Retinal Blood Vessel Segmentation using odd Heavy U-net Architecture

T. Vineela[1], Nagandla Hema Latha[2], Nagalla Vindhya Sree[3], Kandula JayaSree[4], Desaboina TejaSri [5]

[1] Assistant Professor, ECE, Vasireddy Venkatadri Institute of Technology, Andhra Pradesh, India
[2] Student, ECE, Vasireddy Venkatadri Institute of Technology, Andhra Pradesh, India
[3] Student, ECE, Vasireddy Venkatadri Institute of Technology, Andhra Pradesh, India
[4] Student, ECE, Vasireddy Venkatadri Institute of Technology, Andhra Pradesh, India
[5] Student, ECE, Vasireddy Venkatadri Institute of Technology, Andhra Pradesh, India

ABSTRACT

Blood vessel segmentation plays a vital role in computer aided diagnosis and treatment of retinal diseases. This is the reason why blood vessel segmentation has gained wide popularity among researchers. In this project we implement blood vessel segmentation based on an improved Odd heavy U-NET convolutional neural network (CNN) architecture. The architecture is very similar to U-net architecture only even layers have three convolutions followed by ReLU whereas odd layers have two convolutions followed by ReLU. The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization. Multiscale input layer and dense blocks are introduced into the conventional U-NET, so that the network can make use richer spatial context information. Especially for thin blood vessels, which are difficult to detect because of their low contrast with the background pixels, this segmentation results have been improved. This is the simplest architecture used for recognition of various retinal diseases. We show that such a network can be trained end to end from very few images and performs the prior best method. Further, the segmented outputs were able to cover thinner blood vessels better than previous methods aiding in early detection of pathologies.

Keyword : - *Convolution neural networks, retinal blood vessels, ReLU, U-net, Odd heavy U-net*

1. INTRODUCTION

Eye is a sense organ that helps human to watch surrounded objects. There are different types of eye diseases. Some of them are Cataract, Diabetic Retinopathy, Glaucoma. Retinal diseases cause damage to any part of the retina. Untreated retinal diseases can lead to severe vision loss and even blindness. Some of the eye diseases can be identified with the help of retinal images. These retinal images are called fundus images. Studying these fundus images helps doctors in identifying the right diseases. It is difficult to study the fundus images either because of all the other parts of retina might also get reflected on the image or there might be chances for doctor making errors while reading. So, image segmentation comes into picture so that we can extract only blood vessels or required part of an image we need and eliminating others.

2. LITERATURE SURVEY

There are various methods used in extracting retinal blood vessels from fundus images. Some of them involve normal pre-processing techniques while others involve machine learning based techniques. There are few advanced techniques that use deep learning methodologies that include convolution layers. One of such architecture is U-net architecture.

2.1 U-net Architecture

The network architecture is illustrated in figure given below. It consists of a 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 down sampling. At each down sampling step, we double the number of feature channels. Every step in the expansive path consists of an up sampling 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.

