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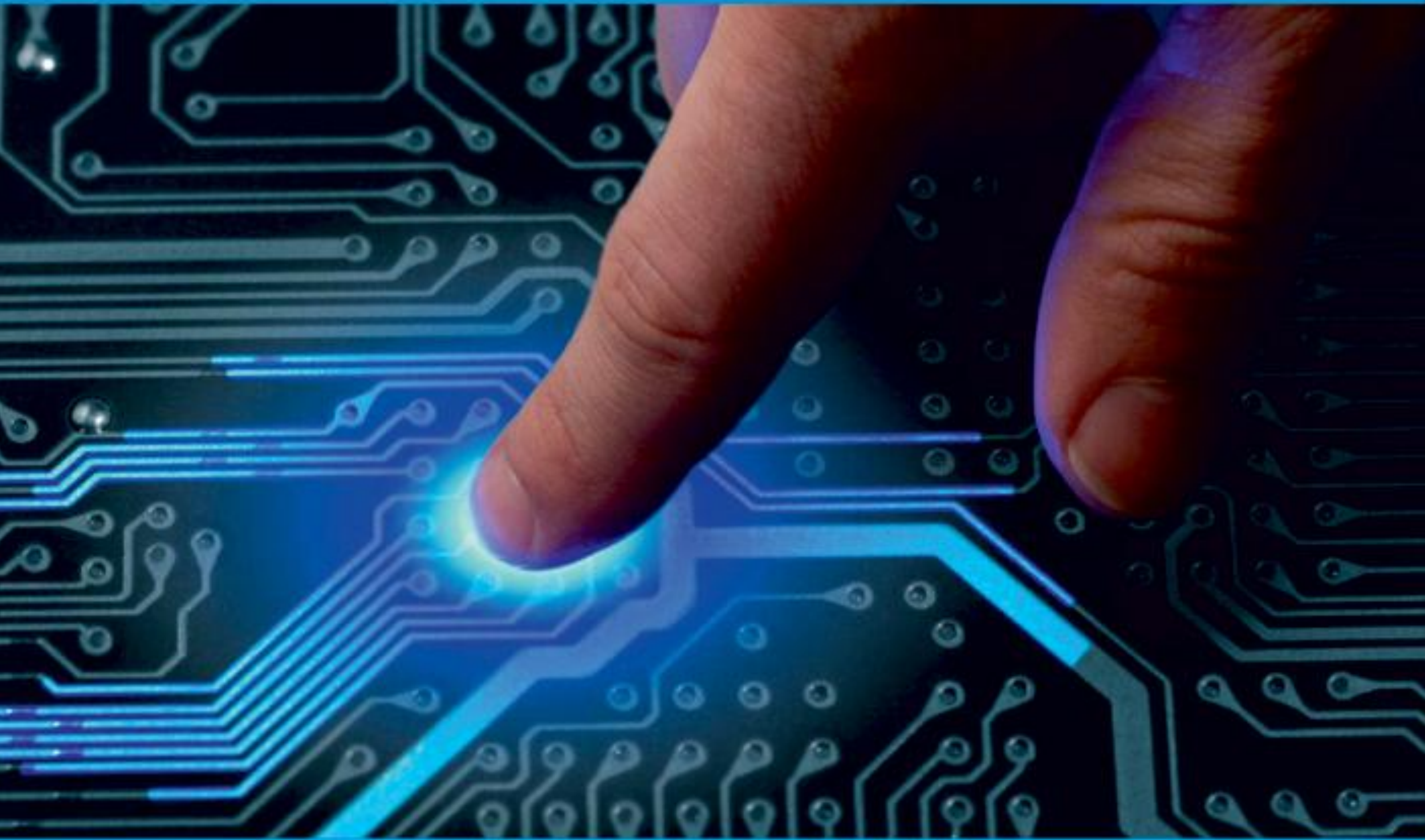

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Retinal Blood Vessel Segmentation using ESOL U-net Architecture

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ABSTRACT: 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. In this paper we are extracting blood vessels from retinal fundus images using ESOL U-net architecture. The architecture is very similar to U-net architecture only even layers have three convolutions followed by ReLU where as odd layers have only single convolution followed by ReLU. U-net has already shown promising results, designing and implementing ESOL U-net technique gave even better results.

