

# Retinal Vessel Segmentation (RVS)

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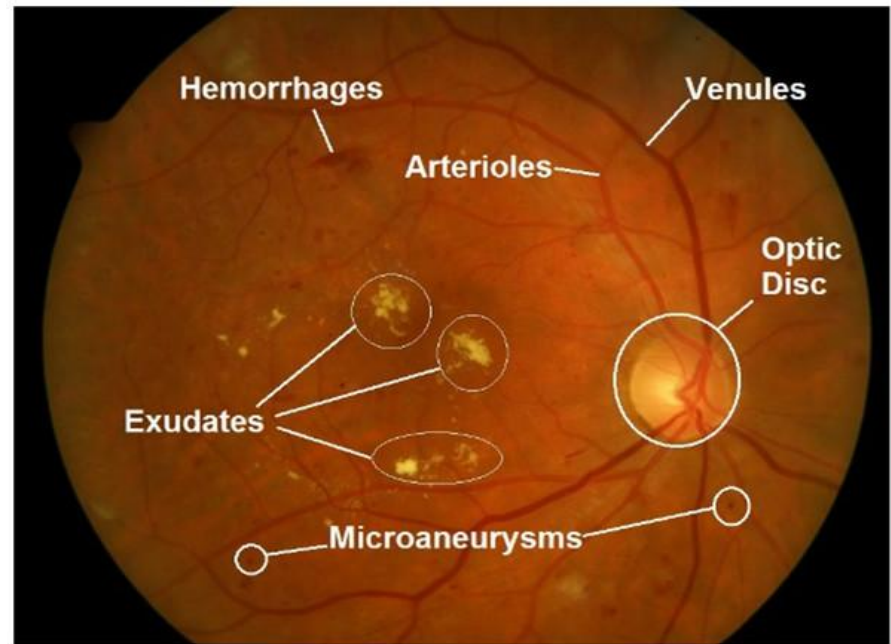
# Background

## □ retinal images

- a digital picture of the back of your eye<sup>[1]</sup>
- it shows the retina, the optic disc, and blood vessels, which helps ophthalmologist find certain diseases<sup>[1]</sup>



fundus camera



Important features in retinal image<sup>[2]</sup>

[1] <https://www.webmd.com/eye-health/what-is-retinal-imaging>

[2] Abdullah, Muhammad, Muhammad Moazam Fraz, and Sarah A. Barman. "Localization and segmentation of optic disc in retinal images using circular Hough transform and grow-cut algorithm."

# Background

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- vessel segmentation
  - an application of semantic segmentation in medical image analysis

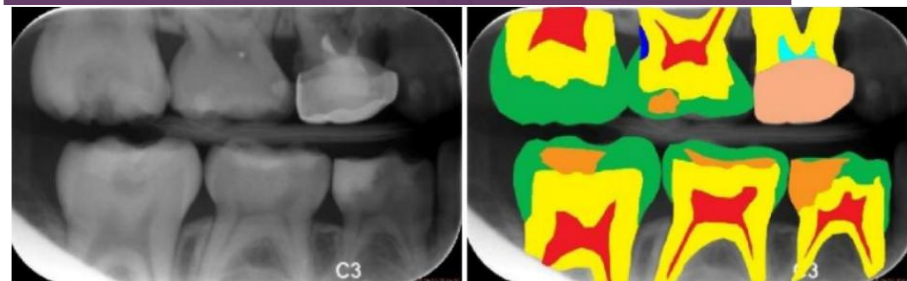
# Background

## □ Semantic Segmentation

- a deep learning algorithm that **associates a label or category with every pixel in an image**<sup>[3]</sup>
- Input: images
- Output: convert them into masks with highlighted regions of interest, each pixel in the image is assigned a class ID based on the object of interest to which it belongs.



