HAL
open science

Deep Learning Architecture with an Optimized Convolutional Processing for the Segmentation of Retinal Blood Vessels

Henda Boudegga, Yaroub Elloumi, Rostom Kachouri, Asma Ben Abdallah, Mohamed Hedi Bedoui

To cite this version:

Henda Boudegga, Yaroub Elloumi, Rostom Kachouri, Asma Ben Abdallah, Mohamed Hedi Bedoui. Deep Learning Architecture with an Optimized Convolutional Processing for the Segmentation of Retinal Blood Vessels. 2023 9th International Conference on Control, Decision and Information Technologies (CoDIT), Jul 2023, Rome, Italy. pp.2451-2456, 10.1109/CoDIT58514.2023.10284289 . hal-04451186

HAL Id: hal-04451186

https://hal.science/hal-04451186v1

Submitted on 11 Feb 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Deep learning architecture with an optimized convolutional processing for the segmentation of retinal blood vessels

Henda Boudegga [1,2], Yaroub Elloumi [1,2], Rostom Kachouri [3], Asma Ben Abdallah [1], Mohamed Hedi Bedoui [1]

***Abstract*— The retinal vascular tree (RVT) is crucial for the diagnosis of various ophthalmological diseases. Efficient segmentation of the RVT with reduced runtime is essential for clinical purposes. Recently, convolutional neural networks (CNNs) have been used for RVT segmentation. However, these architectures typically apply fixed and standard size of convolution kernels for all blocks, which may be unsuitable for accurately capturing vessel scales. In addition, these kernels are applied using 3D convolution layers across all channel depths, leading to higher computational complexity.**

In this work, we propose a novel deep learning architecture. The main contribution consists of performing a convolution processing where kernel size is chosen with respect to vessel scale variation, in order to enhance the quality of the segmentation of vascular trees. In addition, the convolution processing is insured through several layers with 2D kernels, to reduce the computational complexity.

The proposed architecture is evaluated on DRIVE database reaching an average accuracy and sensitivity respectively in the order of 97.69% and 91.69% in 0.75 second per fundus image.

I. Introduction

The retina is a sensory membrane crucial for vision process. Its main anatomical components are the optic disc (OD), the macula and the blood vessels. The blood vessels of the retina have various anatomical features, such as convergence towards the center of the optic disc with a large width and thinning as they move away. Also, they exhibit unbalanced color and shape.

Several ocular pathologies, including diabetic retinopathy [1] [2], age-related macular degeneration, and hypertensive retinopathy [3], resulting abnormal variations in the anatomy of the RVT. As a result, the RVT is widely used for detecting and diagnosing various cardiovascular and ophthalmologic diseases. Thus, the clinical setting requires efficient segmentation to ensure accurate clinical monitoring. Additionally, the segmentation should be performed within a shorter time to facilitate their deployment in computer-aided diagnosis (CAD) systems.

In well, the RVT is characterized by a complicated structure such as a multi-scale representation and irregular shapes. In addition, the permanent increase of fundus image resolution allows modeling more details of vessels even micro-vessels, and thus representing a large gap of multi-scales. Thus, an accurate segmentation of blood vessels with the maximum of details within reduced execution time is a challenging task.

[1]Medical Technology and Image Processing Laboratory, Faculty of medicine, University of Monastir, Tunisia.

[2]ISITCom Hammam-Sousse, University of Sousse, Tunisia.

[3]LIGM, Univ Gustave Eiffel, CNRS, ESIEE Paris, F-77454 Marne-la-Vallée France

Currently, several automated approaches for retinal vessel segmentation have been proposed, employing Convolutional Neural Networks (CNNs). However, despite the integration of convolution blocks to enhance vessel features, the standard configuration with a 3D convolution kernel one is insufficient to achieve high-quality segmentation. Moreover, the convolution processing principle involves the iterative application of a 3D kernel, performing element-wise multiplication and fusion across all channel depths. As a result, the convolution processing incurs higher computational requirements, which present a limitation in achieving efficient segmentation within a shorter computation time.

