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An Operative Approach for Effective Segmentation of Retinal Blood Vessels Based on Multilevel DNN

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Abstract: Vision is obstructed by issues with the retina's blood vessels. Given the rise in patients with visual problems, the frequency of periodic eye exams has increased. Decreasing numbers of ophthalmologists make the screening procedure challenging. Thus, for this field, automated computer-aided diagnostics are required. Over the past few decades, research has advanced to the point that it can now distinguish the different types of illnesses that affect vessels. Risky retinal vessels confirm the occurrence of CAD, DR hypertension, cerebral vascular issues, and stroke. A significant stage of DR called neovascularization involves the growth of many blood vessels without the bifurcation pattern and stiffness and minimal blood loss injuries. Arteriovenous junctions and vesicle width help to identify hypertensive retinopathy in patients. Retinal telangiectasia is a macular condition that affects the retina. The small blood vessels close to the fovea get enlarged or leak blood due to infection. The AV ratio and intersection also provide information on several vessel-related diseases. The suggested DNN is compared to traditional segmentation methods quantitatively and is found to have superior SN while still maintaining respectable SP and Acc. In addition, the area under the curve (AUC) is determined to verify accurate vascular segmentation from the retina. An improved post processing method will aid in accurate binary segmentation and preserve delicate blood vessel structures.

Keywords: *AV ratio, CAD, Cerebral vascular issues, Neovascularization*

1. Introduction

During an eye exam, the fundus can be seen by looking through the pupil. Most often at the arteries, oxygen, and other nutrients leave the blood and pass into the retina. Later, carbon dioxide and other waste products leave the retina and pass into the blood to be eliminated. The central retinal artery, which leaves the optic disc and has a truly typical vessel configuration at the ganglion cell level, is the source of the blood supply for the retina. The veins have a similar pattern [1].

Vision is obstructed by issues with the retina's blood vessels. Given the rise in patients with visual problems. The frequency of periodic eye exams has increased. Decreasing numbers of ophthalmologists make the screening procedure challenging. Thus, for this field, automated computer-aided diagnostics are required. Over the past few decades, research has advanced to the point that it can now distinguish the different types of illnesses that affect vessels [2]. Risky retinal vessels confirm the occurrence of DR hypertension, CAD issues with cerebral vessels, and stroke. Neovascularization is a critical stage of DR that involves the growth of many vessels without the stiffness or bifurcation pattern, and it results in minimum blood loss injuries. Arteriovenous intersections and vessel breadth are indicators of hypertensive retinopathy [3]. The macular infection retinal telangiectasia causes blood to drop from or expand the tiny veins close to the fovea. The AV ratio and intersection also provide information regarding several vessel-related diseases. Occasionally the vessels must be taken out for tasks like glaucoma diagnosis [4].

Low-contrast thin vessels could not be identified using vessels derived from several scales. The region-growing technique is a useful segmentation tactic, but the establishment of seed points and the stopping principle is defined. It takes a lot of time and results in over-segmentation for raucous inputs. Active contour models depend on vessel contour fitting for accuracy and are autonomous and self-modifying while seeking [5]. Unsupervised and supervised methodology are categories for pattern recognition-based techniques. Unsupervised learning runs rapidly and doesn't need much segmentation-related information, but it takes a long time

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to guess the results correctly. To correctly segment the vessels in supervised learning, specified feature vectors and hardcoded rules are required. CNN-based supervised learning has greater robustness and performance in vessel segmentation. The DNN is adept at learning the vessel features without any human intervention using many convolutional layers, in contrast to any supervised technique that relies on hardcoded rules created by humans [6].

The training effectiveness and accuracy of the CNN suffer when input patch images are used. Yet, speed and accuracy are increased with the FCN because it trains and tests the entire image. The FCN and fully linked CRF are coupled to obtain vascular segmentation, which is driven by HED. Researchers created a DS-based FCN that successfully segments the optic disc and vessels. A multilayer FCN with DS for vessel segmentation was provided by a few scientists [7]. The dense CRF is fed the pairwise and unary features that were recovered from the input CNN for binary segmentation. There was shown a Concept that uses the training's ground truth data. Instead, utilizing line segments and appropriate knowledge about the underlying data, a synthetic dataset was produced. The thick and fine vessels are segmented separately and then fused to obtain the full vascular tree using a powerful three-stage DNN. Although this segmentation performs exceptionally well, it is difficult and time-consuming [8].

