AUTOMATIC CLASSIFICATION OF ARTERY/VEIN FROM SINGLE WAVELENGTH FUNDUS IMAGES

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1. Hello everyone, My name is Kevin Raj. I am from the Indian Institute of Science, Bangalore. The title of our presentation is Automatic Classification of artery/vein from single wavelength fundus images. My co-authors are Aniketh Manjunath from University of Southern California, Harish Kumar from Manipal Academy of Higher Education and Chandra Sekhar Seelamantula from the Indian Institute of Science, Bangalore.

Contents

1. This is the overview of my presentation.
2. I shall first present the problem of artery/vein classification and the prior art in the area. I shall then mention the challenges involved and proceed with the proposed method. I will also present validation results on publicly available databases.

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.

1. Vessels are prominent structural regions present in retinal fundus images. Classification of vessels into artery or vein is important in several diagnostic applications, for instance, to determine the oxygen saturation level.
2. Using oxygen saturation levels, pathologies such as retinal vessel occlusion, diabetic retinopathy, and hypertension can be identified.
3. For eg., a lower arteriolar-to-venular ratio (AVR) indicates that the patient is suffering from the risk of hypertension and cardiovascular disease.

- 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.

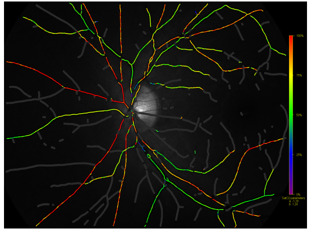


Figure 2: Retinal oximetry map.

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

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

1. 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. The picture here shows a retinal oximetry map obtained using fundus images captured at two wavelengths.

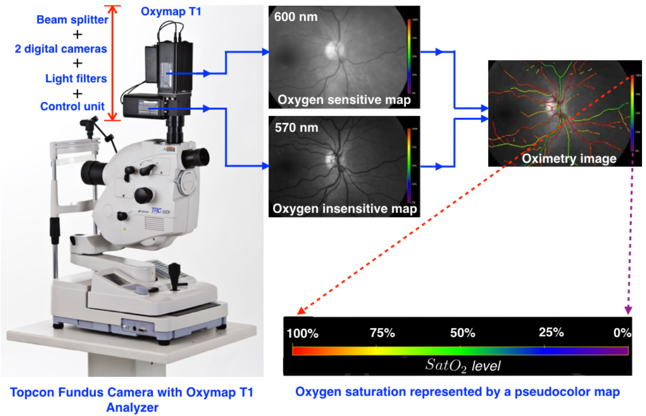
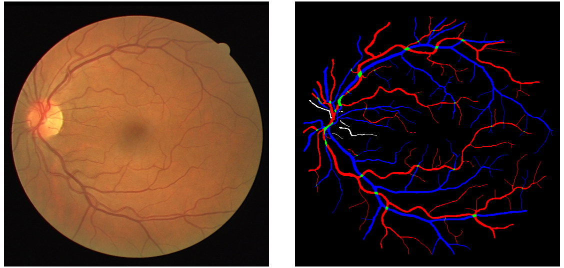


Figure 3: A dual-wavelength fundus imaging setup.

While this is procedure gives precise results, it requires additional hardware, which is expensive.

1. This slide shows a typical two-wavelength fundus imaging setup employing a Topcon fundus camera with oxymap analyzer. Two fundus images, one at 570 nm and the other at 600 nm are obtained from which the artery/vein classification is done and the oxygen saturation level is computed.

- **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.

1. The question that we are asking is the following: Could we perform artery-vein classification using a single-wavelength fundus image?
2. Could we, for instance, treat the problem as a multi-class classification problem? A color fundus image is shown here. The corresponding vasculature map shows the artery in red, vein in blue, crossing-over of artery and vein in white, neither artery nor vein in green.

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.

1. Before proceeding with our approach, we briefly review related prior art. The early techniques were based on image processing approaches, mainly relying on intensity features, topological or geometrical features.

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.

