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Low complexity convolutional neural network for vessel segmentation in portable retinal diagnostic devices

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Introduction

- **Diabetic retinopathy** (DR) can be controlled with regular examination of eyes in early stages.
- Analysis of the **retinal vessels** are useful in eye disease diagnosis.

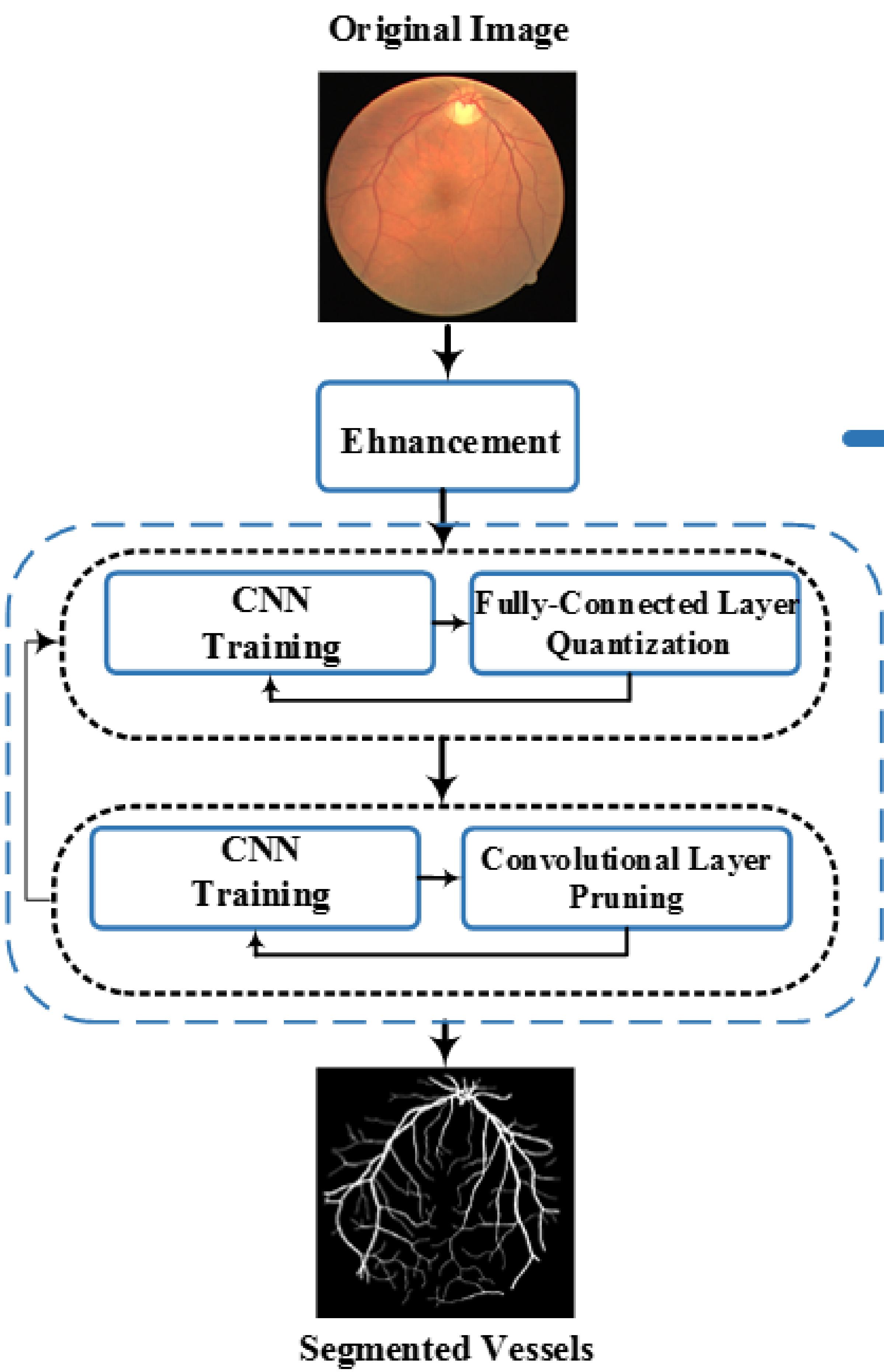
Introduction

- Proper knowledge about retinal vessels could be helpful during any **retinal surgery operation**.
- **Convolutional neural networks** (CNNs) have proper segmentation results, but their structures are **complex**.
- **Simplification methods** including **pruning and quantization**, recently have been developed on the CNN structure.

