**0.932**	**0.932**	**0.975**
LES-AV	UV-AV[18]	✗	0.88	0.85	0.86	0.94
	AV-NET	✗	**0.944**	**0.946**	**0.946**	**0.98**
RITE	FCN	✗	-	-	0.938	-
	UV-AV	✗	0.89	0.9	0.89	0.95
	DS-UNET[19]	✗	0.923	0.911	0.917	-
	DFS-search + RF[20]	✓	**0.94**	0.939	0.939	-
	GrBs[21]	✓	0.9	0.84	0.85	-
	TpEs[22]	✓	0.917	0.917	0.92	-
	GenS[23]	✓	0.71	0.74	0.72	0.78
	AV-NET	✗	0.937	**0.943**	**0.943**	**0.98**

[17] Hemelings et al., *Computerized Medical Imaging and Graphics*, 2019.

[18] Galdran et al., *Proc. IEEE Int. Symp. on Biomed. Imag.*, 2019.

[19] Wang et al., *Proc. Int. Conf. on Biomedical Signal and Image Processing*, 2019.

[20] Srinidhi et al., *IEEE Transactions on Image Processing*, 2019.

[21] Dashtbozorg et al., *IEEE Transactions on Image Processing*, 2013.

[22] Estrada et al., *IEEE Transactions on Medical Imaging*, 2015.

[23] Huang et al., *Computer Methods and Programs in Biomedicine*, 2018.

Conclusions

- We proposed a novel deep learning architecture named AV-Net for artery/vein classification.
- We used low-level to high-level features extracted from residual connections of ResNet-50 pre-trained on the ImageNet database.
- In contrast with previously proposed techniques, AV-Net does not require a segmented vasculature map as the input.
- The network has been validated on publicly available datasets RITE, IOSTAR, LES-AV, and cross-validated on HRF. The validations indicate the efficacy and generalization capability of the AV-Net.

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Thank you