1. Recently, deep learning techniques have also been proposed for performing artery/vein classification.
2. Notably, fully connected convolutional neural networks, U-net architecture, refined U-net model with dual wavelength images have been used for classification.

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.

1. The main challenge is that the features of artery and vein are highly correlated, making it visually as well as technically difficult to classify from single wavelength fundus images. There are also no publicly available datasets with artery/vein annotations for training deep networks.
2. Preprocessing techniques such as illumination compensation, vasculature segmentation, texture feature extraction etc. are needed.
3. Post-processing techniques such as Graph profiling for A/V connectivity, Link labelling, Node type decision for improving the classification are needed.

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.

1. We use ResNet-50 trained on ImageNet as the backbone network to perform feature extraction. Transfer learning is used for better initialization, which leads to faster convergence.
2. In order to preserve both low level features such as edges, corners and high level information such as complex patterns, we concatenate the features from low level to high level.
3. We pass the concatenated features of both low and high level to the squeeze and excite block, in order to explicitly model the interdependencies between various features by assigning corresponding weights.

AV-Net

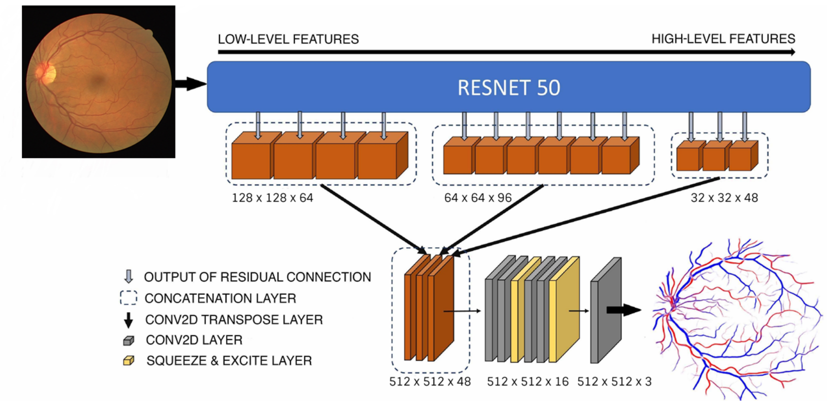


Figure 5: Proposed Artery/Vein Net.

1. This slide shows the architecture of the proposed artery/vein network or AV-Net as we shall call it. The input image is the color fundus image of size 1024×1024 and the output is of size 512×512
2. Features with same filter sizes such as 64, 96 and 48 are concatenated together and passed through the squeeze and excite block which gives weighted filters in the output improving the A/V classification performance.

Training the AV-Net

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

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

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.

1. We deploy the AV-Net for performing three-class classification, the classes being artery, vein, and neither artery nor vein.
2. The AV-Net is trained for 30 epochs with a batch size of two images, minimizing the three-class categorical cross-entropy loss.
3. The loss function is optimized using rectified Adam, which uses Warmup. Warmup is an initial period of training with a much lower learning rate so that adaptive optimizers can offset excessive variance when dealing with limited training data.

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.

[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.

1. The AV-net is trained with three publicly available datasets namely RITE, LES-AV, and IOSTAR. These datasets have images of different contrast, brightness, and illumination.

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

1. This slide shows the details of the datasets – the number of images per dataset and the image resolution. The datasets are not of uniform image resolution. We have resized the images to a common dimension of 1024×1024 which are then input to the AV-Net.

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

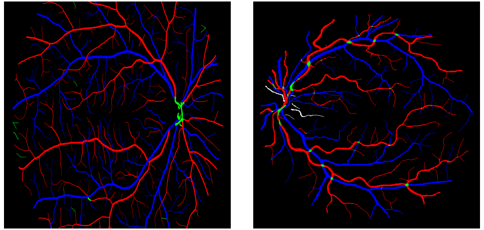


Figure 6: Ground-truth from HRF (left) and RITE (right) datasets. Green: crossing of vessels; and white: uncertainty of vessels being an artery or a vein.

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

1. This figure shows instances of the ground-truth from HRF and RITE datasets. The vessel crossings are marked as green and the uncertainty of the vessel being an artery or vein is marked white.
2. We have not considered these cases. Instead, we consider only three-class classification. This also enables a fair comparison with previous techniques.