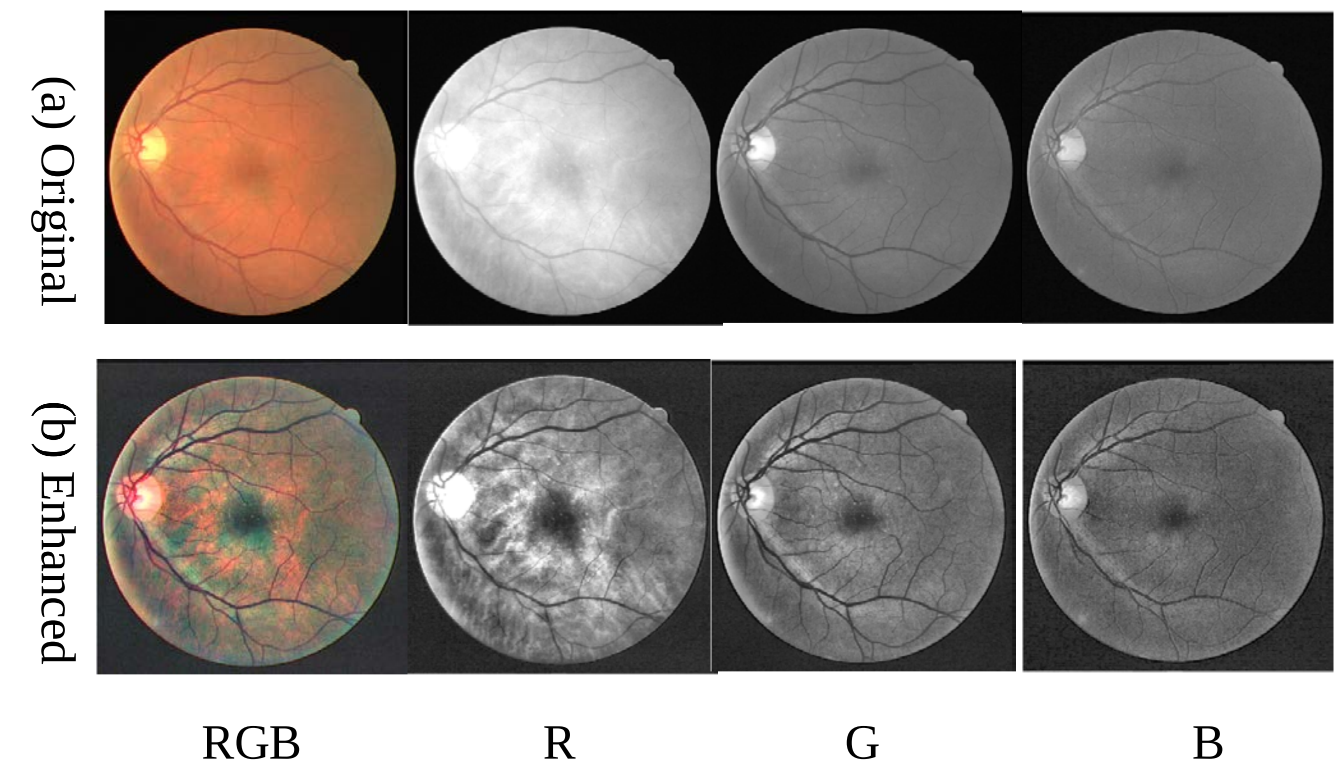
Challenges

- Real time vessel analysis for real time applications such as intraocular surgery and portable devices.
- CNN structural complexity puts on a lot of **arithmetic operations** which should be reduced.
- Simplification techniques on CNN structure may lead to **significant loss of accuracy**.