In this study, we present a deep learning-based method for RVT segmentation. Our approach introduces a novel architecture that emphases on updating the convolution kernel size based on the representation of vessel scales within fundus image resolutions. This kernel size adjustment aims to enhance the quality of segmentation. Additionally, we propose expanding the updated kernel size into convolution layers with multiple 2D kernels to optimize inference speed.

The proposed architecture is trained and tested on retinal sub-image datasets. The segmented patches generated during the process are then merged to produce the final vessel segmentation map. The rest of this paper is structured into four sections. Section II provides a review of relevant works based on deep learning architectures. Section III elaborates on the proposed network, explaining its design and components. In Section IV, we present the experimental results and evaluate the segmentation performance, comparing it to other extended network-based methods. Finally, the conclusion is presented in the last section.

II. Related Works

Fundus imaging blood vessel segmentation methods has been the subject of various reviews, including [7], which examined different categories of approaches. Several well-known CNNs are proposed in the literature and have been applied for this task, which are characterized by the ability of learning complex features. Consequently, they outperform classical machine learning based methods or image processing, such as Alexnet [5], Segnet[6], and in particular the U-net architecture[4]. This latter has been proposed for the segmentation of biomedical images, designed on a U-shaped with Downsampling and Upsampling paths, composed by several blocks based on convolution layers for extracting features.

However, due to the irregular thickness, shape, and orientation of the blood vessels, the conventional

configuration of convolutional layers with a 3D kernel of size 3x3, produces low quality feature maps resulting a lower segmentation quality.

In addition, their convolution processing principle is discriminated by a raised computation complexity leads to longer training and inference times.

Therefore, various extended networks have been proposed to improve the segmentation quality of RVT, by extending the 3D kernel of convolution layers. Some extensions involve expending the convolution kernel, while maintaining the same principle of convolution processing throw applying the 3D kernel over the input feature map and performing an element-wise multiplication and fusion of all channel depth over the input feature map. As examples, the dilated convolution layers and the deformable convolution layers applied into U-net blocks instead of standard convolution layers [8] [9]. The aim is to respectively increase the convolution receptive field of the 3D kernel for learning more distributed information and adapt the convolution receptive field form to the vessel structure, without increasing computation requirements.

Alternatively, the study [7] involves varying the size of the convolution layer's kernel by proposing an identification approach of the 3D convolution kernel size in correlation with retinal image resolution in order to improve the quality of extracted features. However, those proposed extension bring augmentation of computational complexity and thus inference time.

Others ones, suggest extending the processing principle of the convolution such as Inception [10]. The extended processing consists of splitting kernel into parallel path, where each one insure computing convolution with different 3D kernel size. Such processing principle has been applied into U-net convolution blocks, in order to extract multi-scales vessel features.

Another convolution principle proposed by Mobilenet [11] throw Depthwise Convoluton Module (DCM). Such principle consists of extracting features from each channel separately by applying the depthwise convolution layet with several 2D kernels and fuses them later throw the pointwise convolution layer as shown in Fig. 2. Thus a U-net extension has been proposed by [12] through applying such convolution principle instead of their standard convolution processing.

The aim is to reduce computing performance while ensuring high-quality segmentation results. Thus extension has succeeded in achieving a higher correlation between segmentation quality and inference speed.

III. Optimized Deep Learning Network for the Segmentation of Retinal Blood Vessel

Within the objective of enhancing the precision of retinal vessel trees segmentation and optimize the inference speed, we introduce a novel architecture, where the main idea consists of proposing an extended convolution module to be used into the proposed architecture. The proposed convolution module is detailed in section A, whereas the whole architecture in presented in section B.

A. Extended Convolution Module (ECM):

With regards to the stated objective, our main idea involves introducing a new ECM that simultaneously improves both segmentation quality and computational requirements. To achieve this, we propose to combine and integrate extended convolution approaches. To enhance segmentation quality, we adopt the extended convolution approach proposed by [7]. Their contribution focuses on adjusting the size of the 3D convolutional kernel to "mxm" in accordance with the representation of the vascular tree in the fundus image. This modification has led to significant segmentation with respect to the standard configuration, where the sensitivity rate increasing from 75% to 89%.

