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Segmenting Retinal Blood Vessels with Deep Neural Networks : A Review

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Abstract: *The condition of the vascular network of human eye is an important diagnostic factor in ophthalmology. Its segmentation in fundus imaging is a nontrivial task due to variable size of vessels, relatively low contrast, and potential presence of pathologies like microaneurysms and hemorrhages. Many algorithms, both unsupervised and supervised, have been proposed for this purpose in the past. We propose a supervised segmentation technique that uses a deep neural network trained on a large (up to 400; 000) sample of examples preprocessed with global contrast normalization, zero-phase whitening, and augmented using geometric transformations and gamma corrections. Several variants of the method are considered, including structured prediction, where a network classifies multiple pixels simultaneously. When applied to standard benchmarks of fundus imaging, the DRIVE, STARE, and CHASE databases, the networks significantly outperform the previous algorithms on the area under ROC curve measure (up to > 0:99) and accuracy of classification (up to > 0:97). The method is also resistant to the phenomenon of central vessel reflex, sensitive in detection of fine vessels (sensitivity > 0:87), and fares well on pathological cases.*

Keywords: Fundus, STARE, DRIVE, CHASE, Retinal Image etc..

I. INTRODUCTION

Artificial Neural Networks (NNs) have an impressive record of applications in image analysis and interpretation, including medical imaging. Network architectures designed to work with image data, in particular convolutional networks (CNNs), were routinely built already in 1970's [1] and managed to find commercial applications [2] and surpass other approaches on challenging tasks like handwritten character recognition [3]. However, the break of millennia witnessed noticeable stagnation – despite intense research efforts, NNs failed to scale well with task complexity.

The dawn of alternative ML techniques, like support vector machines and Bayesian networks, temporarily demoted the NNs, and it was only the relatively recent arrival of deep learning (DL) that brought them back into the spotlight. Today, large-scale DL-trained NNs successfully tackle generic object recognition tasks with thousands of object classes [4], a feat that many considered unthinkable just ten years ago. The capabilities of deep NNs stem from several developments. Transfer functions of units in conventional NNs are typically squeezing functions (sigmoid or hyperbolic tangent), with derivatives close to zero almost everywhere. This leads to diminishing gradient in training – the backpropagated errors quickly decrease with each network layer, rendering training ineffective or painfully slow. In contrast, the transfer functions used in deep CNNs, most notably the rectifying linear units [5], do not vanish in extremes and so allow effective training of networks with dozens of layers [4]. Secondly, DL brought with it new techniques for boosting network robustness like dropout [6], where randomly selected units are temporarily disabled

This forces a network to form weight configurations that provide correct outputs even if some image features are missing, and so improves generalization. The retina has two sources of oxygen and nutrients: the retinal blood vessels and the choroid, which lies under the retinal pigment epithelium.The blood vessels within the retina itself that carry oxygen and nutrients are called arteries. The main one, the central retinal artery, enters the eye through the optic nerve and splits into the superior (upper) and inferior (lower) branches. These then keep branching out more, like the branches of a tree, until they form a very fine network of very thin blood vessels called capillaries It is mainly at the capillaries that oxygen and nutrients leave the blood, entering the retina, and that carbon dioxide and waste products leave the retina and pass into the blood to be taken away. Most of the problems caused by conditions affecting retinal blood vessels do so by either blocking these capillaries or causing them to become leaky. The capillaries join up to form branch veins and these then

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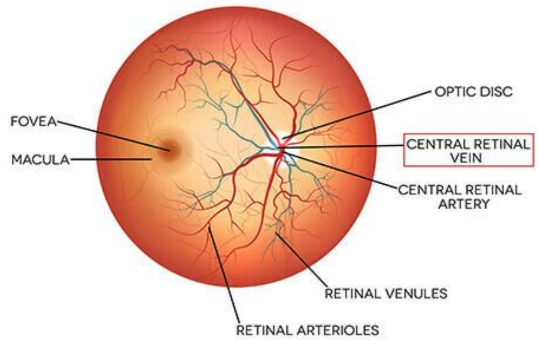
join at the optic nerve to form the central retinal vein that dives into the optic nerve on its way towards the heart. Importantly, any part of the retina is only supplied by one artery and drained by one vein. As a result, if there is blockage of a retinal vein or artery, only the area of retina, and so only that part of the visual field, served by that blood vessel is affected.



