





# **Vessel Segmentation on Low-Resolution Retinal Imaging**

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## Abstract

Retinal vessel segmentation aids diagnosing of various retinal pathologies. A framework is presented for automatic vessel segmentation applied to lower-resolution retinal images taken with a smartphone equipped with D-EYE lens. A private dataset was assembled and annotated, and two CNN based models were trained for retinal localization and vessel segmentation. A Faster R-CNN achieved a Mean Absolute Error of 39 pixels, and a U-Net that reached a Dice Coefficient of 0.7547.

## Introduction

Retinal imaging is a technique that allows recording digitally the rear of the eye. These are typically taken by expensive machines like fundus cameras, that produce high-quality and high-resolution retinal images for analysis. The use of low-cost lenses, such as D-EYE, can bring several advantages such as greater portability, ease of use, greater patient comfort, lower costs and so can be an assessment for unprivileged or remote populations. The drawback is the lower quality of the photos obtained when compared to fundus cameras and as consequence not having the necessary sharpness when used in eyes with small pupils, in eyes with opacity of media (keratitis, cataract), or in very bright environments. These low-resolution and low-quality retinal images create extra difficulties in the use of traditional vessel segmentation methods, which offers attractive opportunities for new developments.

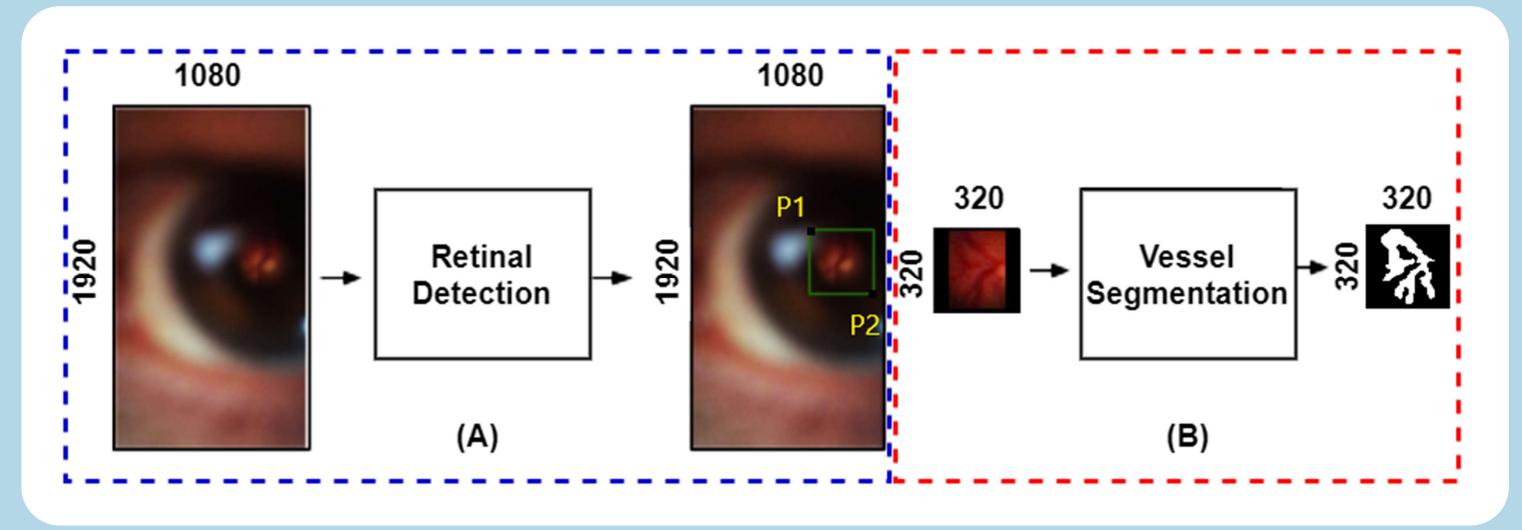
## Methods

This study is divided as the pipeline of Figure 1 and was applied to three datasets (Table 1), to retinal detection - Dataset1 (DS1) and to segmentation of the retinal veins - dataset2 (DS2). The dataset3 (DS3) was used for pre-training the segmentation CNN.

The detection of the retinal visible area (A) consists of computing the location of a rectangle defined by P1 and P2 (Figure 1), that encloses the visible area in the image. It was used a Faster R-CNN model and to evaluate it, the Mean Absolute Error (MAE) for the two coordinates of the upper left corner (P1) and the other two for the lower right corner (P2) were used.

The vessels segmentation was done within the detected retinal areas, with a U-Net model pre-trained with the DS3 and tuned and evaluated with DS2. To evaluate the model, it was used the Dice Coefficient (DICE), between predicted and ground truth segmentations.