The suggested DNN completes a full image-to-image regression. Instead of designing, the network pre-trained on very huge datasets can be used once more. a network model from scratch to address pertinent segmentation issues using the transfer learning idea. Transfer learning is accelerated by the use of pre-trained weights, which also improve performance. In the training phase, pre-trained weights are gradually changed using lower learning rates [9]. Because of the lack of very big medical datasets available for training, this DNN makes use of the first four stages of the pre-trained VGG-16. For the extraction of vessel features, it is further optimized. To reduce erroneous vascular segmentation during fine-tuning, multi-level/multiscale DS layers are integrated during training, and the deep vessel learned characteristics from the numerous convolutional stages. Moreover, the DS layers' receptive FOV is broadened to localize and divide the vessels. The subsections that follow describe it [10].

The multilevel/multiscale DNN's base network is chosen to be the first four stages of a VGG-16 network. These phases make up the convolutional layers, which are crucial building blocks in the DNN. It consists of a set of expandable learnable filters that spans the entire depth of the input image. These filters will be activated to recognize structures like edges, from lower-layer textures to higher-layer patterns and shapes. For each filter layer, the network outputs activation maps after learning many features. The weights in these filters are initialized using initialization. The first two stages each have two separate convolutional layers, whereas the following two stages each have three separate convolutional layers [11].

What follows is the outline for the rest of the paper. The related work is briefly described in part 2, and the methodology and the theoretical foundations of the methods used are described in section 3. The simulation results and analysis are presented in section 4. For the chapter’s final section, “key findings” we summarize the most important results.

2. Previously Done Related Work

With the development of new techniques, vessel segmentation has improved dramatically. The vessels can be segmented using morphological operations on their architecture, but exact results need the combination of several different techniques. The matching filtering technique finds it challenging to segment regions with reduced contrast, central vessel reflex, and proximity to lesions [12]. Low-contrast thin vessels could not be identified using vessels derived from several scales. The region-growing approach is a useful segmentation tactic, but it requires expert knowledge to choose seed locations and define a stopping principle. It takes a lot of time and results in over-segmentation for raucous inputs. Active contour models, which depend on vessel contour fitting for accuracy are autonomous and self-changing while searching. Unsupervised and supervised methodology are categories for pattern recognition-based techniques [13].

Supervised learning-based segmentation techniques educate the classifier on the right segmentation by using artfully created feature vectors. This feature extraction and selection is challenging and demands in-depth understanding. Deep learning-based approaches could provide solutions to the challenges in segmentation tasks without employing artificial characteristics to train the network as the CNN develops. Because CNN makes use of numerous convolutional layers that mimic the human brain, this methodology offers superior segmentation performance [14]. Sometimes it was even able to identify vessels that a skilled ophthalmologist was unable to. Therefore, conducting the feature extraction operation does not necessitate considerable mathematical expertise [15].

The approach suggested by researchers employed CNN to extract features, and then used the features as input for the RF classifier to segment the data. Both adjustments in rotation and scale do not affect it. The input image was converted into a vessel probability map with a size identical to that of the input image using a five-layer NN that serves as an autoencoder. The ground truth and the input are automatically used by this network to learn the mapping, which transforms the input into a vessel probability map [16]. Even close to diseased lesions, it exhibits superior segmentation and divides the thin arteries. A few researchers suggested segmenting the vessels in the XCA pictures using a straightforward two-layer patch-based CNN. Although this approach is less complicated, the segmentation accuracy is rather low. A DNN is created with and without a pooling layer, and it is trained using a dataset of 4 lakh retinal image patches. Both DNNs' training phases make use of the pre-processed and enhanced patches. The no-pool DNN outperforms the other as computational complexity rises and is resistant to FP, FN, and central vessel reflex difficulties [17].

The vessel probability map is provided by Holistically-Nested Edge Detection (HED) inspired FCN that was put forth by a few researchers. The Conditional Random Field (CRF) classifier uses this map as input to produce binary segmentation, although some of the vessels are missed. Segmenting the vessels and the optic disc in the input retinal picture can both be done by a DNN that is learned from HED. Using the DS layers obtained from the foundational VGG-16 network model, this DNN is adept at learning vessel-specific properties. The vessels in the vessel probability map are wider than those seen in the ground reality [18].