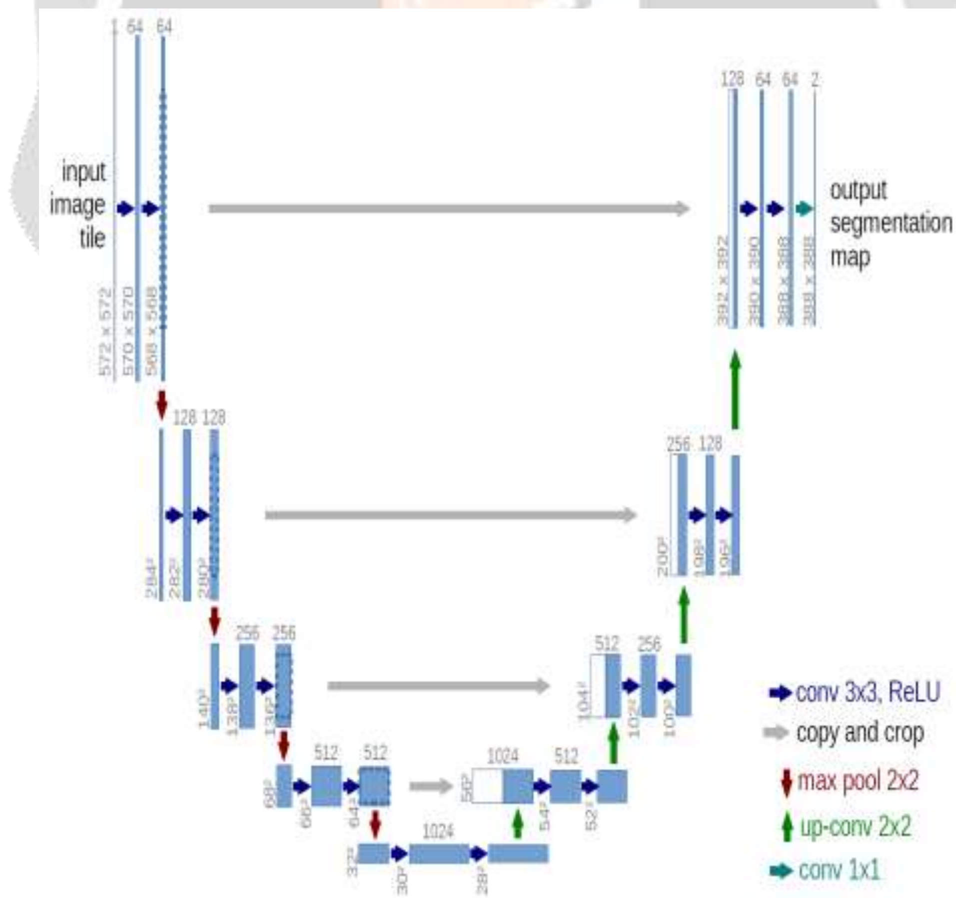

Chart -1: Architecture of U-net

2.2 Different types of U-net Architectures

- Internet Architecture
- Deformable U-net
- Ladder Net
- BCD U-net

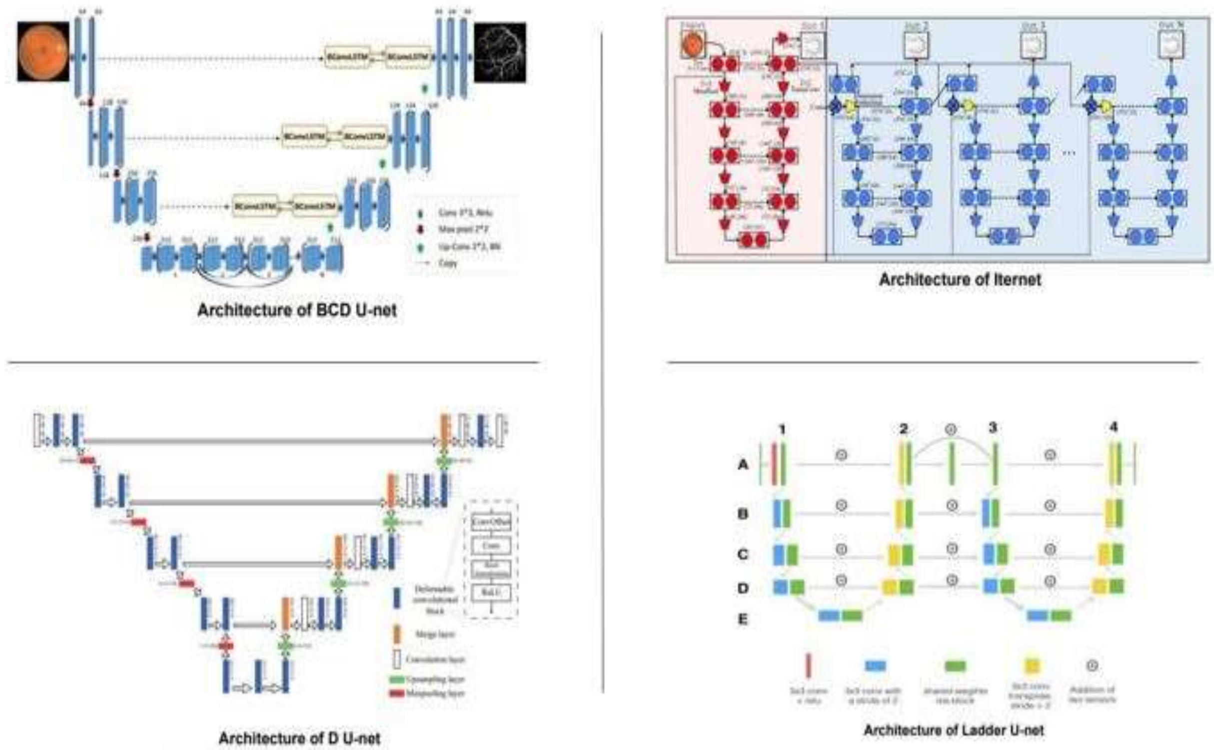

Chart -2: Different types of U-net

3. PROPOSED METHOD

Inspired from U-net architecture we have designed, trained and tested a different U-net architecture. It gave decent results in few evaluation metrics, and it gave almost equal result with the reduced complexity as that of parent U-net architecture. The different U-net architecture we proposed is Odd Heavy U-net.

3.1 Odd Heavy U-net

In Odd Heavy U-net we add a convolution layer or convolution followed by a non-linearity in odd numbered layers and kept the two convolutions followed by non-linearity in even numbered layers. Hence, that is the reason behind the naming convention of this U-net as the number of layers in odd places is more compared to even place. The left side part of the U-net is known as contraction path which involves three 3x3 convolutions in odd places and in even places two 3x3 convolutions followed by non-linearity. The right-side part is known as expansion path which involves same type convolutions in the contraction path. The expansion path is meant for image reconstruction. Between the two paths a network is present which acts like bridge between them.