KEYWORDS: Convolution neural networks, retinal blood vessels, ReLU, U-net, ESOL U-net

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 get the blood vessels segmented. Some of them involve image pre processing techniques and other involves machine learning techniques.

II. RELATED WORK

From past two decades researchers are coming with multiple algorithms that segment blood vessels from retinal fundus images. Some of them involve 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. Inspired from U-net there are many architectures designed such as [1], [2] and [3]. These works also showed some decent results in terms of accuracy.

III. PROPOSED ALGORITHM

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 designed a new architecture based on U-net. We named this architecture as Even Strong and Odd Lite U-net in short ESOL U-net. It is named because in the each odd step of U-net we removed a convolution layer and at each even step we added an extra convolution layer. We added this to shift the complexity for each layer in the normal U-net. If we compare the architecture of ESOL U-net with U-net architecture the number of convolutions changes at even number of steps we have additional convolution layer and at even step we have removed a convolution layer at the odd step of the U-net. Since there are more number of convolutions in even step and single convolution at even step we call it as Even Strong Odd Lite U-net or ESOL U-net.

The architecture takes an image as input and we apply convolution followed by rectified linear unit (ReLu) and then a max pooling is applied in the first step. In second step we have three convolutions each followed by ReLu and then a max pooling is applied. The third and fifth step involved similar to that of first step while fourth layer is similar to second step. At the end of fifth step we do up sampling similar to the step we do at U-net. We can observe the difference between the ESOL U-net and U-net is given in below pictures.

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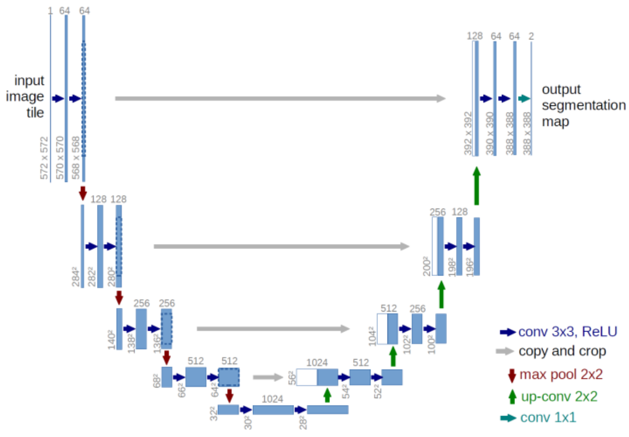

Fig1. U-net architecture

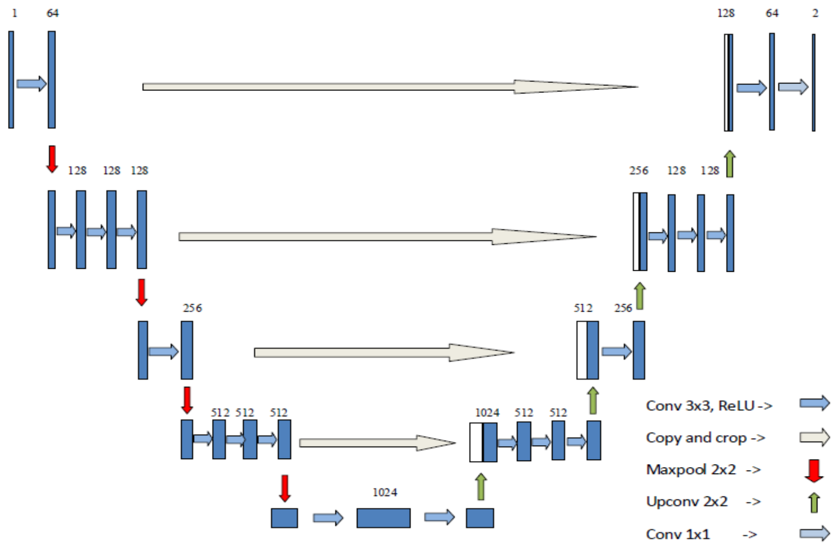

Fig2. ESOL U-net Architecture (our method)

IV. EXPERIMENT

We used two public datasets DRIVE and STARE to train and test our model. 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 we used two hundred epochs with learning rate of 0.001 and dropout would be 0.1. To estimate the performance we calculated the accuracy, area under ROC curve, sensitivity, specificity and f1 score of the model.

V. 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 0.9674 and specificity 0.9889 and for STARE dataset we achieved sensitivity of 0.8395.