Proposed Method

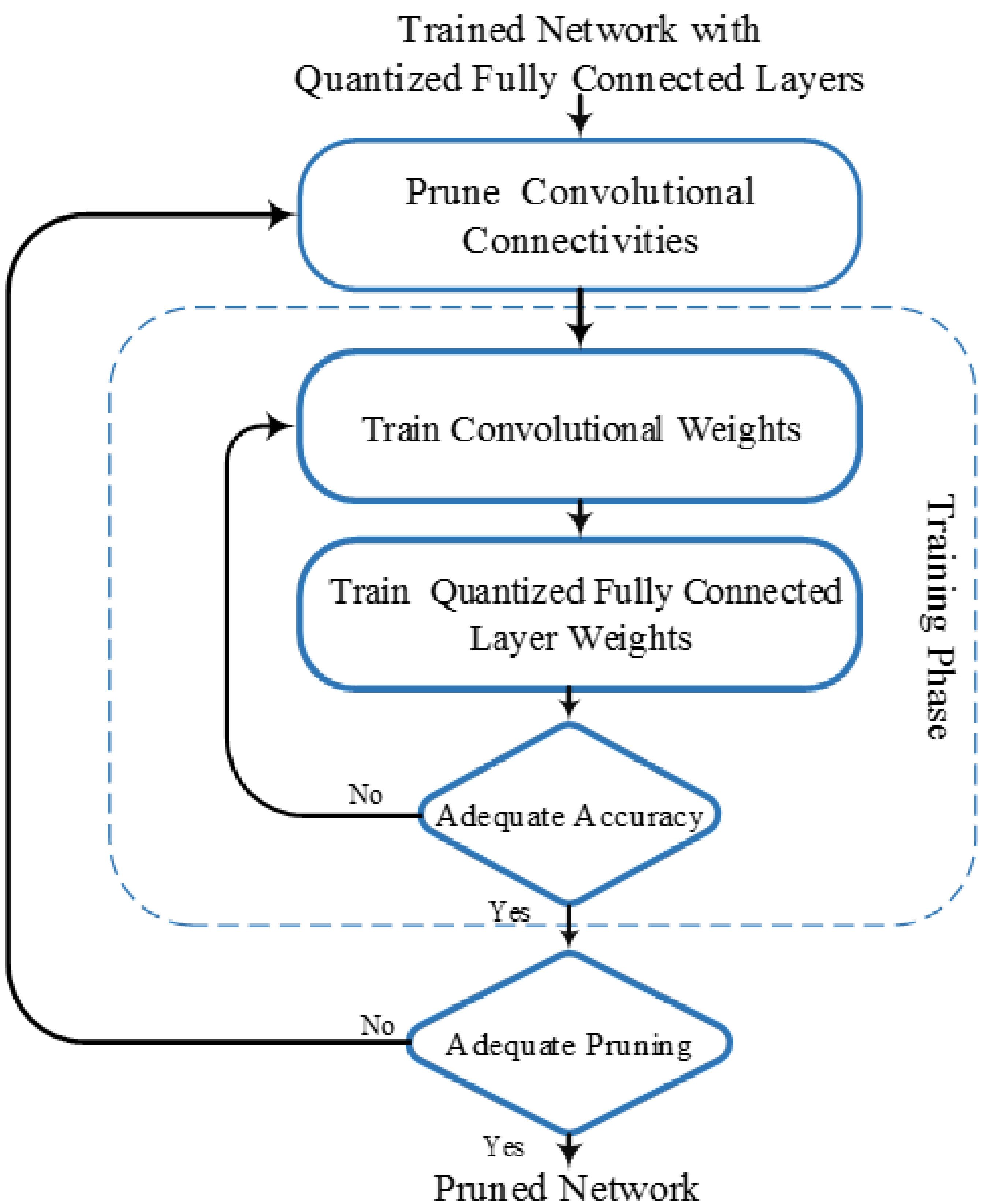


Local histogram equalization



Proposed Method

Flowchart of the proposed simplification Method



Quantization

$$W_b = \begin{cases} -1 & if\ W < 0 \\ 0 & if\ W = 0 \\ 1 & if\ W > 0 \end{cases}$$