Some researchers created a domain-specific fake noisy dataset using line segments to train the DNN without using ground truth. Compared to traditional methods, the dataset evaluation in DRIVE and STARE produces somewhat better results. This new project can be used for label-free network training. Some studies suggested segmenting the vessels, which would provide an intermediate vessel probability map by feeding the two-channel CNN the relevant patches from the live and mask XCA pictures [19]. The ROI is determined from the map, and it is then provided to a single-channel CNN for pixel-wise classification. This procedure is intricate and lengthens the testing's computational time. The multiscale top hat transform-enhanced XCA pictures are provided to the two-stage CNN for segmentation [20].

The input image is transformed using Stationary Wavelet Transform (SWT) and then provided as input to the multiscale algorithm because the vessels are of different width and orientations. CNN to divide the containers into halves, as some employees proposed. Images produced consequently display minimum FP and FN. To obtain the full vessel probability map, multichannel inputs, such as the live and aligned mask CA images (dense matching), are provided to the U-Net-based FCN [21]. Some researchers have developed a CNN that combines the multiscale properties for retinal vascular segmentation while utilizing the idea of cross-connections. It demonstrates how challenging it is to segment fine vessel systems. Divided the retinal fundus image into thick and thin vessels and gave it to the thick, thin, and combination fusion segmenter as input so that the vessels would be accurately segmented. Low contrast microvessel segmentation, thin vessel segmentation, and the presence of central vessel reflex are not challenges for this approach [22].

3. The Purpose of the Proposed Work

1) Constructing a Deep Neural Network (DNN) model capable of performing reliable vascular segmentation for images of the retinal fundus collected for medical purposes.
2) To guarantee that this framework won't compromise segmentation accuracy and that its execution time will be kept to a minimum.

4. The Proposed Work:

The proposed work is discussed in detail below, where each section is elaborated.

4.1. Pre-processing:

During pre-processing, the input is transformed into a more usable form. Pre-processing is performed to scale the intensity range and enhance the contrast of the ROI, and it is especially important when employing a deep learning strategy. Adjusting the intensity during training reduces the amount of computing effort required. The most common pre-processing technique used for a full RGB input image collection is mean value subtraction. Input images are darker in the vessel parts and contrast is not increased, even though the algorithm scales the input intensity range. The standard RGB plane is eschewed in favour of a more complex setup using three separate planes. With RGB colour space, the green plane is the starting point. When CLAHE is used to the green plane, the result is the plane that comes after it. After the gamma corrections are subtracted out, the green plane becomes linear, and this is the third plane. The three planes are combined and scaled by a factor of two before being used to enclose the pre-processed image as shown in Figure I.

