Deep Learning segmentation of tubular structures with topological constraints

Dhia ZNAIDI, Rayen BEN ISMAIL & Patrick GUILLEVIC
Supervisor : Pierre-Henri CONZE
IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

Abstract

Retinal vessel segmentation remains an essential approach used in fundoscopic examinations for disease diagnosis. Many image processing and machine learning-based approaches. However, they are unable to precisely pixel-wise segment blood vessels due to insufficient illumination and periodic noises. During our work, we have investigated deep learning-based vessel segmentation methods.

Keywords: Retinal vessels, UNet, ResNet-50, DiceLoss, clDiceLoss.

Introduction

To alleviate this problem, we propose in the present work a comparative study between the performance of Deep Learning architectures with different metrics and cost functions aimed at preserving the topology of retinal vessels as well as an approach to better view the fine ramifications. Mixed approach between medical and satellite remote sensing imagery satellite would conclude our work.

Loss functions & Approachs

The following materials were required to complete the research:

- Architectures: Standard UNET, pretrained encoder(RESNET50)
- inputs: DRIVE Dataset, cropped images, augmented images

Metrics:

- Dice : $DSC(f,x,y) = \frac{2\times\sum_{i,j} f(x)_{ij}\times y_{ij}+\epsilon}{\sum_{i,j} f(x)_{ij}+\sum_{i,j} y_{ij}+\epsilon}$
- clDice :

$$clDice(S_P, V_L) = 2\times\frac{\text{Tsens}(S_L,V_P)\times\text{Tprec}(S_P,V_L)}{\text{Tsens}(S_L,V_P)+\text{Tprec}(S_P,V_L)}$$

Loss functions :

- DiceLoss : $\mathcal{L}_{Dice} = 1 - \text{DSC}$
- clDiceLoss : $\mathcal{L}_{clDice} = 1 - clDice$
- Dice-clDice Loss (α is a tunable parameter): $\mathcal{L} = (1-\alpha)\mathcal{L}_{Dice} + \alpha\mathcal{L}_{clDice}$