Similarly, within the aim of reducing computational requirements, we adopt the contributions of [12], which propose a lightweight convolution module as an extension to the convolution principle. This module enables feature extraction by applying a Depthwise convolution layer with a 2D kernel for each channel, followed by fusion using a

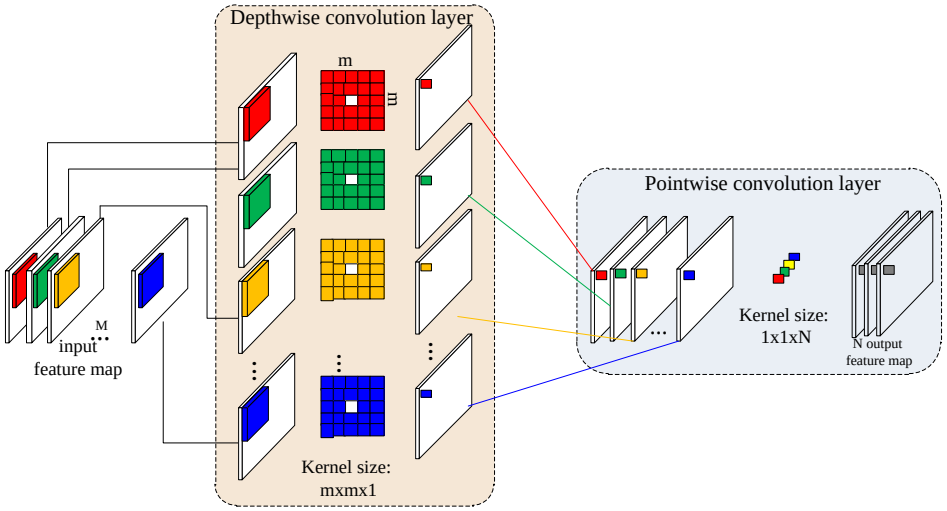

Figure 1. Processing of Extended Convolution Module (ECM)

Pointwise convolution layer. This contribution has effectively reduced computation requirements compared to standard convolution processing. The execution time is decreased from 3.1s to 0.5s, and the number of trainable parameters is reduced from 30M to 10M.

Therefore, our main extension contribution involves expanding the convolution principle and configuration. This extension entails configuring the lightweight convolution module proposed by [12] using the updated convolution kernel size "mxm" suggested by [7]. The modification involves parameterizing the 2D kernels of the Depthwise convolution layers with the updated size "mxm", as shown in Fig. 1. The goal is to emphasize segmentation performance and optimize computational efficiency. To achieve this objective, we propose an extended network, which will be described in the following section.

B. *Proposed network:*

The proposed network of this work consists of extending the well-known architecture U-net through configuring their blocks by the ECM proposed in section III.2. The objective is to ensure accurate segmentation results while reducing computation performances.

The downsampling path of the extended U-Net network comprises five blocks, illustrated by pink boxes in Fig. 4. Each block is composed of two ECMs, indicated by yellow and blue boxes. The Depthwise convolution layers within the ECMs employ "mxm" kernel, as depicted in Fig. 2. These convolution layers are parameterized with a stride value of "s=1" and employ the ReLU activation function.

Furthermore, in each block except the last one, the ECMs are followed by a max pooling layer, denoted by the red arrows in the Fig.2. This pooling layer is configured with a kernel size of "2x2" and a stride of "2" to extract the maximum value from the input feature map "I". The initial downsampling block involves convolving 64 feature maps, which is doubled in the subsequent blocks, as depicted in Fig. 2.

The upsampling path in our proposed architecture adopts a similar structure to the original U-net architecture, consisting of four blocks. Each block in the upsampling path includes an upsampling layer, indicated by the green arrows in Fig. 4, followed by two ECMs with the same configuration as the downsampling ECMs. The upsampling layers utilize a kernel size of "2x2" and a stride of "2", enabling the restoration of the spatial size and information of feature map.