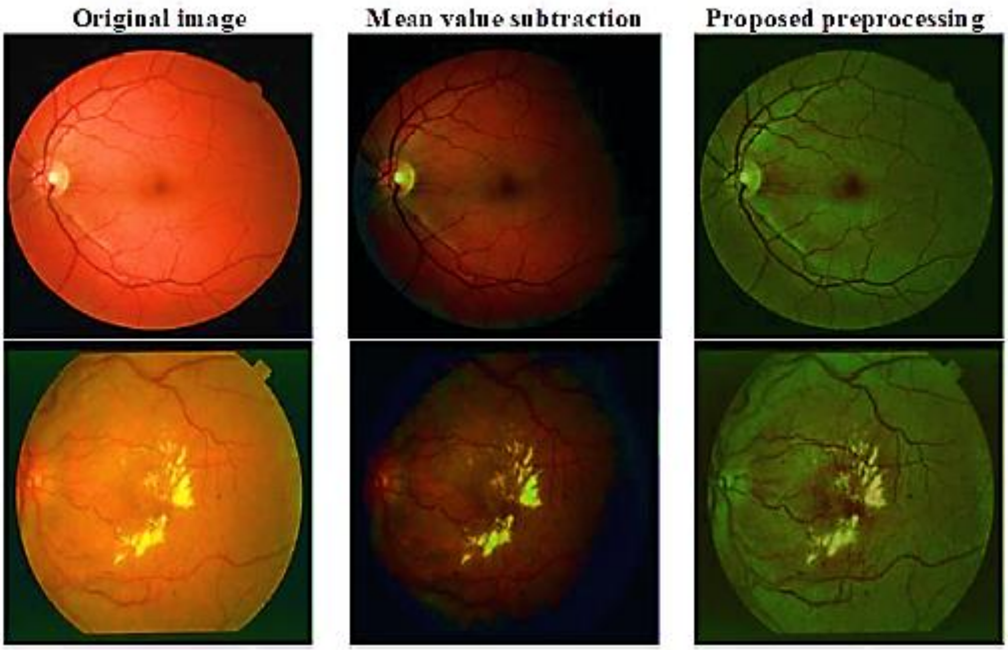

Fig I: Pre-processing input retinal images

4.2. Multi-level DNN application:

So in all, the suggested DNN does a full-fledged image-to-image regression. Rather than starting from scratch when trying to solve a segmentation problem, the network can be re-used after it has been trained on a big dataset. Transfer learning, which makes advantage of previously-trained weights, speeds up the learning process and improves performance. In the training phase, the pre-trained weights are modified gradually using lower learning rates. This DNN uses the first four layers of a pre-trained version of VGG-16 due to the scarcity of suitable very big medical datasets for training. To extract vessel traits, it is further fine-tuned. Fine-tuning is accomplished by combining numerous DS layers to make use of the deep vessel features learned across the many convolutional stages during training, hence decreasing the likelihood of incorrect vessel segmentation. Moreover, the DS layers' receptive FOV is widened so that they can better pinpoint and divide the vessels.

- Base Network: The multilevel/multiscale DNN uses the first four layers of a VGG-16 network as its foundation network. Convolutional layers, the ReLU, and the pooling layers make up these levels. With the VGG-16's layer-by-layer improvement, unnecessary coarse characteristics are filtered out. In light of this, the VGG-16 model only retains the first four convolutional layers.
- D1 layer: The four convolutional layers of the foundational network reveal crucial details about the cardiovascular system. Instead of focusing on the activation map in the last layer, it is more fruitful to delve deeply into the activation outputs in each of the four layers. Retinal fundus vascular architectures have a Gaussian distribution as shown in Figure II.

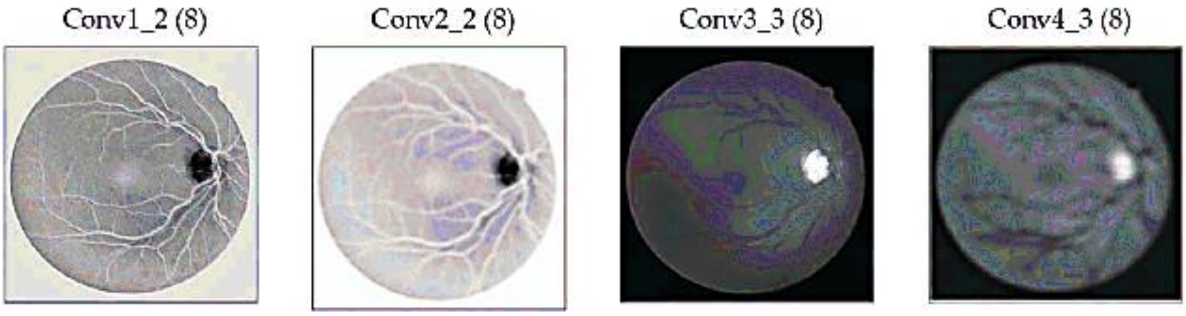

Fig II: The argument maximum of D1 layer output

- D2 Layer: With the Gaussian kernel's standard deviation initialised at 0.0002, the D 2 layer is generated. Each of the four steps employs a Gaussian convolution, but the number of features output by the map has been increased to 16. Standard deviations of 0.0004, 0.0006, and 0.0008 are used for the second, third, and fourth Gaussian convolution kernels, respectively, to account for vessels of varying diameters. Each of the four final convolutional layers yields 16 feature map outputs, which are then combined as shown in Figure III.

