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RETINAL BLOOD VESSEL SEGMENTATION WITH CONVOLUTIONAL NEURAL NETWORKS

Devireddy SaiDurga[1], Gnanasri Gorripati[2], Gopu Sirisha[3], Doddala Yasaswini[4]

Vasireddy Venkatadri Institute of Technology, Nambur, Guntur District, Andhra Pradesh

Abstract

In this paper, a hierarchical image matting model is proposed to extract blood vessels from fundus images. Moe specifically, a hierarchical strategy utilizing the continuity and extendibility of retinal blood vessels is integrated into image matting model for blood vessel. Normally the matting models require the user specified trimap, which separates the input image into three regions manually: the foreground, background and unknown reasons. However, since creating a user specified trimap is a tedious and time-consuming task, region features of blood vessels are used to generate the trimap automatically in this paper.

We make use of deep Convolutional Neural Networks (CNNs), which have proven revolutionary in other fields of computer vision such as object detection and image classification , and we bring their power to the study of eye fundus images. We present experimental validation, both qualitative and quantitative, in four public datasets for these tasks.

Key Words

MATLAB, Image segmentation, Convolutional Neural Network, Pooling, Deep neural netwoks, Image matting.

1.Introduction

Medical image processing deals with the development of problem-specific approaches to the enhancement of raw medical image data for the purposes of selective visualization as well as further analysis. There are many topics in medical image processing: some emphasize general applicable theory and some focus on specific applications. We mostly focus on image segmentation and multi-spectral analysis.

Image segmentation is defined as a partitioning of an image into regions that are meaningful for a specific task; it is a labeling problem. This may, for instance, involve the detection of a brain tumor from MR or CT images. Segmentation is one of the first steps leading to image and interpretation.

1.1 Classification of Image Segmentation

Image segmentation approaches can be classified according to both features and the type of techniques used. Techniques based on these features can broadly classified into structural and statistical methods.

1.1 Structural Methods

Structural methods are based on the spatial properties of the image, such as edges and regions. Various edge detection algorithms have been applied to extract boundaries between different brain tissues. Region growing is another popular structural technique. The performance of the method depends on seed selection and whether the regions are well defined, and therefore is also not considered robust.

1.2 Statistical Methods

Statistical Methods label pixels according to probability values, which are determined based on intensity distribution of the image. Gray-level Thresholding is the simplest, yet often effective, segmentation method. In this approach, structures in the image are assigned a label by comparing their Gray-level value to one or more intensity thresholds.

2. Literature Survey

2.1Deep Learning Using Convolutional Neural Network

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs use a variation of multilayer perceptron designed to require minimal preprocessing.[1] They are also known as shift invariant or space invariant artificial neural networks, based on their shared-weights architecture and translation invariance characteristics.[2][3]

Convolutional networks were inspired by biological processes [4][5][6][7] in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network leans the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

Convolutional layers apply a convolutional operation to the input, passing the result to the next layer. Each convolutional neuron processes data only for its receptive field.

2.2 Pooling

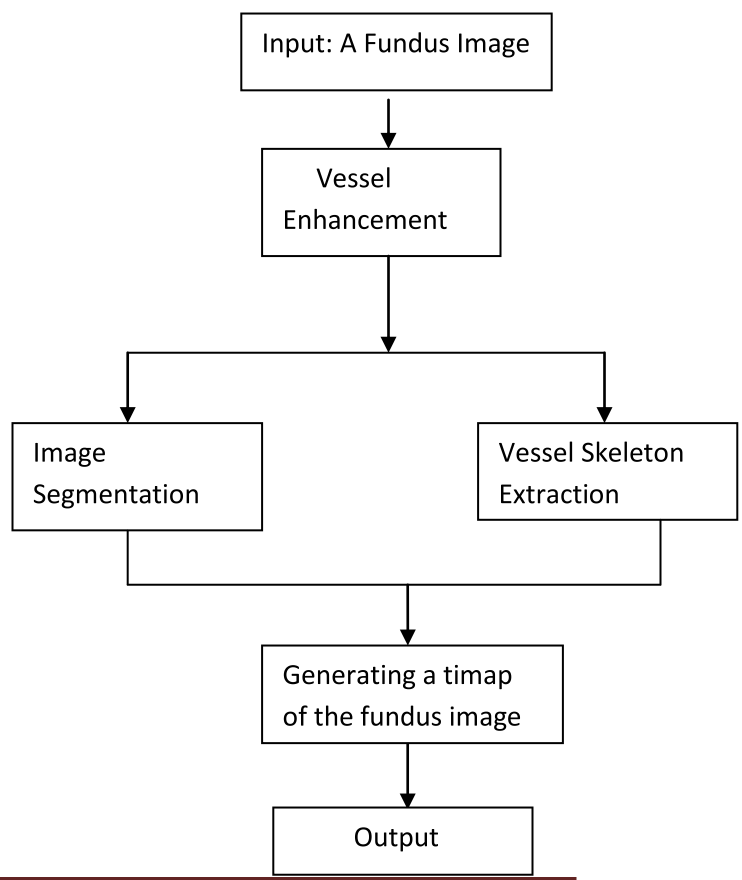
Convolutional networks may include local or global pooling layers. Pooling layers reduce the dimensions of the data by combining the outputs of neuron clusters t one layer into a single neuron in the next layer. Local pooling combines small clusters, typically 2*2. Global pooling acts on all the neurons of the convolutional layer. In addition pooling may compute a max or an average. Max pooling uses the maximum value from each of a cluster of neurons at the prior layer. Average pooling uses the average value from each of a cluster of neurons at the prior layer.