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.

1. A total of 92 images taken from the RITE, IOSTAR, and LES-AV datasets were partitioned into training and validation data. Since the data available for training is small, we used data augmentation techniques comprising rotation, shearing, horizontal and vertical flip to increase the size of the training set.

A/V Classification Results

RITE LES-AV IOSTAR

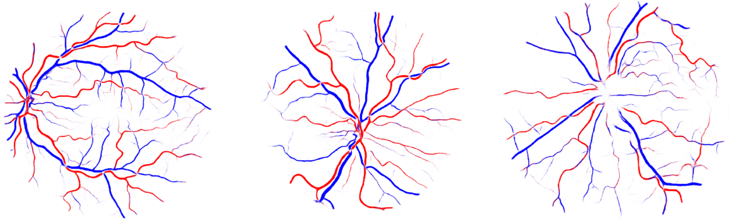


Figure 7: Artery-vein vasculature using AV-Net. (blue: vein; red: artery).

1. This slide shows some results of the proposed artery/vein classification. The three sample images are taken from different databases and have different levels of illumination and nonuniformity of illumination. However, the AV-Net classifier seems to give artery and vein outlines with continuity and without breaks.

A/V Classification Results

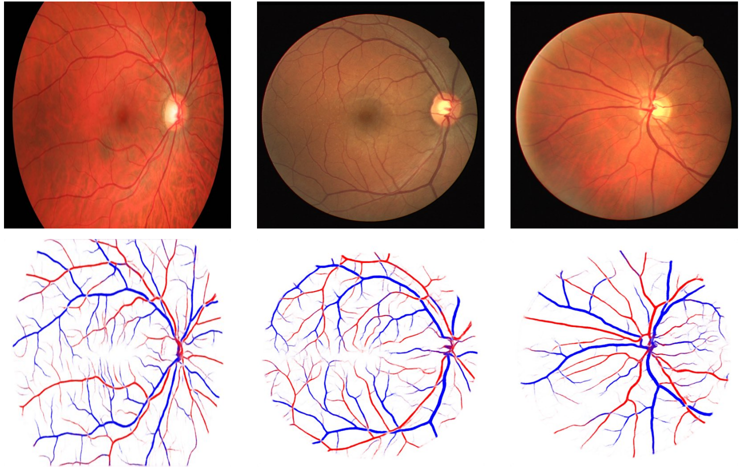


Figure 8: Artery-vein vasculature using AV-Net. (blue: vein; red: artery).

This slide shows another set of results. Again, we observe that there are no spurious pixels classified as artery or vein. The artery vein contours are also well connected with continuity maintained. This is a subjective assessment. We shall next perform a quantitative assessment of the accuracy of classification.

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

1. We consider the standard metrics namely Sensitivity, Specificity, and Accuracy for quantifying the classification performance of the AV-Net.

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.

1. The table shows a detailed comparison of the AV-Net with respect to the state of the art techniques for A/V classification.
2. The AV-Net gives competitive results across the datasets considered.
3. The generalization capability of the AV-Net is demonstrated by the cross-validation performance on the HRF dataset.
4. The AV-Net takes in the color fundus image as input. It does not require a segmented vasculature map as a starting point to perform artery/vein classification. This is a key advantage of the proposed network.

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.

1. To summarize, we proposed a novel deep learning architecture named AV-Net for artery/vein classification.
2. We used low-level to high-level features extracted from residual connections of ResNet-50 pre-trained on the ImageNet database.
3. An attractive feature of the proposed network is that it does not require the segmented vasculature map as the input. It can directly operate on the color fundus image.
4. The validations on publicly available datasets have shown that the accuracy is high and the generalization capability is also good.

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1. This research was supported by an IMPRINT project funded by the Ministry of Human Resource Development and the Indian Council for Medical Research, and a fellowship from the Science and Engineering Research Board.

Thank you

1. That brings me to the end of my presentation. Thank you for your kind attention.