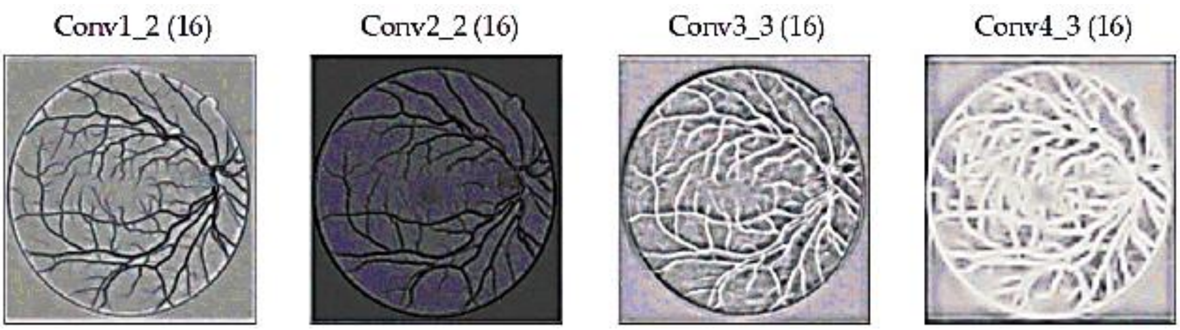

Fig III: The argument maximum of D2 layer output.

- Expanding the receptive FOV of the DS layers: Experiments reveal that the quality of the vessel map is restricted by the immediate fusion and convolution of the derived feature maps from DS layers. Separately convolving D1 and D 2 yields a more accurate probability map, which can be used for exact extraction of the blood vessels. Through experimenting, we also discover that adding two more convolutional layers on top of the D1 and D2 output activation maps expands the receptive field of view (FOV).

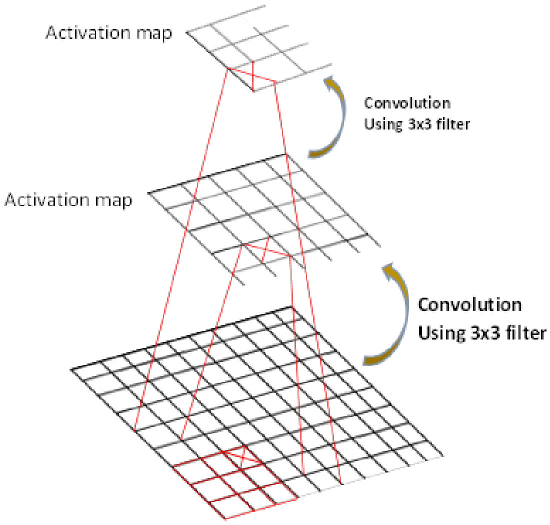

Fig III: Illustration of the increase in receptive FOV

4.3. Input image intensification:

The following changes are applied to the dataset input training images to improve their quality as training input.

- Technique for pre-processing
- Images can be rotated in one of fifteen different ways.
- Inverting all the photos that were rotated
- Targeted cropping of photos after rotation and inversion
- Using a half- and a double-size scaling factor for the flipped and rotated output

4.4. Backpropagation and optimization

One important method for training the DNN is called backpropagation. Errors are kept to a minimum by finding the optimal value of the weight that will lead to the lowest possible loss function (also known as the goal function). During the training phase, minima of the functions are typically found using optimization techniques such as gradient descent.

5. Result and Discussion:

For transfer learning, the weights are stacked using the first five stages of the pre-trained VGG-16 model as the underlying caffemodel. The proposed DS layers and additional convolutional layers are built on top of this foundational network to achieve model convergence. For training the DNN, we make use of the augmented dataset. The developed CAFFE model was then evaluated on test photos taken from the DRIVE, STARE, HRF, and real-world datasets after 18,000 iterations. Otsu thresholding is used to transform the pictures into binary. The quantitative evaluation measures compare the generated photos to the gold standard. These metrics include SN, SP, Acc, and AUC and presented in Figure IV.

