RETINAL BLOOD VESSEL SEGMENTATION USING LITE U-NET ARCHITECTURE

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ABSTRACT

Retinal image analysis is an effective technique to identify retinal diseases more accurately. There are various techniques in retinal image analysis. Some of them use deep learning algorithms and Convolutional Neural Networks (CNN). U net is one among them. The proposed algorithm that is Lite U-net extract blood vessels from retinal fundus images and applying different preprocessing operations on extracted fundus images before applying to U-net. So that it showed some decent results in terms of accuracy(0.9659),sensitivity(0.9913).

KEYWORDS: Convolutional Neural Networks, ReLU, U-net, DRIVE, STARE, Lite U-net

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I.INTRODUCTION

Eye is an important sense organ of human body. There are various diseases that cause loss of vision in human eye. Diabetic Retinopathy is one such kind of disease. The disease swells retina and blood vessels in it. This causes loss of vision if cannot be detected at early stages. In general doctors analyse the retinal fundus images and based on the size of blood vessels ophthalmologists identify the severity of the disease. But it is difficult to directly identify from the images and an expert is required who can plot only blood vessels of the retinal images. This is time taking process and may lead to human errors very often. So researchers came up with various techniques to extract the blood vessels. Some of them involve image pre processing techniques and other involves machine learning and deep learning techniques.

II. RELATED WORK

From past two decades researchers are coming with multiple algorithms that segment blood vessels from retinal fundus images. Some involves general preprocessing techniques and others involve machine learning and deep learning techniques. U-net is one of the important deep learning architecture that created an impact in retinal blood vessel segmentation. The network architecture of U-net is illustrated in figure given below. It consists of two paths such as contracting path (left side) and an expansive path (right side). The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. The number of feature channels get doubled at every step of down sampling. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution (“up-convolution”) that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64- component feature vector to the desired number of classes. In total the network has 23 convolutional layers.

III.IMAGE PREPROCESSING

In the data science community image data processing is one of the most under-explored problems. Every developer has a unique way of doing it. Tools and platforms used in image preprocessing include Python, Pytorch, OpenCV, Keras, Tensorflow, and Pillow. When building a machine learning/computer vision project, one thing we always need is data. In this case, image data is processed.
Unfortunately, a few problems associated with image data include complexity, inaccuracy, and inadequacy. This is why before building a computer vision model, it is essential that the data is preprocessed (cleaned and processed to the desired format) to achieve the desired results.It is often used to increase a model’s accuracy, as well as reduce its complexity. There are several different techniques used to preprocess image data. Examples include; image resizing, converting images to grayscale, and image augmentation etc. In this we used 4 different types of Image Pre-Processing techniques and they are listed below.

1.Edge Detection
2.Gray Scale conversion
3.Histogram Equalisation
4.Gray scale conversion

IV. PROPOSED ALGORITHM

Lite U-net is derived from the actual U-net. Assume that the U-net is divided into five layers as showed in U-net figure. Each layer has different feature channels and based on that we divided them into five layers. In U-net all the layers have same number of convolutions followed by ReLu and in order to change the complexity and number of convolutions at each step of U-net . We named this architecture as Lite U-net. This U-net takes input image, applies convolution and then a non-linearity and performs down sampling with max pooling operation and this output is given to layer two or next layer. In this layer we repeat the same process as that of previous one. This is true for contraction path and for expansion path instead of having down sampling we have an up sampling operation to reconstruct the image.