II. LITERATURE REVIEW

Literature 1:
In This literature they used graph based approach for blood vessel boundary delineation.The widths of the retinal blood vessels are measured and its edges are segmented. The graph is constructed based on the vessels weight. The REVIEW database was used in this work. This paper has some deficiencies, such as the crossing points and branching points are currently not treated individually, and consequently the blood vessel detection points are not clearly indicated[1].

Literature 2:
In this they proposed line-shape concavity measuring model to remove dark lesions which have an intensity structure different from the line shaped vessels in a retina.
This method achieved 95.67% of an average accuracy for the blood vessel detection with respect to ground truth images in DRIVE database.
While provided 95.56 % of an average accuracy for the blood vessel detection with respect to ground truth images in STARE database.

Literature 3:
In this they presented multi-scale feature extraction and region growing algorithm for retinal blood vessels segmentation. This implementation allowed a faster processing of these images and was based on a data partitioning.

Literature 4:
In this they proposed a pixel feature based method that additionally analysed the vessels as elongated structures.The edge-based methods can be further classified into window based and tracking-based methods.Window-based method estimates a match at each pixel against the pixel's surrounding window.In order to trace the vessels, the tracking approach makes use of local image properties from an initial point.

Literature 5 :
Artificial neural networks have been extensively investi- gated for segmenting retinal features such as the vasculature [28] making classifications based on statistical probabili ties rather than objective reasoning. These neural networks employ mathematical weights to decide the probability of input data belonging to a particular output. This weighting system can be adjusted by training the network with data of known output typically with a feedback mechanism to allow retraining.

Literature 6 :
Lupascu et al. [37] introduces another supervised method known as the feature-based AdaBoost classifier (FABC) for

vessel segmentation. The 41-D feature vector is a rich collec- tion of measurements at different spatial scales ($\sqrt{2}$, 2, $2\sqrt{2}$ and 4), including the output of various filters (Gaussian and derivatives of Gaussian filters, matched filters, and 2-D Gabor wavelet transform), and the likelihood of structures like edges and ridges via numerical estimation of the differential prop- erties of the intensity surface (principal and mean curvatures, principal directions, and root mean square gradient).

Literature 7 : Li et al. [7] proposed a segmentation technique by combining a multiscale matched filter and dual-threshold method.

Literature 8 : Kaur and Sinha [8] proposed a segmentation algorithm on the basis of Gabor filter and gray cooccurrence matrix.

Literature 9 : Wang et al. [9] processed the coarse and fine blood vessels by using the multiscale 2D Gabor wavelet.

Literature 10 ; Singh and Srivastava [10] proposed a method on the basis of the extended matched filter.

Literature 11: Cruz-Aceves et al. [11] segmented blood vessels by using a multiscale Gabor filter and threshold segmentation method on the basis of multiobjective optimization.

Literature 12: Aguirre-Ramos et al. [12] enhanced the blood vessel struc- ture and its profile by using the Gabor filter and Gaussian dis- tribution derivatives.

Literature 13: Singh and Srivastava [13] proposed a matched filtering technique centered at the Gumbel proba- bility distribution function to improve retinal vessel segmen- tation performances. These methods, which are based on windows, can maintain the original vessel structure but require the processing of each pixel, thus leading to heavy computational workloads and long segmentation time.

Literature 14: Frangi et al. [14] introduced the Hessian matrix into the extraction of characteristic directions of images.

Literature 15: Kumar et al. [15] extracted blood vessels from retinal images on the basis of inherent characteristics of LoG and MF, which avoided misclassification of nonvascular pixels.