In contrast to the downsampling path, the number of output feature maps is halved for each block in the upsampling path, as depicted in Fig. 4. The network concludes with a 1x1 convolution layer, highlighted in the purple box in Fig. 2, which applies the softmax function to map the 64 feature maps for generating vessel and background predictions. Additionally, a skip connection is established between the downsampling blocks and their corresponding upsampling blocks, indicated by the grey arrows in Fig. 4. This connection allows for the integration of detailed information from lower-level layers with global information, enhancing the accuracy of the predictions.

The propounded network is validated on DRIVE database. Basing on [7], the identified suitable size of convolution kernel size on DRIVE database is in the order of “5x5”. Thus, basing on this result, we proceed to set the size “mxm” of the 2D kernels of the Depthwise convolution layers to “5x5”.

C. *Training parameter setting*

To fine-tune the weight nodes and achieve a precise model, a training process is performed using a specific set of training parameters. These parameters are selected through a combination of experimental choices and references to recent studies. The table below provides an overview of the training parameters utilized in this process.

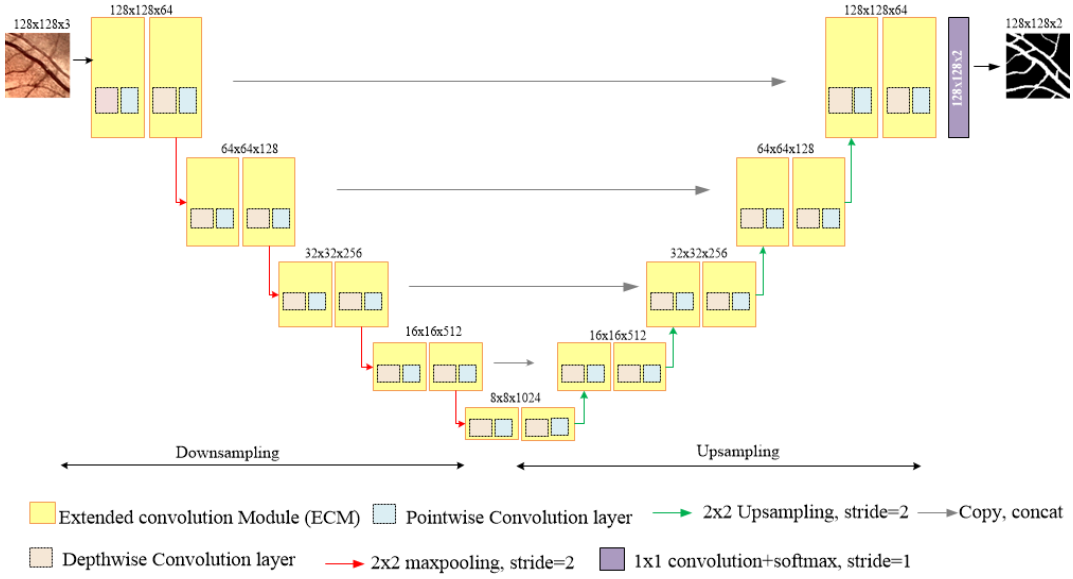

Figure 2. Proposed network for retinal blood vessel segmentation.

TABLE I. TRAINING PARAMETER SETTING

Training parameter	Values
Optimizer	Adam
Learning rate	0.001
Initialization	Xavier technique
Regularization	dropout technique(0.5)
Epoch number	40
Loss Function	Cross entropy

D. Computation complexity and training parameter setting

The objective of this section is to examine the complexity of the proposed architecture to assess the computational efficiency of utilizing the extended convolution module. In a standard convolution layer, a 3D kernel of size K×K×M is convolved with a sub-image of the input map, considering all M channels. This process is repeated iteratively for all feature maps with dimensions "WxH" to generate N feature maps. Hence, the computational complexity of a convolution layer is represented by equation (1).