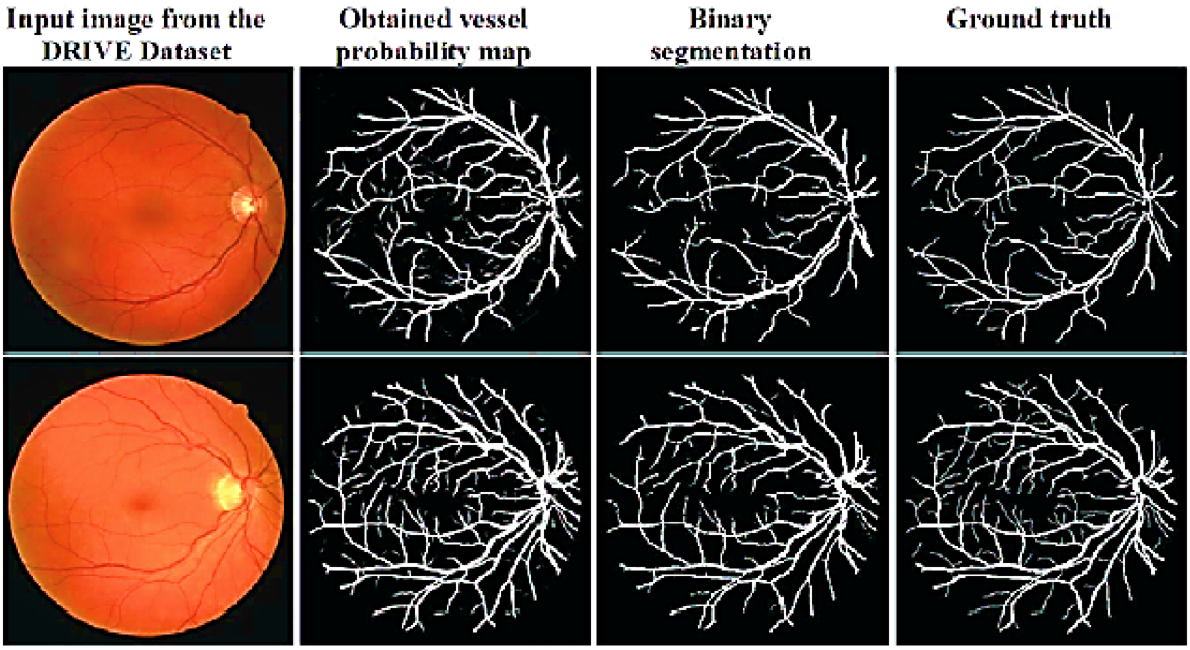

Fig IV: Output vessel segmentation using the proposed DNN

The proposed network model's output images are compared with well-known supervised segmentation methods so that a subjective analysis of the vessel segmented images may be performed. Despite the lack of ground truth during training, the approach proposed by (Chen, 2017) is able to segment the vessels, albeit with many missing segments. The DRIVE provides a unique environment for testing. When it comes to segmenting vessels, the dense CRF model that use CNN to extract the feature sets (Yan et al., 2019) does so, however the resulting vessel regions are not connected. The suggested DNN successfully dissects nearly all major blood artery types while missing only a small percentage of minor ones. Blood vessel segmentation from non-vessel features in confusing locations is aided by contrast-enhanced vessels using the proposed pre-processing.

Table I also includes the derived and added quantitative performance markers. Using only one dataset for both training and testing, this method achieves the greatest AUC value of all of the cited sources. Not only is the peak SN value higher, but the segmented vessel width is larger as well.

Table I: Quantitative evaluation of performance for different methods.

Parameters	Chen, 2017 [23]	Yan et al., 2019 [24]	Proposed method
Sensitivity	0.7431	0.7625	0.835
Specificity	0.9812	0.984	0.979
Accuracy	0.9467	0.9626	0.976
ACC	0.9548	0.983	0.981