Autonomous Driving



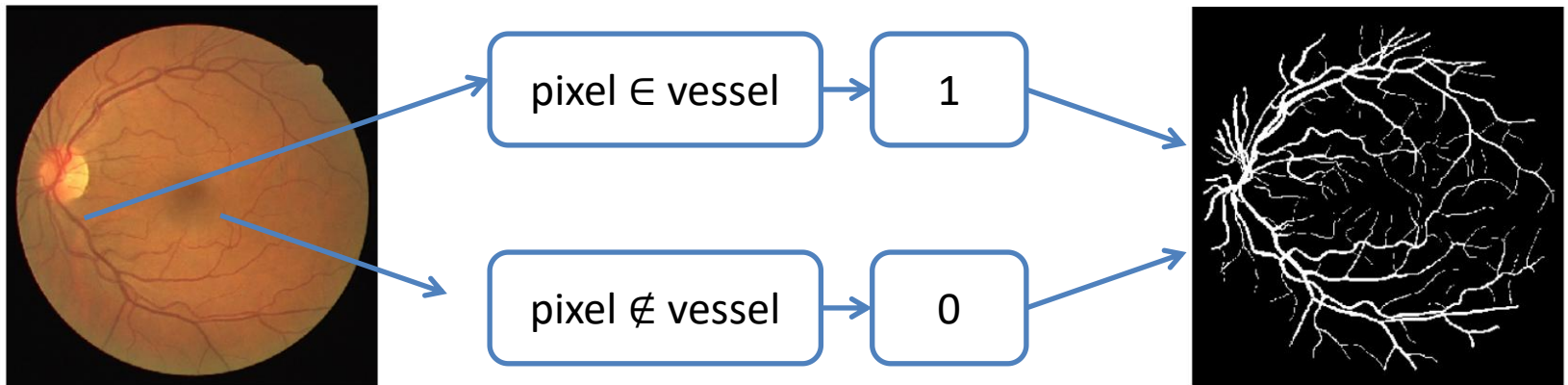
Caries diagnosis

# Background

## □ vessel segmentation

- an application of **semantic segmentation** in medical image analysis

associates a label or category with every pixel in an image



vessel segmentation  $\rightarrow$  to correctly classify the vessel pixels and background pixels in the retinal image

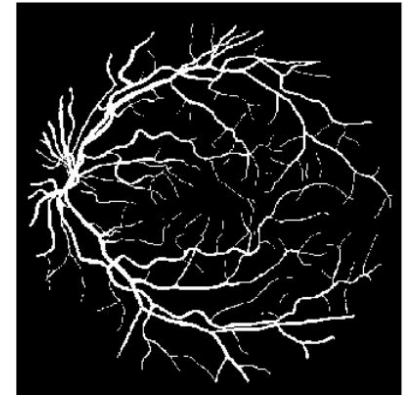
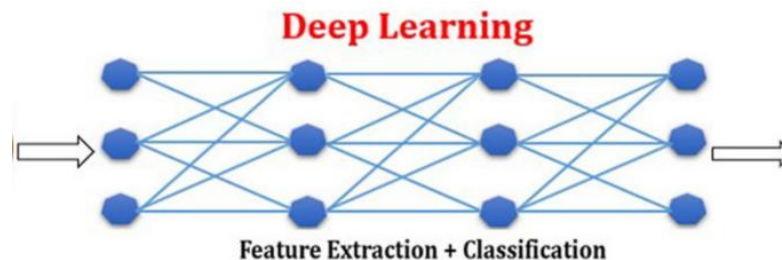
# Goal statements

## □ Goal

- generate the final retinal blood vessel segmentation images
  - Input: retinal images (RGB image)
  - Output: corresponding vessel segmentation image (Binary Image)