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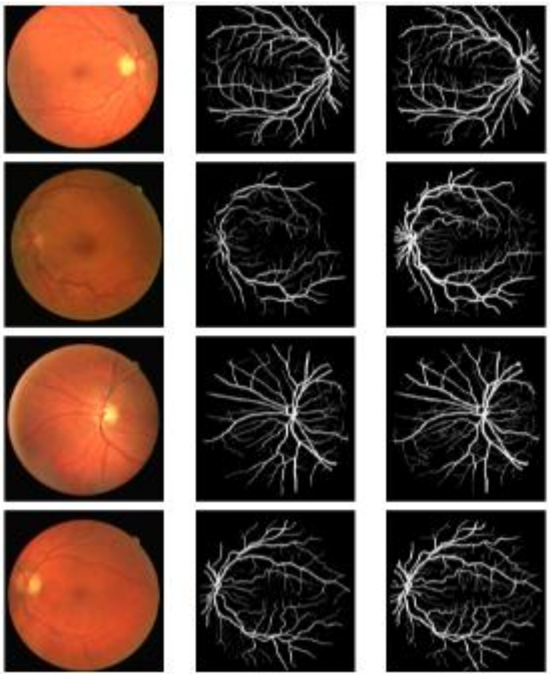

Fig 4. DRIVE dataset color images, image predicted by model and ground truth

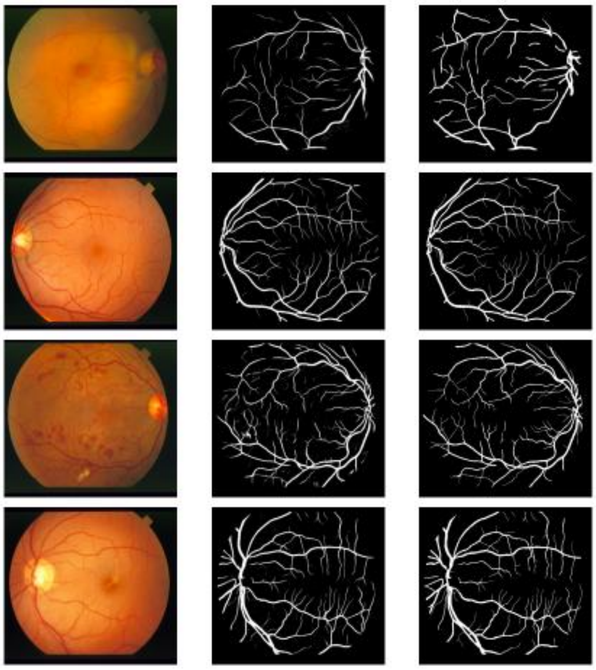

Fig3. STARE dataset color images, image predicted by model and ground truth

Tabel 1: Results on DRIVE dataset

Metrics	Acc	AUC	Sensitivity	Specificity	F1 Score
U net [1]	0.9531	0.9755	0.7537	0.9820	0.8012
R2 U net [2]	0.9556	0.9784	**0.7792**	0.9813	0.8171
Recurrent U net [2]	0.9556	0.9782	0.7751	0.9816	0.8155
Iternet(patched) [3]	0.9573	**0.9816**	0.7735	0.9838	**0.8205**
ESOL	**0.9674**	0.9809	0.7423	**0.9889**	0.7993

Tabel 2: Results on STARE dataset

Metrics	Acc	AUC	Sensitivity	Specificity	F1 Score
U net [1]	0.9578	0.9772	0.8288	0.9701	0.7770
R2 U net [2]	**0.9712**	**0.9914**	0.8298	0.9862	0.8171
Recurrent U net [3]	0.9706	0.9909	0.8108	0.9871	**0.8396**
Iternet(patched) [3]	0.9701	0.9881	0.7715	**0.9886**	0.8146
ESOL	0.9700	0.9882	**0.8395**	0.9815	0.8198

VI. CONCLUSION

In this paper, we presented ESOL U-net and implemented it to segment blood vessels from retinal images. DRIVE and STARE public datasets are used for training and testing. The ESOL U-net is introduced to get better results by reducing a convolution layer in odd steps and increasing a convolution layer in even steps in the U-net. The results are decent enough and obtained better results for few evaluation metrics when compared with actual U-net architecture.

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