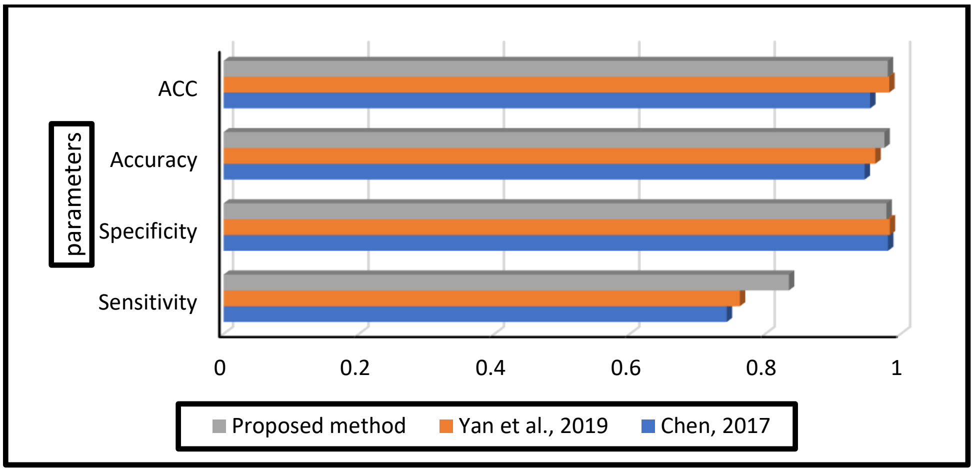

Fig VI: Quantitative evaluation of performance for different methods.

Important quantitative parameters for analysing DR, neovascularization, hypertension, cerebrovascular, and cardiovascular issues can be extracted from the vessel tree after it has been segmented from the retinal image. The width, curvature, tortuosity, AV ratio, etc. of a vessel can be determined using these parameters. In the same way, segmenting the optic disc for glaucoma detection is aided by the careful removal of the vascular tree. The examination of vascular abnormalities is facilitated by this computer-aided automated diagnostics, which is both quick and informative. While automation will never be able to take the position of a trained ophthalmologist, it can speed up the analytical process and improve the accuracy of quantitative estimates.

6. Conclusion:

Since the accuracy of vessel segmentation relied on familiarity with hand-built features, the segmentation process was laborious and inefficient. That's why scientists have come up with deep learning algorithms to automatically learn the feature sets and carry out the segmentation using increasingly complex convolutional layers. Initially, we apply a pre-processing procedure to the input in order to increase the contrast on all three planes and to normalise the intensity range. In contrast to previous methods, the proposed multilevel/multiscale DNN can segment blood vessels without the aid of supervised features. The network has the ability to pick up vessel features at several scales and depths. Real-world clinical datasets are used to evaluate the segmented vascular pictures produced as output. Other deep learning models are used for subjective appraisal of the vascular segments. When compared to existing models, the suggested network successfully segments the vast majority of blood arteries. The suggested DNN is compared to traditional segmentation methods quantitatively and is found to have superior SN while still maintaining respectable SP and Acc. In addition, the area under the curve (AUC) is determined to verify accurate vascular segmentation from the retina. An improved post processing method will aid in accurate binary segmentation and preserve delicate blood vessel structures. The segmented images that are generated as a result can be used to assess parameters such as vessel diameter, bending radius, and amplification factor. It has been discovered that the alterations in vessel morphology can diagnose not just DR and hypertension but also several cardiovascular and cerebrovascular illnesses.

Conflict of Interests:

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] Albargathe SMBK, Kamberli E, Kandemirli F, Rahebi J (2021) Blood vessel segmentation and extraction using H-minima method based on image processing techniques. Multimed Tools Appl 80(2):2565–2582. https://doi.org/10.1007/s11042-020-09646-3

[2] Al-Bander, B., Williams, B. M., Al-Nuaimy, W., Al-Taee, M. A., Pratt, H. and Zheng, Y. (2018), 'Dense fully convolutional segmentation of the optic disc and cup in color fundus for glaucoma diagnosis', Symmetry 10(4), 87.

[3] Mateen, M.; Wen, J.; Nasrullah; Song, S.; Huang, Z. Fundus image classification using VGG-19 architecture with PCA and SVD. Symmetry 2019, 11, 1.

[4] Popescu, D.; Ichim, L. Intelligent image processing system for detection and segmentation of regions of interest in retinal images. Symmetry 2018, 10, 73.

[5] Adapa D, Raj ANJ, Alisetti SN, Zhuang Z, Naik G (2020) A supervised blood vessel segmentation

technique for digital Fundus images using Zernike Moment based features. PLoS ONE 15(3):e0229831. https://doi.org/10.1371/journalpone0229831

[6] Moss, H.E. Retinal vascular changes are a marker for cerebral vascular diseases. Curr. Neurol. Neurosci. Rep. 2015, 15, 40.

[7] Hassan, S.S.A.; Bong, D.B.L.; Premsenthil, M. Detect on of neovascularization in diabetic retinopathy. J. Digit. Imaging 2012, 25, 437–444.