	DS1	DS2	DS3
Resolution (pixels)	$1920 \times 1080$	320x320	80x80
Train	18 videos; 3,881 images (64%)	2 videos; 252 images (73%)	14 images; 1,967 patches (70%)
Validation	$\begin{array}{c} 3 \text{ videos; } 776 \\ (13\%) \end{array}$	1 video; 40 images (11%)	3  images;  421  patches  (15%)
Test	5 videos; 1,375 images (23%)	$\frac{1 \text{ video; } 55}{\text{images } (16\%)}$	3  images; 422  patches  (15%)
Total	26 videos; 6,060 images	4 videos; 347 images	20 images; 2,810 patches



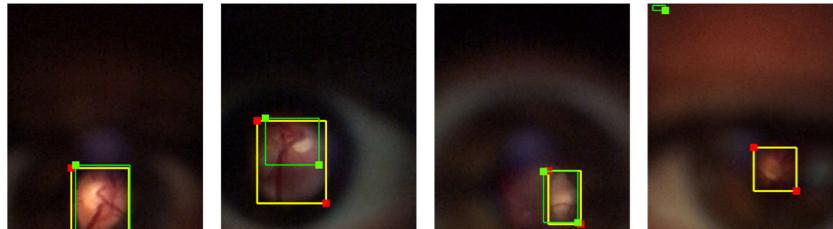
#### Table 1: Datasets.

Figure 1: Pipeline.

### Results

Classification	Frequency	P1 MAE	P2 MAE	P1 and P2
score	Frequency	$(pixels)^*$	$(pixels)^*$	MAE (pixels)*
0.0	30~(2%)	311 (414)	252 (321)	281(371)
0.1	4(0%)	46(28)	41(20)	43(25)
0.2	12~(1%)	63(41)	40(31)	51(38)
0.3	6~(0%)	47 (27)	30(8)	38(22)
0.4	7(1%)	37(23)	41(26)	39(24)
0.5	11 (1%)	76~(69)	50(37)	63(57)
0.6	11 (1%)	91(60)	37(20)	64(52)
0.7	14 (1%)	61(62)	35(26)	48 (49)
0.8	29~(2%)	67(50)	36(20)	52 (41)
0.9	1,251 (91%)	47 (49)	28(13)	37(37)
Total images	$1,\!375$			

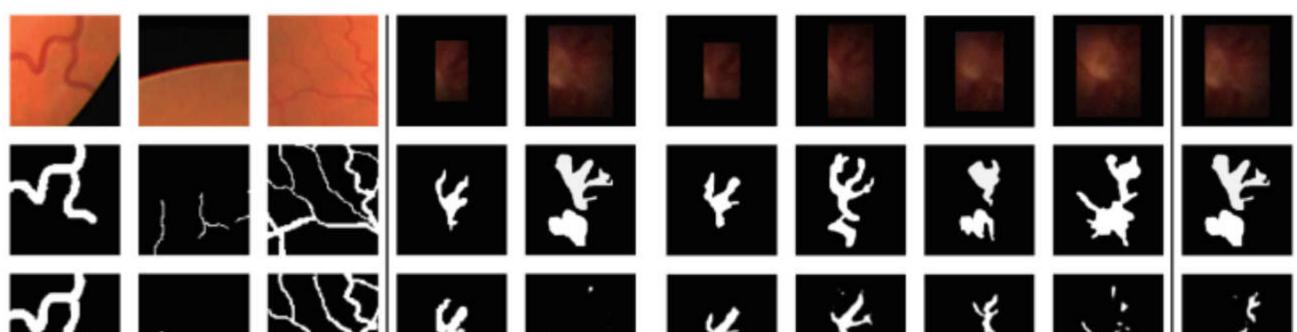
\* MAE: mean (standard deviation)



	Model 1	Model 2	Model 3
(DS3) Testset	0.7824	-	0.5784
(DS2 & DS3) Testset	0.7474	0.7312	-
(DS2) Testset	0.4797	0.7547	0.5580



#### B) Model 2



	,		
Score: 0.997;	Score: 0.963;	Score: 0.0075;	Score: 0.000;

Figure 2: Evaluation and examples for experience (A).

DICE: 0.9350; DICE: 0.0512; DICE: 0.8571; DICE: 0.8009; DICE: 0.0480; DICE: 0.7510; DICE: 0.6054; DICE: 0.5100; DICE: 0.3136; DICE: 0.4304

#### Figure 3: Evaluation and examples for experience (B).

## Conclusions

A framework for vessels segmenting on lower-resolution retinal images was proposed, evaluated, and the attained results were presented. A dataset of train models was assembled and annotated for automatic localization of retinal areas and for vessel segmentation.

For the framework, two CNN-based models were successfully trained, a Faster R-CNN that achieved a 96% correct detection of all regions with a MAE of 39 pixels, and a U-Net that achieved a DICE of 0.7547.

This study is a precursor to future works to the determination of eye diseases, such as glaucoma and diabetes, applied to low-resolution images.

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