Input

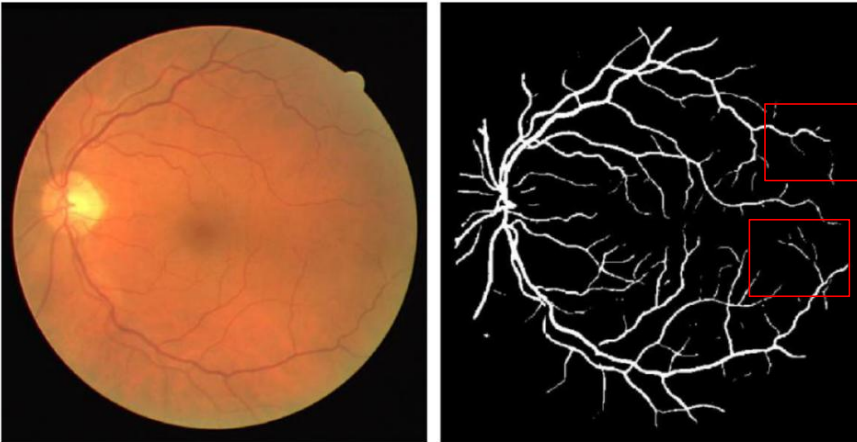


Output

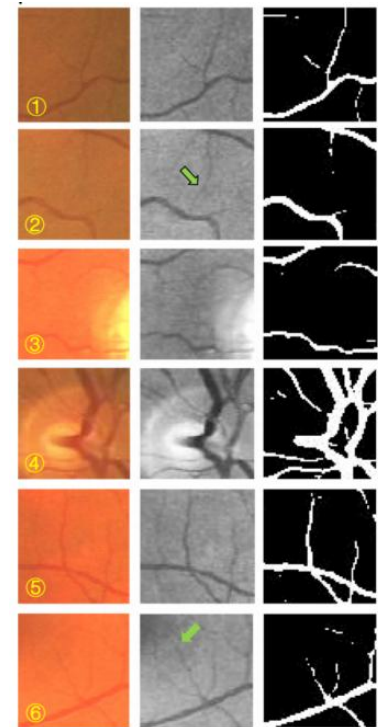
# Goal statements

## □ Stretch Goals

- repair some breakpoints on blood vessel segmentation images



Examples of breakpoints on the segmentation images<sup>[4]</sup>



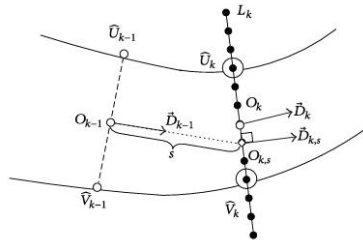
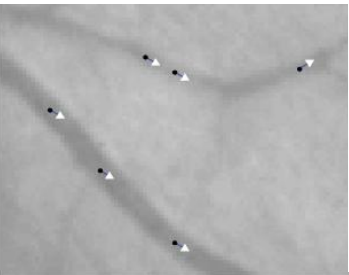
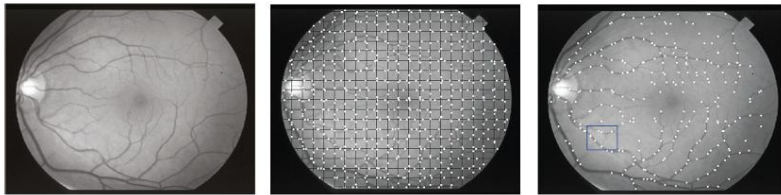
some patches on DRIVE dataset<sup>[4]</sup>



# Model I

## □ Classic methods

- attempt to find inherent patterns of retinal vessels without any manual annotation.
- most of these approaches are **rule-based techniques**, including vessel tracking<sup>[5]</sup>, matched filtering<sup>[6]</sup>, thresholding<sup>[7]</sup>, etc.



vessel tracking methods

[5] Y. Yin, M. Adel, and S. Bourennane, "Automatic segmentation and measurement of vasculature in retinal fundus images using probabilistic formulation," *Comput. Math. Methods Med.*, vol. 2013, 2013, Art. no. 260410.