Max pooling with a 2*2 filter and stride=2

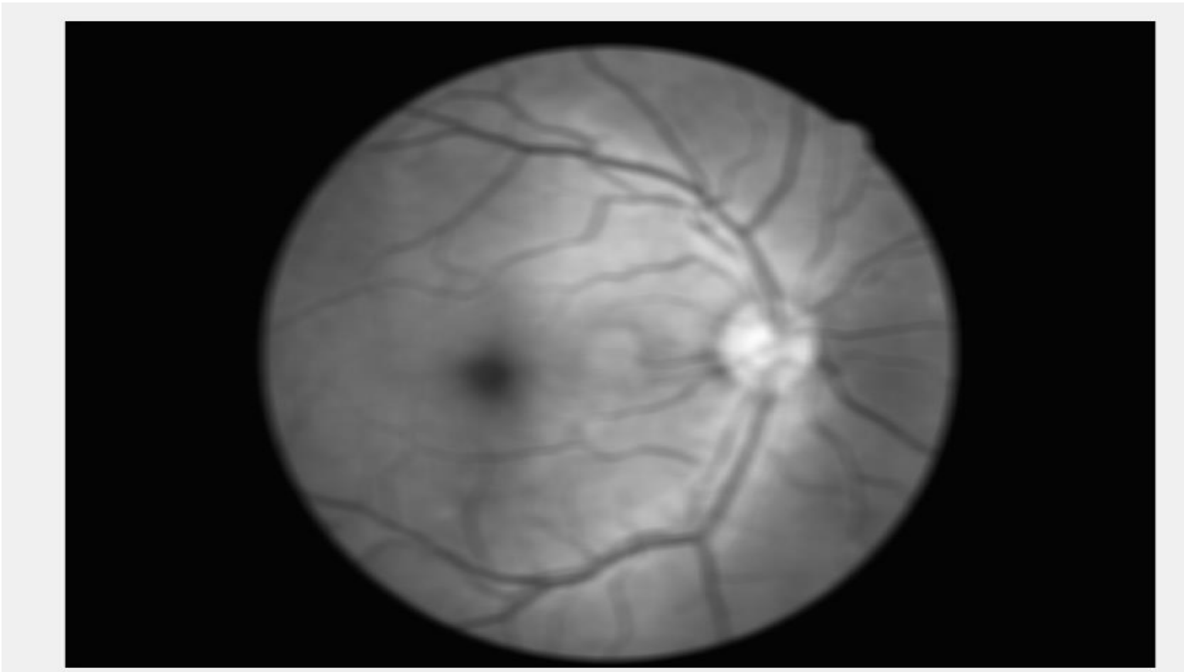
1	0	2	3
4	6	6	8
3	1	1	0
1	2	2	4

→