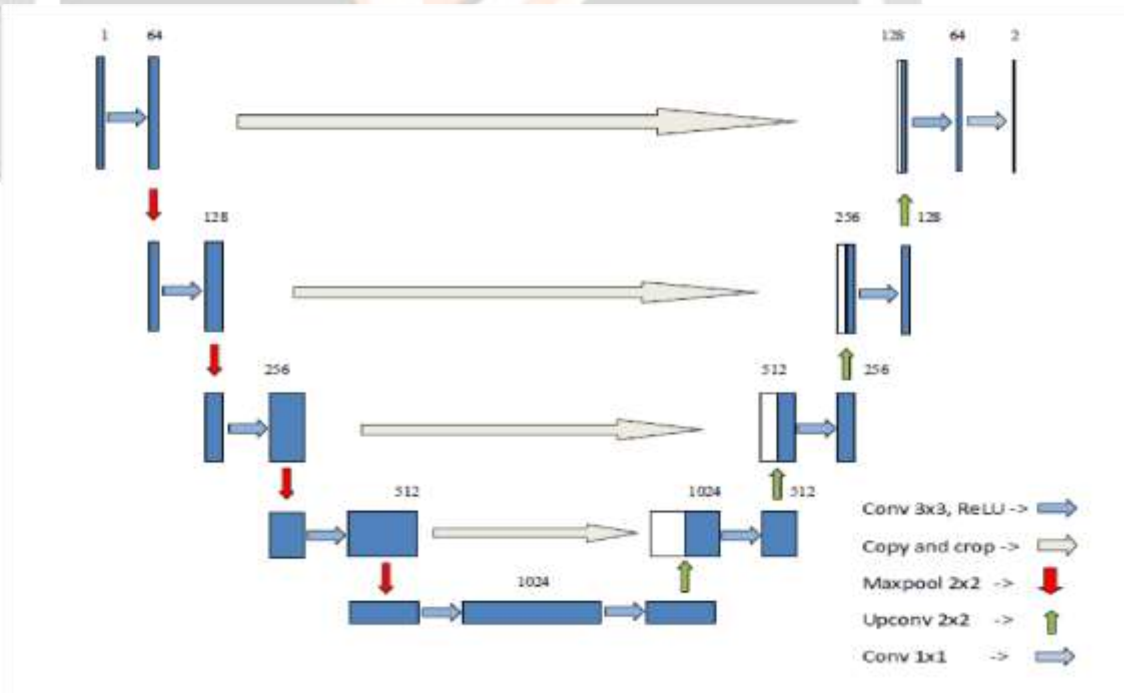

Fig1.Lite U-net architecture

V.EXPERIMENT

We used two public datasets DRIVE and STARE to train and test our model. DRIVE dataset (Staal et al., 2004) is publicly available, and has become a frequently used benchmark for research on retinal vessel segmentation. The set consists of both 20 training and 20 test fundus images, all having the same resolution of 584 × 565. The

DRIVE set has also been used to evaluate A/V discrimination. DRIVE dataset has forty images and among those we used twenty images for training and twenty images for testing. STARE dataset has twenty images without any division among training and testing. We randomly selected sixteen images to train and four images to test the STARE dataset. We used GPU in Google Colab. to train the dataset and we used two hundred epochs with learning rate of 0.001 and dropout would be 0.1. To figurize the performance we calculated the accuracy, area under ROC curve, sensitivity, specificity and f1 score of the model.

VI.RESULTS

The table given below shows the results when trained and tested on our model with DRIVE and STARE datasets and comparing with other models and architectures. The images given below are colored images, image predicted by our model and ground truth of the images. The metrics in bold indicate the highest value in the given architectures. For DRIVE dataset we got an accuracy of **0.9659** and specificity of **0.9820** and for STARE dataset we achieved sensitivity of **0.7827**.

Metrics	Acc	AUC	Sensitivity	Specificity	F1 Score
U net	0.9531	0.9755	0.7537	0.9820	0.8012
D U net	0.9529	**0.9868**	0.7428	**0.9920**	0.8079
R2 U net	0.9556	0.9784	**0.7792**	0.9813	0.8171
Recurrent U net	0.9556	0.9782	0.7751	0.9816	0.8155
Iternet(patched)	0.9573	0.9816	0.7735	0.9838	**0.8205**
Lite U net	**0.9659**	0.9788	0.7009	0.9913	0.7815

Table 1: Comparison of results on DRIVE dataset with other models

Metrics	Acc	AUC	Sensitivity	Specificity	F1 Score
U net	0.9578	0.9772	0.8288	0.9701	0.7770
D U net	**0.9729**	0.9868	0.7428	**0.9920**	0.8079
R2 U net	0.9712	**0.9914**	0.8298	0.9862	0.8171
Recurrent U net	0.9706	0.9909	0.8108	0.9871	**0.8396**
Iternet(patched)	0.9701	0.9881	0.7715	0.9886	0.8146
Lite U net	0.9727	0.9873	0.7827	0.9893	0.8225