$$\zeta_{conv.layer}=O\,(M * N * W * H * K^2) \quad (1)$$

In contrast, the ECM follows a step-wise process. Initially, a 2D kernel of size mxm×1 is applied iteratively to M feature maps with dimensions WxHx1. Subsequently, a kernel of size 1×1×N is applied iteratively to generate N feature maps. As a result, the computational cost of the ECM is defined by equation (2).

$$\zeta_{ECM}= O\,(M * H * W * m^2 + M * N * W * H) \quad (2)$$

Based on our analysis, we can conclude that the ECM exhibits a lower computational complexity compared to the standard convolution layer. The computational complexity is reduced by $O(\max(N, m^2))$. Furthermore, since the proposed architecture consists of "L" blocks, each containing two ECMs, it results in a significant reduction in computational complexity of approximately $O(2\times L\times\max(N, m^2))$..

E. Workload of the segmentation method

To assess the effectiveness in detecting blood vessels, we applied the proposed network throw the highlighted approach in [12]. The processing pipeline is shown in Fig.3. The processing is initialized with a pre-processing step to enhance the image quality. Subsequently, a cropping processing is applied to segment several sub-images having size in the order of 128*128. Once the sub-images are segmented throw the proposed network, a post-processing step is applied to merge the segmented sub-images and produce a whole segmented image of the RVT.

IV. EXPERIMENTAL RESULT

In this section, we present the outcomes of the proposed method for segmenting the RVT. For this context, a well-known retinal image database is used for evaluation throw computing several metrics described in the subsection A. In addition, we propose comparing the generated performance to its context basing on the used retinal image database.

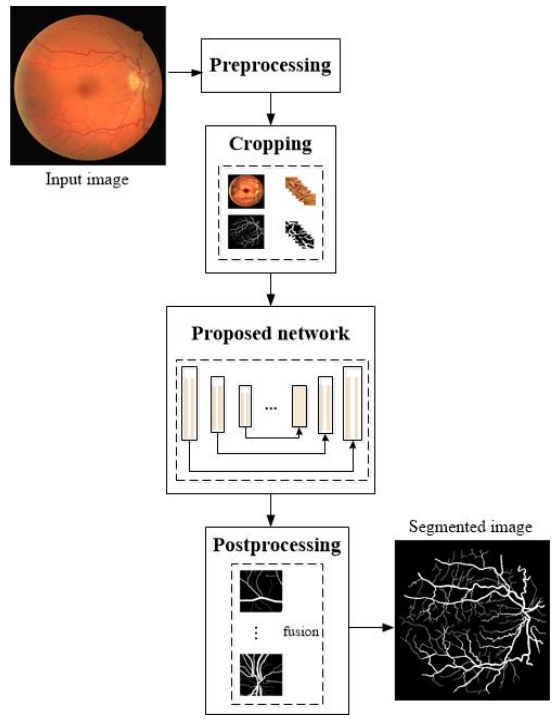

Figure 3. Workload of the segmentation method.

A. Evaluation metrics and working environment

- Evaluation metrics

Different evaluation metrics, including Accuracy (Acc), Sensitivity (Sens), Specificity (Spec), DICE, and Precision (Pre), can be calculated based on the pixel classification results, which are determined by True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These metrics evaluate the correctness of pixel segmentation compared to the manual annotation of blood vessel segmentation. The specific evaluation metrics mentioned are calculated using equations (3-7).

$$\text{Accuracy (Acc)} = TN+TP/(TP+FP+FN+TN) \quad (3)$$

$$\text{Sensitivity (Sens)} = TP/(TP + FN) \quad (4)$$

$$\text{Specificity (Spec)} = TN/(TN + FP) \quad (5)$$

$$\text{DICE}= 2*TP/\ 2 * TP + F\ N + FP \quad (6)$$

$$\text{Precision (Pre)} = TP/(TP + FP) \quad (7)$$

- Working environment

All experiments of this work were done using Python developing language 3.5.2, OpenCV library 3.4 and Tensorflow GPU framework 1.12, using CUDA 9.0 with CUDNN 7.6.3. The experiments were run on an Intel core i7 processor with a frequency of 3.67 GHZ, 8GB of RAM and an NVIDIA GTX 980 GPU.