[8] Ünver, H.; Kökver, Y.; Duman, E.; Erdem, O. Statistical edge detection and circular hough transform for optic disk localization. Appl. Sci. 2019, 9, 350.

[9] Al-Bander, B.; Williams, B.M.; Al-Nuaimy, W.; Al-Taee, M.A.; Pratt, H.; Zheng, Y. Dense fully convolutional segmentation of the optic disc and cup in color fundus for glaucoma diagnosis. Symmetry 2018, 10, 87.

[10] Sarathi, M.P.; Dutta, M.K.; Singh, A.; Travieso, C.M. Blood vessel inpainting based technique for efficient localization and segmentation of optic disc in digital fundus images. Biomed. Signal Process. Control 2016, 25, 108–117.

[11] Almotiri, J.; Elleithy, K.; Elleithy, A. Retinal vessels Segmentation techniques, and algorithms: A survey. Appl. Sci. 2018, 8, 155.

[12] Li R., Shen S., Chen G., et al. Multilevel risk prediction of cardiovascular disease based on AdaBoost plus RF ensemble learning. Proceedings of the 2019 5th International Conference on Electrical Engineering, Control, and Robotics; January 2019; Guangzhou, China.

[13] Yao Q., Wang R., Fan X., et al. Multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based time-incremental convolutional neural network. Information Fusion. 2019; 53

[14] Zhang X., Li R., Dai H., Liu Y., Zhou B., Wang Z. Localization of myocardial infarction with the multi-lead bidirectional gated recurrent unit neural network. IEEE Access. 2019; 7: 161152–161166. doi: 10.1109/access.2019.2946932.

[15] Hannun A., Rajpurkar P., Tison G. H., et al. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine. 2019; 25

[16] Saman P., Rubin J. Electrocardiogram monitoring and interpretation: from traditional machine learning to deep learning, and their combination. Proceedings of the Computing in Cardiology; September 2018; Maastricht, Netherlands.

[17] Chen Y.-J., Liu C.-L., Tseng V. S., Hu Y.-F., Chen S.-A. Large-scale classification of 12-lead ECG with deep learning. Proceedings of the 2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI); May 2019; Chicago, IL, USA. IEEE;

[18] Rozenwald MB, Galitsyna AA, Sapunov GV, Khrameeva EE, Gelfand MS. A machine learning framework for the prediction of chromatin folding in Drosophila using epigenetic features. PeerJ Comput Sci. 2020; 6:307.

[19] Amrit C, Paauw T, Aly R, Lavric M. Identifying child abuse through text mining and machine learning. Expert Syst Appl. 2017; 88:402–18.

[20] Hossain E, Khan I, Un-Noor F, Sikander SS, Sunny MSH. Application of big data and machine learning in smart grid, and associated security concerns: a review. IEEE Access. 2019;7:13960–88.

[21] Al-Dulaimi K, Chandran V, Nguyen K, Banks J, Tomeo-Reyes I. Benchmarking hep-2 specimen cells classification using linear discriminant analysis on higher order spectra features of cell shape. Pattern Recogn Lett. 2019;125:534–41.

[22] Deldjoo Y, Elahi M, Cremonesi P, Garzotto F, Piazzolla P, Quadrana M. Content-based video recommendation system based on stylistic visual features. J Data Semant. 2016;5(2):99–113.

[23] Chen, Y. (2017), 'A labeling-free approach to supervising deep neural networks for retinal blood vessel segmentation', arXiv preprint arXiv:1704.07502 .

[24] Fan, J., Yang, J., Wang, Y., Yang, S., Ai, D., Huang, Y., Song, H., Hao, A. and Wang, Y. (2018), 'Multichannel fully convolutional network for coronary artery segmentation in x-ray angiograms', IEEE Access 6, 44635–44643.

[25] Kulkarni, A. P. ., & T. N., M. . (2023). Hybrid Cloud-Based Privacy Preserving Clustering as Service for Enterprise Big Data. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 146–156. https://doi.org/10.17762/ijritcc.v11i2s.6037

[26] Ahammad, D. S. K. H. (2022). Microarray Cancer Classification with Stacked Classifier in Machine Learning Integrated Grid L1-Regulated Feature Selection. Machine Learning Applications in Engineering Education and Management, 2(1), 01–10. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/18