6	8
3	4



Results and Discussion



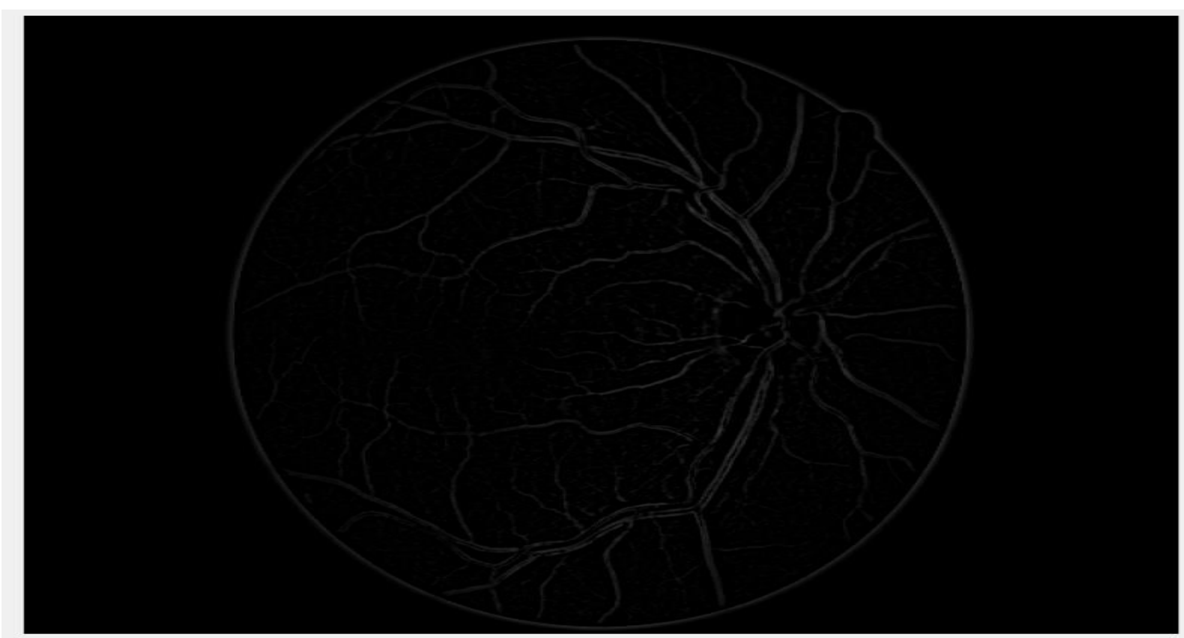
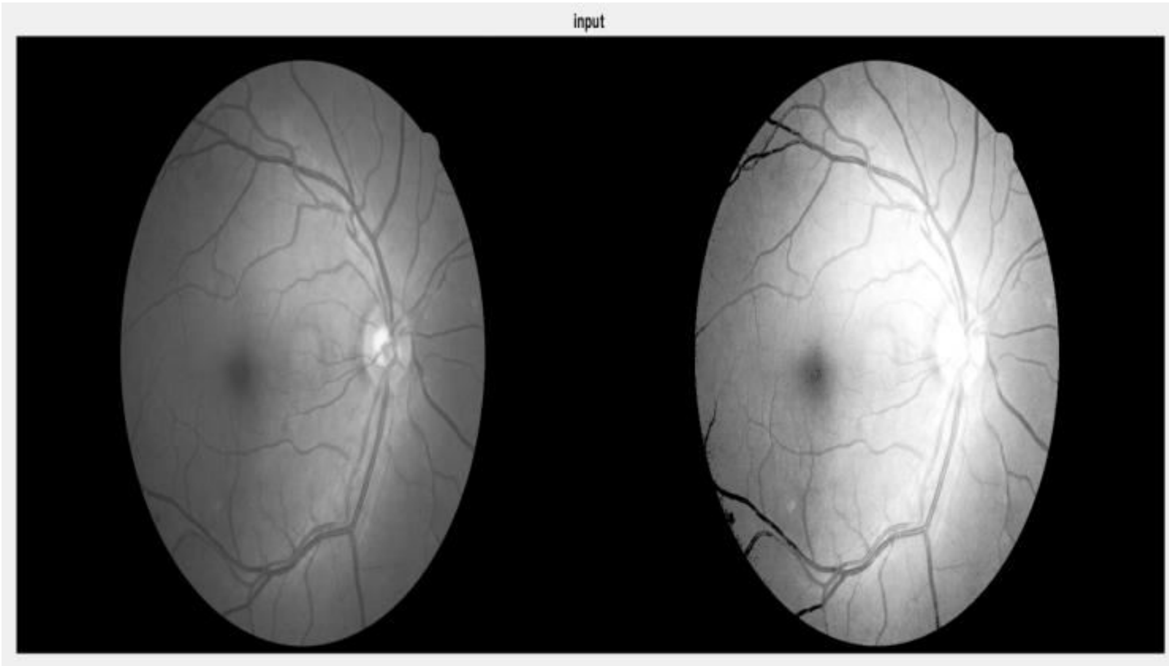