B. *Segmentation and Computation performance*

Within this section, we assess both the segmentation performance and the computational efficiency of the suggested method.

Therefore, for evaluating the segmentation performance we propose applying the 4-fold cross validation approach proposed by [12] basing on Acc, Sens, Spec, DICE and Pre. The experiments have demonstrated higher segmentation performances as provided in table II, where the average values of Acc, Sens, Spec, DICE and Pre are respectively in the range of 97.25%, 90.31%, 97.86%, 86.74% and 78.4%. In addition, in order to confirm a higher correlation between the four for cross validation, we propose illustrate the box plot in Fig.4 for the four performances basing on the metrics Accuracy, Sensitivity, Specificity, DICE and Precision. The representation reveals a significant correlation among the 4-fold cross validations datasets. The Acc values are very close to the average with a minimal variation of 1% is revealed, demonstrating a high correlation between 4-fold datasets. Similarly to the Sens, Spec, DICE and Pre, the generated results are very close to average with a variation respectively in the order of 2%, 1%, 2% and 4%. Furthermore, we asses the execution time of the proposed method. The whole execution time needed to perform an end-to-end segmentation process of an entire image is about 0.75s. Consequently, the proposed method has succeeded to guarantee and accurate segmentation result into a short time.

TABLE I. PERFORMANCE MEASURE FOR 4-FOLD CROSS VALIDATION

	Acc	Sens	Spec	DICE	Pre
1st experiment	97.62	91.69	98.11	85.12	80
2nd experiment	96.99	89.64	97.64	82.16	76.07
3rd experiment	97.06	89.92	97.7	83.78	78.54
4th experiment	97.365	90	98.011	83.90	79.012

C. *Comparison with state of the art:*

In this section, we suggest evaluate our out-coming performance against the baseline extension and the state of the art methods.

From Table II, basing on the baseline extensions their segmentation accuracy rates are in the range, due to the unbalanced vessel and background pixels count. Hence, for RVT segmentation tasks the sensitivity is an important metric as it highlights the model's ability to identify the subtle vessel details. In this context, basing on the sensitivity rates of Table II and Fig.5, the segmentation quality of the segmented RVT has improved with respect to the two baseline extensions [7] and [12], where sensitivity is respectively improved from 85% to 91% and from 89% to 91%. Thus improvement against [12] is explained by the standard configuration of their LCM, where their kernel size is about "3x3". Additionally, we can conclude that the proposed method's sensitivity rate outperforms DL-based methods such as [8] [9] [13] [14] exhibiting a notable difference of approximately 12%. Consequently, the proposed network demonstrates a robust capability to detect vessel pixels. This significant performance can be attributed

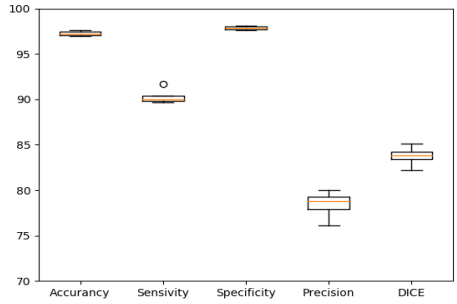

Figure 4. Boxplot of four-fold cross validation results

to the integration of the identified convolutional kernel sizes in the order of "5x5" into the U-Net model.

In addition, we suggest comparing our computation performances against the baseline models and state of the arte extensions. For this purpose, the execution time and parameter number are identified, as presented in Table 8.