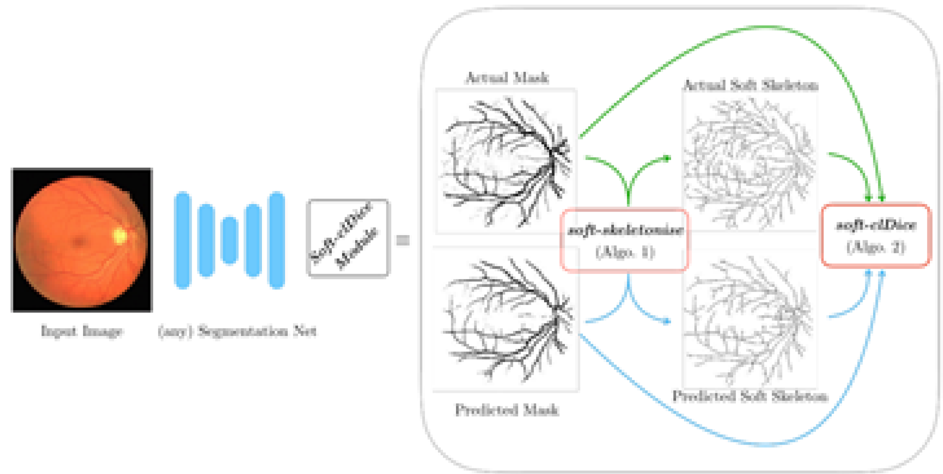


Figure 1: clDice illustration

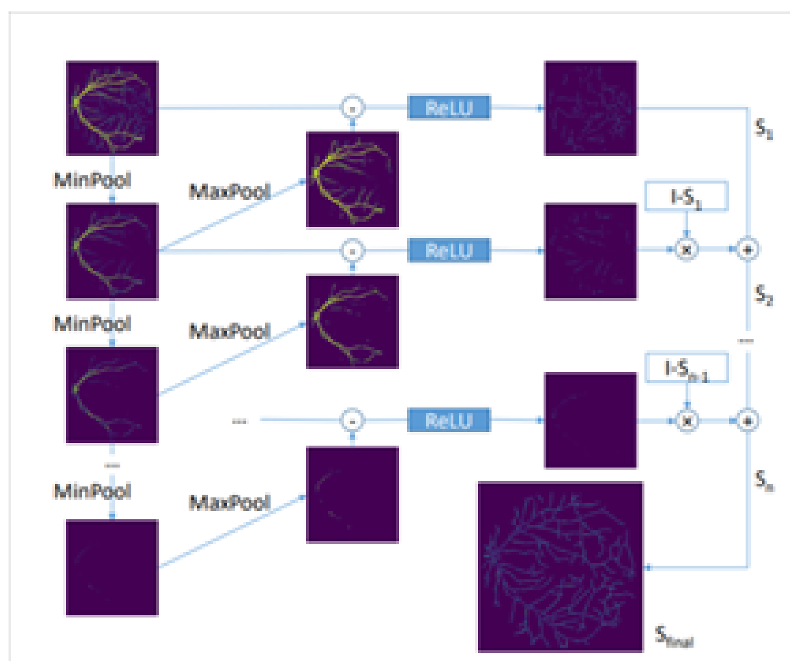
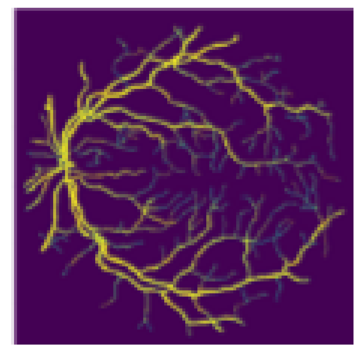
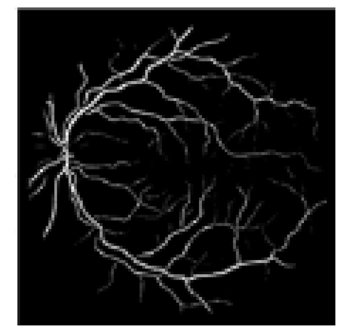
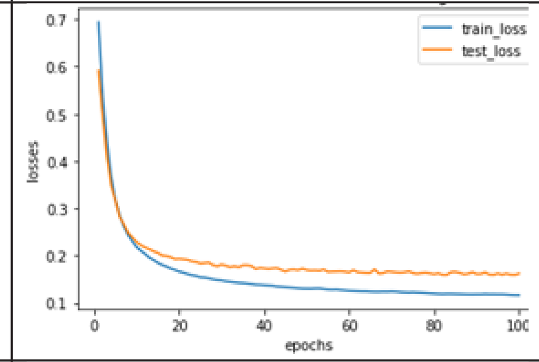
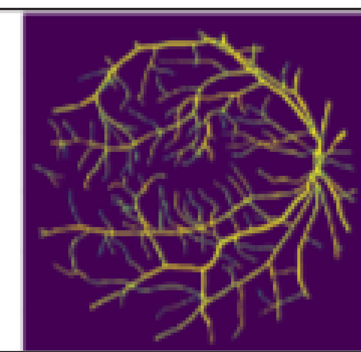
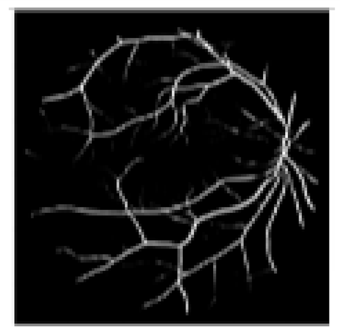
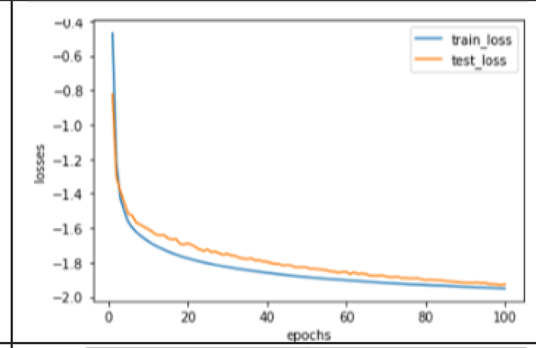
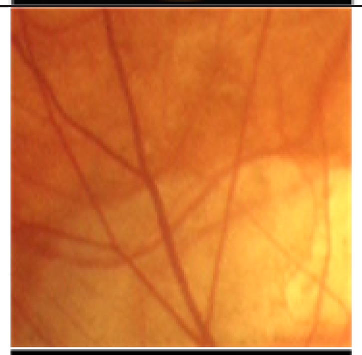
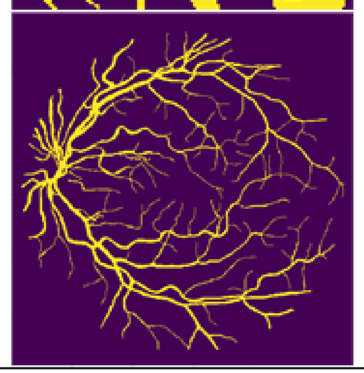
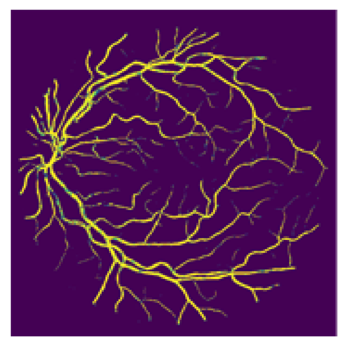
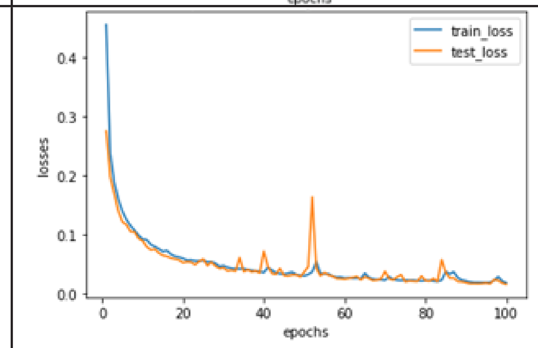
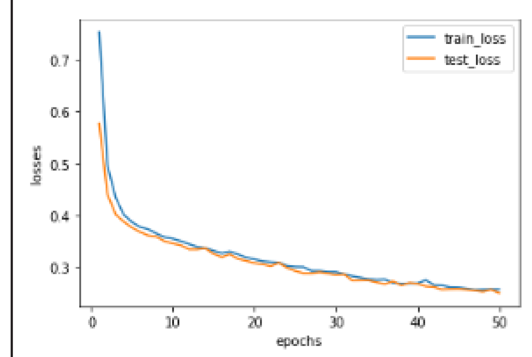