Table 2: Comparison of results on STARE dataset with other models

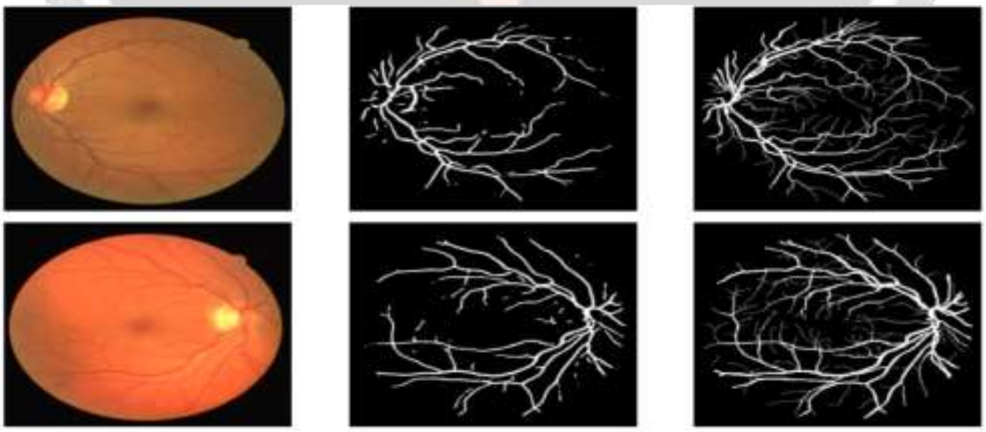

Fig2.Preprocessed output from an images in DRIVE Dataset on Lite u-net

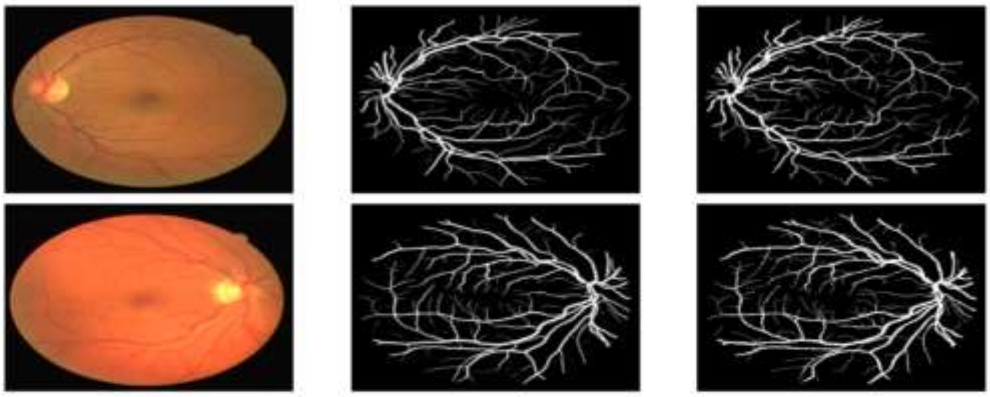

Fig3. Tested output from an images in DRIVE Dataset on Lite u-net

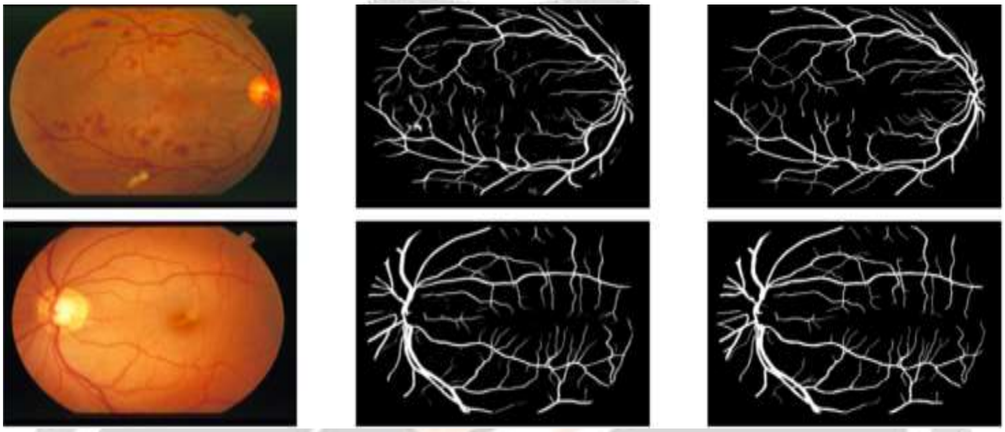

Fig4.Tested output from an images in STARE Dataset on Lite u-net

VII.CONCLUSION

Retinal blood vessel segmentation has an important role in medical industry. By segmenting retinal blood vessels many diseses can be identified. Diabetic retinopathy and glaucoma are few among them. Some of the blood vessel segmentation techniques involve normal preprocessing techniques while others involve machine learning and deep learning algorithms.