TABLE II. SEGMENTATION PERFORMANCE COMPARAISON ON DRIVE DATABASE

		Acc	Sens	Spec
[8]		95.77	77.18	97.08
[9]		96.41	75.95	98
[13]		95.42	76.53	98.18
[14]		95.57	78.9	97.99
Base extensions	[7]	98.71	89.80	99.37
	[12]	98	85.86	98.9
Our model		97.68	91.69	98.11

Comparing to the baseline model of [7], our model achieves a lower parameter cost. Specifically, the execution time is reduced from 1.45s to 0.75s, and the number of trainable parameters is reduced from 73M to 10M. Thus reduction is explained by the employment of ECM in the Downsapmling and Upsampling blocs.

Additional, our proposed model has occurred similar configuration cost with respect to [12], where the parameter number is about 10M and execution time are in the range of 6±1 second. Thus reduced computation costs are explained by the employment of ECM in our model and the LCM in

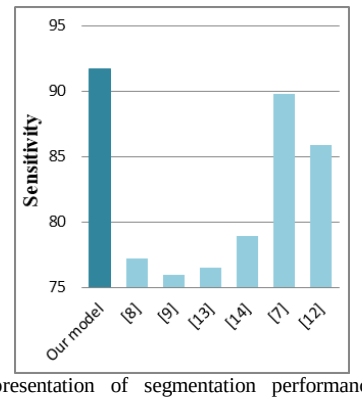

Figure 5. Representation of segmentation performance in term of sensitivity

the model of [12]. Comparing to others state of the arte extensions, the segmentation of RVT ensured by our proposed model is faster than [9] and [18]. Moreover, our model has a lower parameterization cost than the model presented in [17] since the employment of ECMs in the architecture blocks.

TABLE III. COMPUTATION PERFORMANCE COMPARAISON

		Ex.Time(s)	NB.Params (M)
[17]		-	31.03
[9]		15.3	0.88
[18]		6.42	1.037
Baseline extensions	[7]	1.45s	73.29
	[12]	0.5	10.875
Our model		**0.75**	**10.985**

V. CONCLUSION

The detection of the RVT is crucial for detecting and diagnosing numerous ocular pathologies, which are always inferred based on vessel morphology. Therefore, an accurate segmentation of the vascular tree into a shorter time is required to response to such clinical needs. Within this objective, we propose a novel network that ensures an efficient segmentation into a shorter execution time. The proposed network is an extension of a well-known network, which introduce an ECM module. The idea consists of configuring the 2D kernel of the lightweight convolution module proposed by [12] by the updated convolution kernel size “mxm” identified by [7].

The proposed approach is assessed on the DRIVE database using a four-way cross-validation technique. As a result, the method has achieved an average accuracy and sensitivity rates respectively in the range of 97% and 91% within 0.75 seconds. The proposed method was assessed against existing works and achieving superior segmentation performance while reducing execution time.

Several ophthalmological diagnostic systems such as [15], [16], [19] and [20] or retinal abnormalities detection systems as [21] expect sensitive segmentation of RVT into a shorter execution time [22]. For this context, the proposed method can be employed in function to the diagnosis system in order to take benefit to the accurate segmentation performance while keeping shorter computation time.

REFERENCES

[1] S. S. Kar and S. P. Maity, ‘Detection of neovascularization in retinal images using mutual information maximization’, Computers & Electrical Engineering, vol. 62, pp. 194–208, Aug. 2017.

[2] S. Yu, D. Xiao, and Y. Kanagasingam, ‘Automatic detection of neovascularization on optic disk region with feature extraction and support vector machine’, in 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Aug. 2016, pp. 1324–1327.

[3] S. Khitran, M. U. Akram, A. Usman, and U. Yasin, ‘Automated system for the detection of hypertensive retinopathy’, in 2014 4th International Conference on Image Processing Theory, Tools and Applications (IPTA), Oct. 2014, pp. 1–6.

[4] O. Ronneberger, P. Fischer, and T. Brox, ‘U-Net: Convolutional Networks for Biomedical Image Segmentation’, in Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, 2015, pp. 234–241.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ‘ImageNet classification with deep convolutional neural networks’, Commun. ACM, vol. 60, no. 6, pp. 84–90, May 2017.