III. PROPOSED SYSTEM

Deep neural networks

A convolutional neural network (CNNs) is a composite of multiple elementary processing units, each featuring several weighted inputs and one output, performing convolution of input signals with weights and transforming the outcome with some form of nonlinearity. The units are arranged in rectangular layers (grids), and their locations in a layer correspond to pixels in an input image (Fig. 3). The spatial arrangement of units is the primary characteristics that makes CNNs suitable for processing visual information; the other features are local connectivity, parameter sharing and pooling of hidden units.

Local connectivity means that a given unit receives data only from its receptive field (RF), a small rectangle of image pixels (for the units in the first layer) or units in the previous layer (for the subsequent layers) The RFs of neighboring units in a layer typically offset by stride. Image size, RF size and stride together determine the dimensions of a layer. For instance, a layer of units with 3 × 3 RFs with one pixel stride needs only 9 units when applied to a 5 × 5 monochromatic (single-channel) image, because three RFs of width 3 each, overlapping by two pixels, span the entire image. Larger stride and larger RFs lead to smaller layers (Fig. 3). Local connectivity substantially reduces the number of weights in comparison to the fully-connected conventional networks. It is also consistent with the spatial nature of visual information and mimics certain aspects of natural visual systems [1].

Parameter sharing consists in sharing weights across units in the same layer. When the units in a given layer share the same vector of weights, they form a feature map, with each of them calculating the same local feature, albeit from a different part of the image. This reduces the number of parameters even further and makes the extracted features equivariant. For instance, a layer of units with 3×3 RFs connected to a single channel image has only 10 parameters (nine per channel for the pixels in the RF and one for neuron threshold), regardless the number of units

Pooling (subsampling) consists in aggregating outputs of multiple units by other means than convolution. In the most popular aggregation scheme, max-pooling, each aggregating unit returns the maximum value in its RF. Like local connectivity, pooling reduces the resolution w.r.t. previous layer and provides for translational invariance.