Figure 2: skeletonization procedure

Results

Approach	Image and ground truth		Prediction	Performance
• Resnet50 Encoder-UNet • DiceLoss				
• Resnet50 Encoder-UNet • (clDice + Dice)loss				
• Resnet50 Encoder-UNet • DiceLoss • cropped portions • reconstructing full prediction from portions	 	 	 	
• Application on roads segmentation • Resnet50 Encoder-UNet • DiceLoss				

Conclusion

- At each new step we managed to improve the segmentation of the tubular structures and in particular the visualization of the fine vessels
- Promising results have been achieved
- We settled for diceloss for the application because of the limitation in memory allocation of the GPU in the working environment
- Our divide and conquer approach allows a better estimation of fine ramifications
- The disadvantage of this method is the computation time and memory allocation
- This method can be improved with for example the RVGAN [1]

Contact Information

- Supervisor : pierre-henri.conze@imt-atlantique.fr
- rayen.ben-ismail@imt-atlantique.net
- dhia.znaidi@imt-atlantique.net
- patrick.guillevic@imt-atlantique.net

References

[1] Rv-gan: Segmenting retinal vascular structure in fundus photographs using a novel multi-scale generative adversarial network. 2021.

[2] *clDice – A Novel Topology-Preserving Loss Function for Tubular Structure Segmentation*. arXiv:2003.07311v7, 2020.

Future Research

- What makes the task difficult is mainly due to the thinness of the vessels and their low contrast, which easily lose spatial information in the traditional UNet segmentation network.
- To alleviate this problem, we will be trying GAN-based architecture such as RV-GAN to produce highly accurate segmentation of blood vessel with strong confidence scores.