Pruning

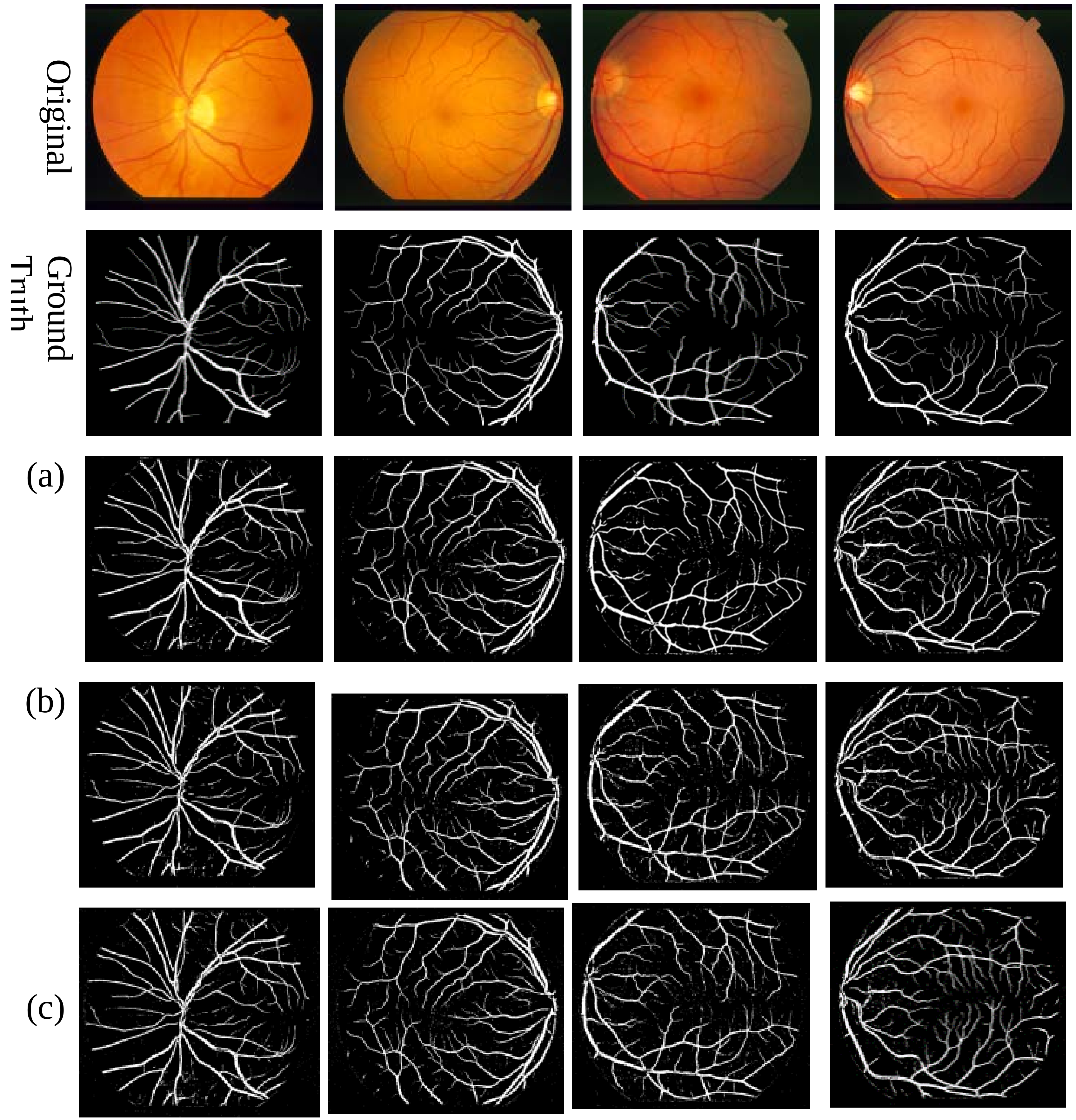
Learning rate Cost function Pruning Mask

$$W(i,j) = W(i,j) - \eta\left(\frac{\partial C}{\partial W(i,j)} * Mask_l(i,j)\right)$$

$$Mask_l(i,j) = \begin{cases} 0 & W_l(i,j) < Pruning\ Rate * std(W_l) \\ 1 & Otherwise \end{cases}$$

Simulation Results

Segmentation results on STARE image dataset



Visual illustration of segmnetation. (a) CNN with original parameters, (b) CNN with FCLs quantization, (c) CNN with FCLs quantization and CLs pruning.

Simulation Results

Performance Comparison

Method	SEN	SPE	ACC
[1] (2015)	0.7716	0.9701	0.9497
[2] (2016)	0.7412	--	0.9585
[3] (2016)	0.7140	--	0.9545
[4] (2014)	0.7305	0.9688	0.9440
[5] (2018)	0.7538	0.9608	0.9440
(Proposed CNN with original parameters)	0.7823	0.9770	0.9617
(Proposed Quantized CNN)	0.7792	0.9740	0.9587
(Proposed Pruned-Quantized CNN)	0.7599	0.9757	0.9581

Structure of original and simplified CNNs

Layer	Type	Maps and Neurons	Filter Size	Original Weights	Simplified Weights
1	Input	1M × 9×9N	-	-	-
2	Convolution	64M × 9×9N	3×3	576	395
3	Max Pooling	64M × 5×5N	2×2		-
4	Convolution	32M × 5×5N	3×3	18432	7555
5	Max Pooling	32M × 3×3N	2×2	-	-
6	FC	50N	1×1	14400	Quantized
7	FC	20N	1×1	1000	Quantized
8	FC	2N	1×1	40	Quantized

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