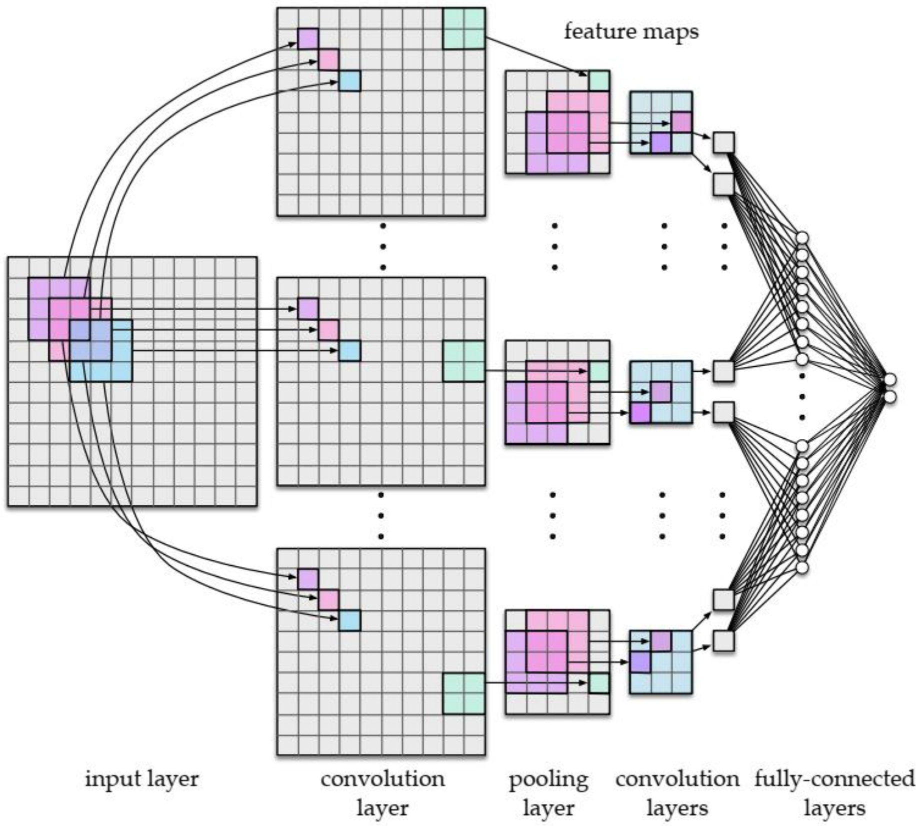


Figure 3: Architecture of a convolutional neural network with three convolutional layers, one pooling layer, and two fully connected layers. The network uses 3 × 3 convolution units with stride 1 and 2 × 2 pooling units with stride 2

A typical CNN architecture consists of several convolutional feature maps intertwined with max-pooling layers, finalized with at least one fully-connected layer that 'funnels' the excitations into output neurons, each corresponding to one decision class (Fig. 3). Sliding RFs by the number of pixels defined in stride across the input image causes consecutive layers to be smaller, so that the final grid fed into the fully connected is usually much smaller than the input image. There are often several feature maps working in parallel, each of them responsible for extracting one feature (see convolution and pooling layers in Fig. 3). Large networks may involve even several dozens of feature maps [4]. In case of multi-channel (e.g., RGB) images, separate feature maps are connected to all channels. The subsequent layers fetch data from multiple maps in the previous layer and so combine the information from particular channels. In such a case, each unit has multiple RFs with separate weight vectors, and the weighted signals coming from all input maps together form its excitation.

IV. FACILITIS REQUIRED FOR PROPOSED WORK

The ground-truth data provided in the manual segmentations (Figs. 1 and 2) frames the blood vessel detection as a binary classification problem. As in many other studies, in our approach the decision on the class of a particular pixel is based on an m × m patch centered at that pixel. A triple of such patches, each reflecting image content at the same location for

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the RGB channels, forms the input fed into a neural network. Together with the associated class label of the central pixel it forms an example. In this study, we use m = 27, so an example is a vector of length 3 × 27 × 27 = 2187. Figure 4 shows examples of positive and negative patches.

Deep learning architectures can effectively learn from raw image data. However, they tend to perform better on appropriately preprocessed images. In the following, we describe the preprocessing applied in this study.

Global Contrast Normalization (GCN)

The images in Figs. 1 and 2 clearly indicate that brightness may vary across the FOV. In order to help the learning process to abstract from these fluctuations and focus on vessel detection, we perform local (per-patch) brightness and contrast normalization. Every patch is standardized by subtracting the mean and dividing by the standard deviation of its elements (independently in the R, G, and B channel), which also maps the originally byte-encoded brightness to signed reals. Figure 5 presents the outcome of this processing for the patches from Fig. 4.1