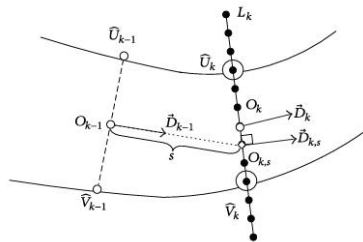
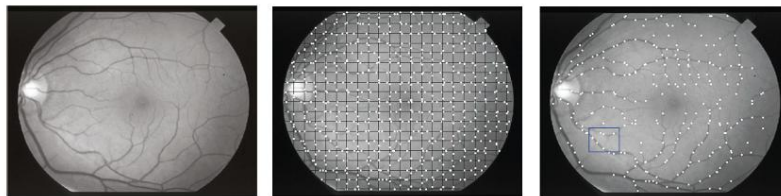
[6] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Trans. Med. Imag.*, vol. 8, no. 3, pp. 263–269, Sep. 1989.

[7] X. Jiang and D. Mojon, "Adaptive local thresholding by verification-based multithreshold probing with application to vessel detection in retinal images," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 1, pp. 131–137, Jan. 2003.

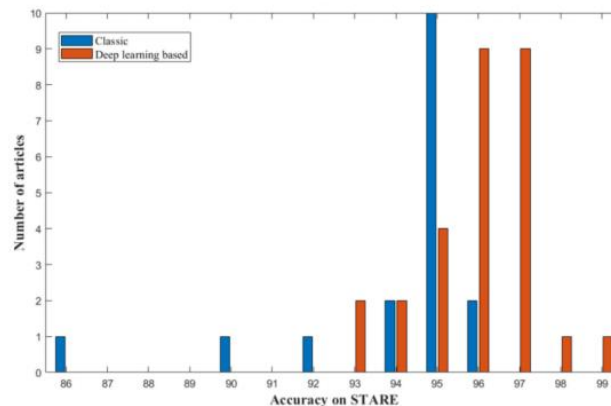
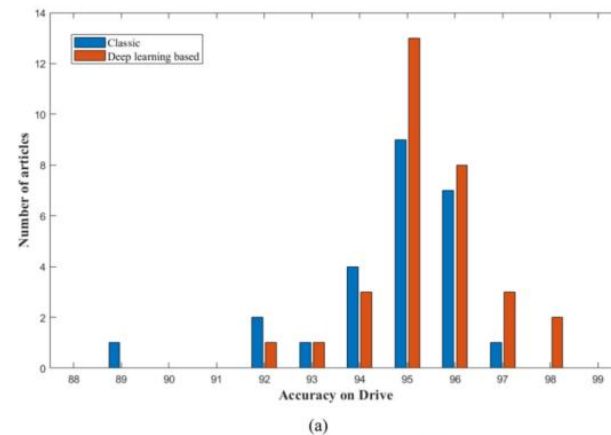
# Model