[6] V. Badrinarayanan, A. Kendall, and R. Cipolla, ‘SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation’, arXiv:1511.0056.

[7] H. Boudegga, Y. Elloumi, R. Kachouri, A. Ben Abdallah, and M. H. Bedoui, ‘Extended U-net for Retinal Vessel Segmentation’, in Advances in Computational Collective Intelligence, Cham, 2022, pp. 564–576.

[8] S. V. and I. G., ‘Encoder Enhanced Atrous (EEA) Unet architecture for Retinal Blood vessel segmentation’, Cognitive Systems Research, vol. 67, pp. 84–95, Jun. 202.

[9] Q. Jin, Z. Meng, T. D. Pham, Q. Chen, L. Wei, and R. Su, ‘DUNet: A deformable network for retinal vessel segmentation’, Knowledge-Based Systems, vol. 178, pp. 149–162, Aug. 2019.

[10] Z. Zhu, Q. An, Z. Wang, Q. Li, H. Fang, and Z. Huang, ‘ILU-Net: Inception-Like U-Net for retinal vessel segmentation’, Optik, vol. 260, p. 169012, Jun. 2022, doi: 10.1016/j.ijleo.2022.169012.

[11] A. G. Howard et al., ‘MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications’, arXiv:1704.04861 [cs], Apr. 2017

[12] H. Boudegga, Y. Elloumi, M. Akil, M. Hedi Bedoui, R. Kachouri, and A. B. Abdallah, ‘Fast and efficient retinal blood vessel segmentation method based on deep learning network’, Computerized Medical Imaging and Graphics, vol. 90, p. 101902, Jun. 2021.

[13] Z. Yan, X. Yang, and K.-T. Cheng, ‘Joint Segment-Level and Pixel-Wise Losses for Deep Learning Based Retinal Vessel Segmentation’, IEEE Transactions on Biomedical Engineering, vol. 65, no. 9, pp. 1912–1923, Sep. 2018.

[14] H. Li et al., ‘MAU-Net: A Retinal Vessels Segmentation Method’, in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC), Jul. 2020, pp. 1958–1961.

[15] R. Boukadida, Y. Elloumi, M. Akil, and M. H. Bedoui, ‘Mobile-aided screening system for proliferative diabetic retinopathy’, International Journal of Imaging Systems and Technology, Feb. 2021.

[16] Y. Mrad, Y. Elloumi, M. Akil, and M. Bedoui, ‘A fast and accurate method for glaucoma screening from smartphone-captured fundus images’, IRBM, 2021.

[17] O. Ronneberger, P. Fischer, and T. Brox, ‘U-Net: Convolutional Networks for Biomedical Image Segmentation’, in Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, 2015, pp. 234–241.

[18] M. Z. Alom, M. Hasan, C. Yakopcic, T. M. Taha, and V. K. Asari, ‘Recurrent Residual Convolutional Neural Network based on U-Net (R2U-Net) for Medical Image Segmentation’, May 2018, arXiv:1802.06955.

[19] Y. ELLOUMI, Manef BEN MBAREK, Rahma BOUKADIDA, Mohamed AKIL, Mohamed Hedi BEDOUI, “ Fast and accurate mobile-aided screening system of moderate diabetic retinopathy”, 13th conference on machine vision.

[20] Y. ELLOUMI, “Cataract Grading Method Based on Deep Convolutional Neural Networks and Stacking Ensemble Learning”, Int. Journal of Imaging Systems and Technology, 2022.

[21] M. Akil, Y. Elloumi, R. Kachouri Detection of retinal abnormalities in fundus image using CNN deep learning networks, State of the Art in Neural Networks and their Applications Academic Press (2021), pp. 19-61

[22] S. B.Sayadia, Y. Elloumi, M. Akil, M. Hedi Bedoui, R. Kachouri, and A. B. Abdallah, “Automated Method for Real-Time AMD Screening of Fundus Images Dedicated for Mobile Devices”, Med Biol Eng Comput, 60, 1449–1479 (2022).