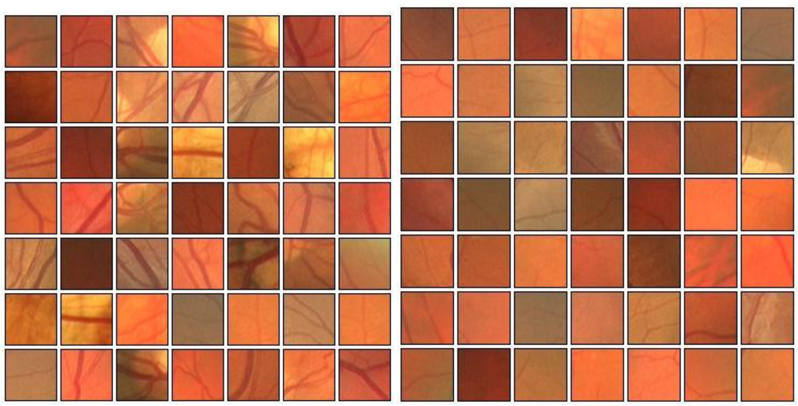
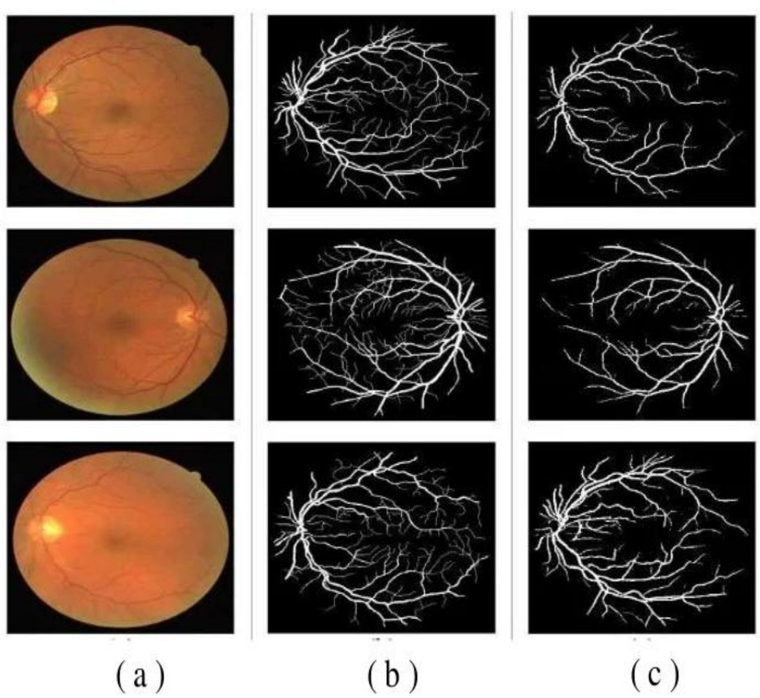


Fig. 4.1 Examples of positive (left) and negative (right) 27× 27 training patches extracted from the DRIVE images.



Retinal images from DRIVE database, B. Results of the proposed method, C. The ground truth manual.

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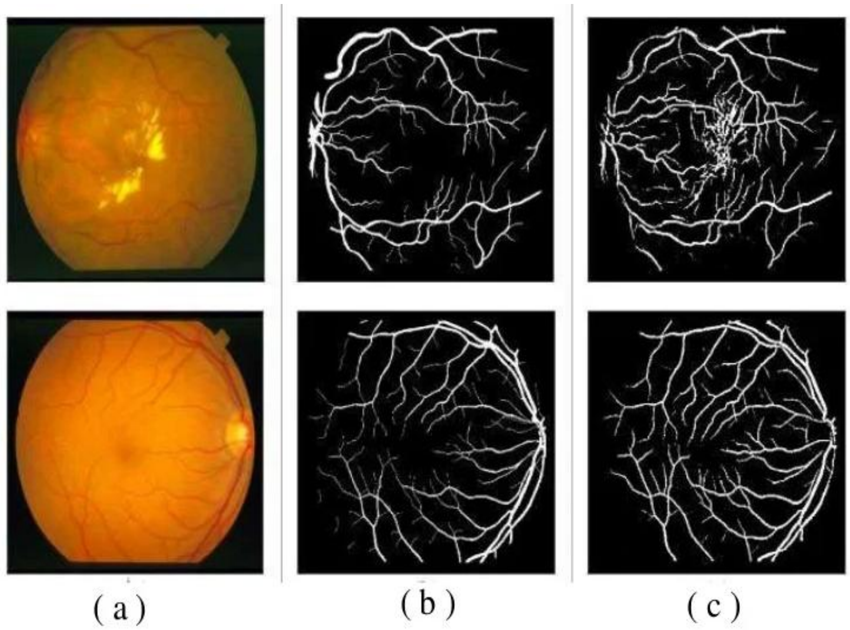

Retinal images from STARE database, B. Results of the proposed method, C. The ground truth manual.

V. CONCLUSION

- SO Proposed Method successfully.
- Detected retinal blood vessels.
- Tested on the DRIVE, STARE and CHASE_DB1 databases.
- Result higher than many of the state-of-the-art methods
- Method applicable to all types of retinal images, healthy as well as abnormal.

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