U-net is one of the retinal deep learning techniques which gave very promising results. Inspiring from this U-net we designed architecture based on Unet. The designed architecture is Lite U-net .

And it gave best results in terms of metrics such as sensitivity and specificity when applied on DRIVE and STARE datasets. There are few disadvantages with our model. It gave good results when compared to existing methodologies.

VIII.APPLICATIONS

U-net is an image segmentation technique developed primarily for biomedical image analysis that can accurately segment images using a scarce amount of training data. Analyzing these segmented images with automated U-net techniques help in identifying the disease and give the proper treatment to the patient. From the below example,the image segmented by our Lite U-net is showing better accuracy and segmentation compared to actual U-net. Thus using our model by doctors will help them spending less time in analyzing the images.

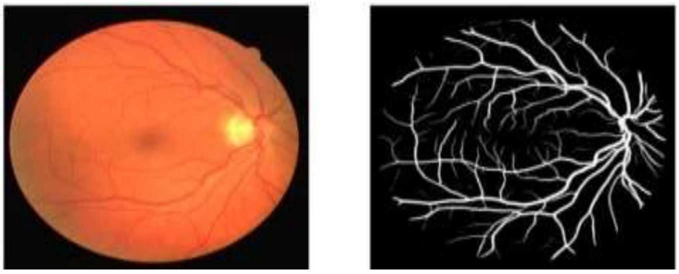

Fig 5.U-net showing vessels segmented with Acc = 0.9531

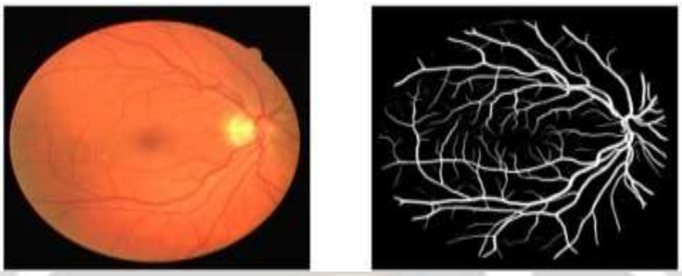

Fig 6.Lite U-net (Acc = 0.9727) segmenting better than unet

REFERENCES

1.M. D. Abràmoff, M. K. Garvin, and M. Sonka. Retinal imaging and image analysis. IEEE transactions on medical imaging, 3:169–208, 2010

2. U. T. V. Nguyen, Al. Bhuiyan, L. A. F. Park, and K. Ramamohanarao. An effective retinal blood vessel segmentation method using multi-scale line detection. Pattern Recognition, 46(3):703–715, 2013.

3.Ronneberger, O., Fischer, P., Brox, T.: U-Net: convolutional networks for biomedical image segmentation. In: Navab, N., Hornegger, J., Wells, W.M., Frangi, A.F. (eds.) MICCAI 2015. LNCS, vol. 9351, pp. 234– 241. Springer, Cham, 2015.

4.J. Dai, H. Qi, Y. Xiong, Y. Li, G. Zhang, H. Hu, and Y. Wei, “Deformable

Convolutional Networks,” in International Conference on Computer Vision, 2017, pp. 764–773

5.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,” arXiv preprint arXiv:1802.06955, 2018. Wang B., Qiu S., He H. (2019) Dual Encoding U-Net for Retinal Vessel Segmentation. In: Shen D. et al. (eds) MICCAI 2019. Lecture Notes in Computer Science, vol 11764. Springer, Cham, 2019.

6. Li, L., Verma, M., Nakashima, Y., Nagahara, H., Kawasaki, R.: Iternet: Retinal image segmentation utilizing structural redundancy in vessel networks. In: The IEEE Winter Conference on Applications of Computer Vision. pp. 3656–3665 (2020)

7. Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon. Cbam: Convolutional block attention module. In The European Conference on Computer Vision (ECCV), September 2018.

8. Fang Z., Chen Y., Nie D., Lin W., Shen D. (2019) RCA-U- Net: Residual Channel Attention U-Net for Fast Tissue Quantification in Magnetic Resonance Fingerprinting. In: Shen D. et al. (eds) Medical Image Computing and Computer Assisted Intervention – MICCAI 2019. Lecture Notes in Computer Science, vol 11766. Springer, Cham, 2019