## □ Classic methods

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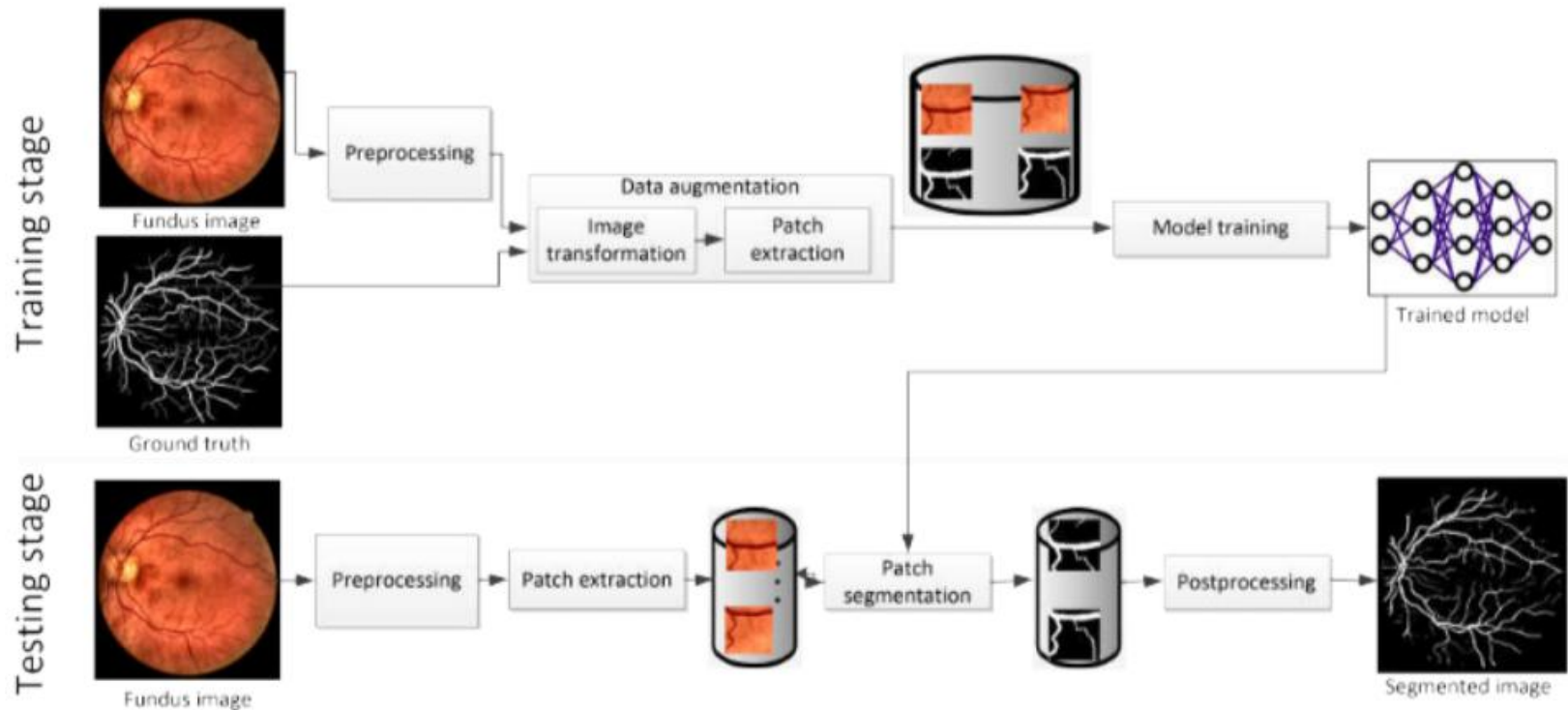
vessel tracking methods



- [5] Y. Yin, M. Adel, and S. Bourennane, "Automatic segmentation and measu using probabilistic formulation," Comput. Math. Methods Med., vol. 2013, [6] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," IEEE Trans. Med. Imag., vol. 8, no. 3, pp. 263–269, Sep. 1989. [7] X. Jiang and D. Mojon, "Adaptive local thresholding by verifica\_x0002tion-based multithreshold probing with application to vessel detection in retinal images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 1, pp. 121–127, Jan. 2003.

# Model I

## □ Deep Learning Methods



# Model

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## □ Loss Function

- choose the **binary cross entropy** as segmentation loss function
  - $L = -\frac{1}{n} \sum_{i=1}^n y_i \log p(y_i) + (1 - y_i) \log (1 - p(y_i))$ , where  $n$  represents the total number of training pixels,  $y$  is the label (0 or 1) and  $p(y_i)$  represent predicted probability of label (0 for background pixels and 1 for blood vessel pixels).
- it is used to judge how well a binary classification model predicts an outcome

# Model

## □ Loss Function

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for

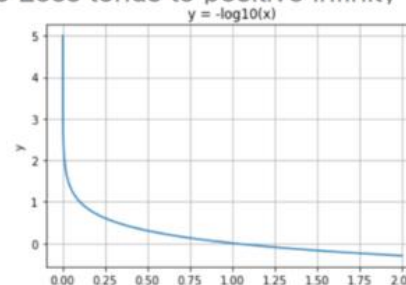
- it is used to judge how good the model predicts a

the label is 1 (blood vessel pixels)