FIGURE: REPRESENTING THE INITIAL LAYER OF BLOOD VESSEL FOR ESTIMATING THE CONVOLUTIONAL FILTER



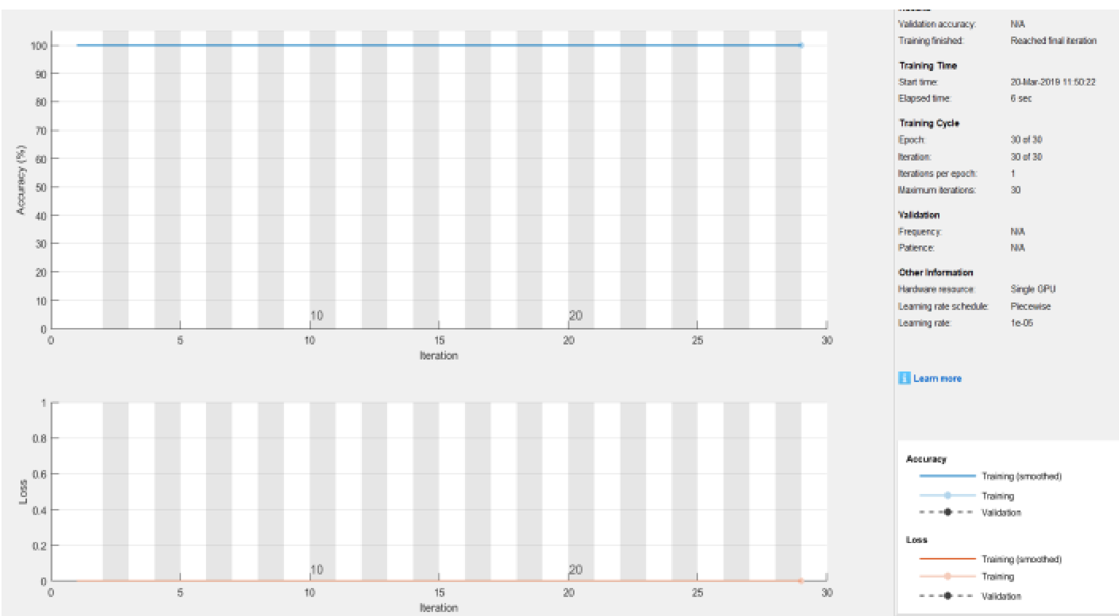


FIGURE: a)Representing the histogram modeling for Blood vessel

b)Classification plot for Trained and Test vector

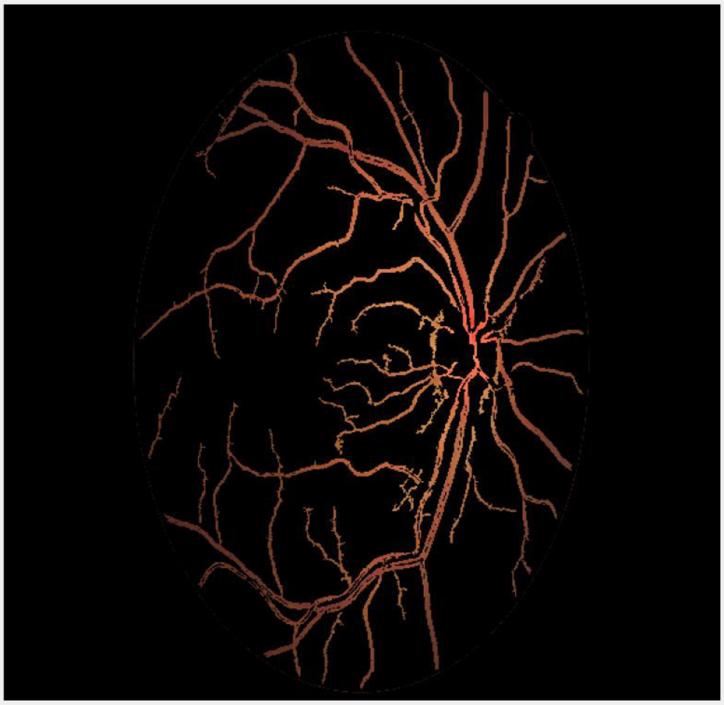


Figure: Representing the final segmented image using CNN

Conclusions

We presented DRIU, a method for retinal blood vessel segmentation that is fast and accurate. DRIU brings the power of CNNs, which have proven ground-breaking in other fields of compute Vision, to retinal image analysis by the use of a base shared CNN network and per task specialized layers. The experimental validation in single datasets creation on both qualitative and quantitative, shows that the designed work has better performance characteristics.

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