(1) if the predicted value  $p(y_i)$  is close to 1, then the value of the loss function should be close to 0

(2) if the predicted value  $p(y_i)$  is close to 0 at this point, then the value of the loss function should be very large

Taking a single output as an example, when the label is  $y = 1$ , **Loss** =  $-\log p(y)$ , when the predicted value is close to 1, Loss=0, otherwise Loss tends to positive infinity



# Model

## □ Evaluation Criteria

- **Accuracy**—a widely used evaluation metric for the task of binary segmentation, computes the percentage of correctly classified pixels in the whole image

- $$ACC = \frac{TP + TN}{TP + FN + TN + FP}$$

- **Sensitivity**—measures the proportion of actual positives that are correctly classified as such

- $$Sen = \frac{TP}{TP + FN}$$

- **Specificity**—measure the proportion of actual negatives that are correctly identified as such

- $$Spec = \frac{TN}{TN + FP}$$

Tab. Parameter meanings in the formula

TP (true positive)	the number of pixels that belongs to vessels and also classifies them as the same
FP (false positive)	the number of pixels that predict as vessels but belong to the background
TN (true negative)	pixels that are predicted as background and belong to it
FN (false negative)	vessel pixels, but the algorithm assigns them to the background

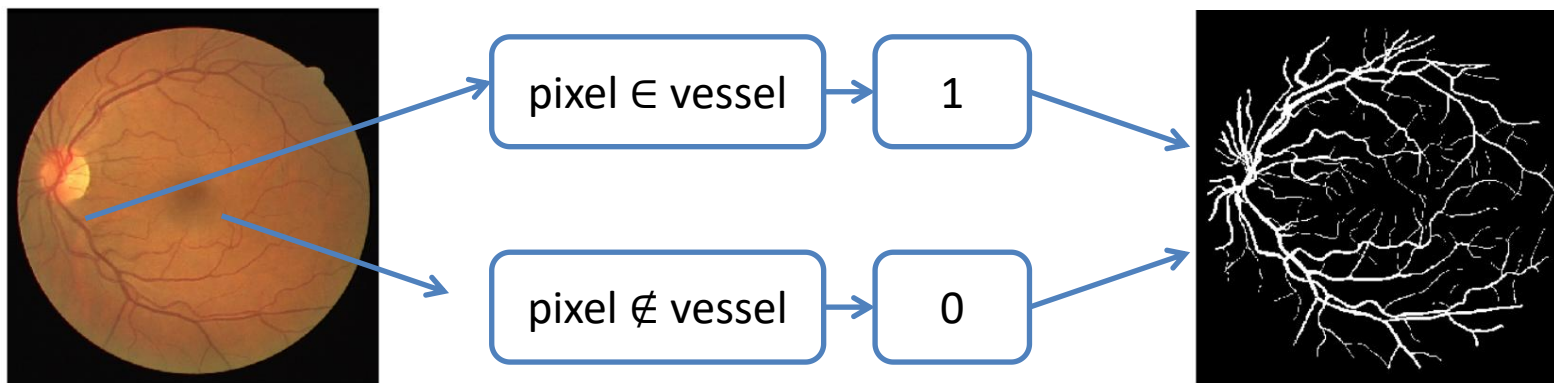
# Conclusion

## □ Goal

- Generate the final retinal blood vessel segmentation images
- Stretch Goals: repair some breakpoints on blood vessel segmentation images

## □ Deep Learning Method

- loss function:  $L(p, q) = -\frac{1}{n} \sum_{k=1}^n q_k \log p_k + (1 - q_k) \log (1 - p_k)$
- Evaluation Criteria: Accuracy, Sensitivity, Specificity



vessel segmentation  $\rightarrow$  to correctly classify the vessel pixels and background pixels in the retinal image

# Questions?