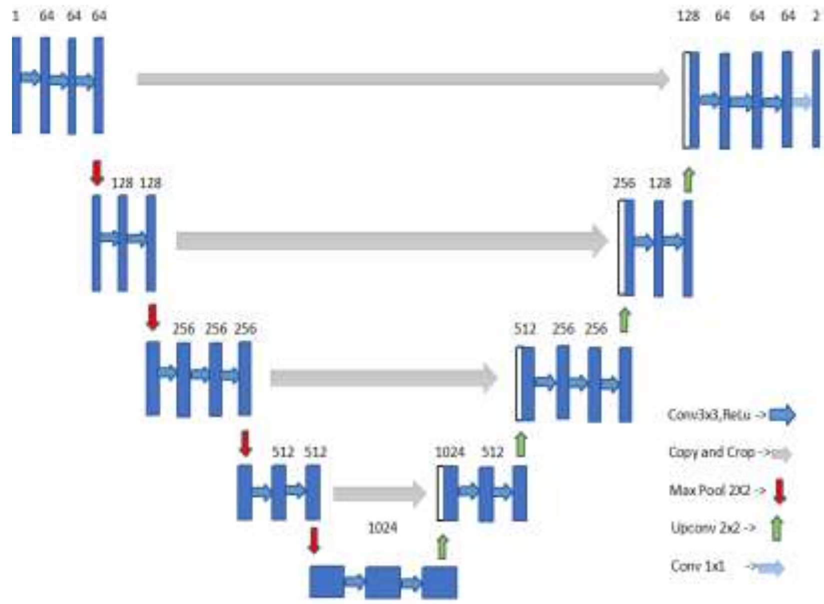

Fig -3: Odd Heavy U-net

3.2 Experiment setup

We used two public retinal fundus images datasets to perform our operation. They are DRIVE and STARE. We performed experiments on both datasets. The details of both the datasets are given below.

DRIVE Dataset

- Number of Images = 40
- Number of Training images = 20
- Number of Testing images = 20
- Resolution = 565 x 584

STARE Dataset

- Number of Images = 20
- Number of Training images = 16
- Number of Testing images = 4
- Resolution = 700 x 605

3.3 Observations and Results

Table -1: Test results for DRIVE dataset

Type of U-net	Accuracy	AUC	Sensitivity	Specificity	F1 Score
U net	0.9531	0.9755	0.7537	0.9820	0.8012
D U net	**0.9729**	**0.9868**	0.7428	**0.9920**	0.8079
R2 U net	0.9556	0.9784	**0.7792**	0.9813	0.8171
Iternet(patched)	0.9573	0.9816	0.7735	0.9838	**0.8205**
ESOL	0.9674	0.9809	0.7423	0.9889	0.7993
ELOS	0.9682	0.9821	0.7599	0.9882	0.8073
Odd Heavy U-net	0.9674	0.9819	0.7506	0.9881	0.8012

Table -2: Test results for STARE dataset

Type of U-net	Accuracy	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
Iternet(patched)	0.9701	0.9881	0.7715	0.9886	0.8146
ESOL	0.9700	0.9882	**0.8395**	0.9815	**0.8198**
ELOS	0.9692	0.9848	0.7835	0.9855	0.8045
Odd Heavy U-net	0.9647	0.9773	0.6895	0.9889	0.7598

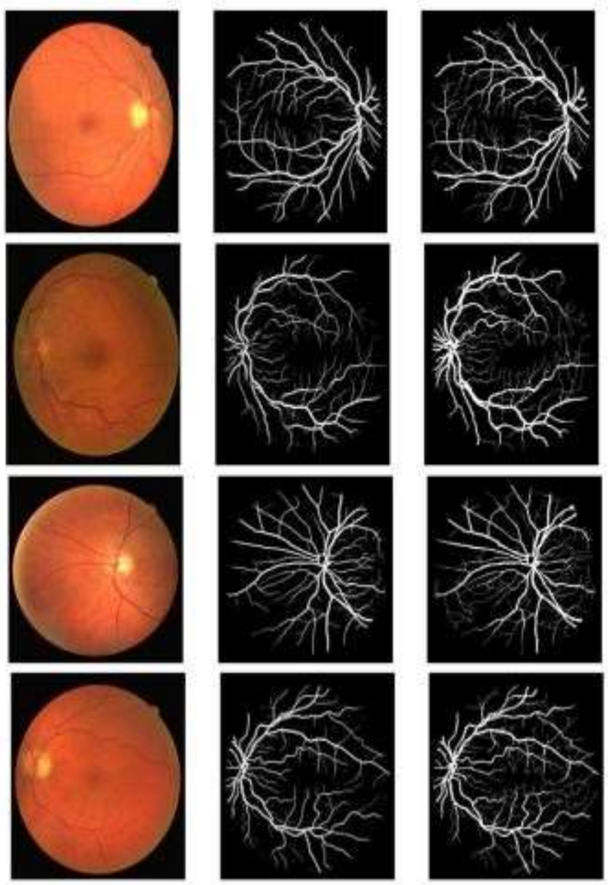

Fig -4: Tested output from an image in DRIVE Dataset

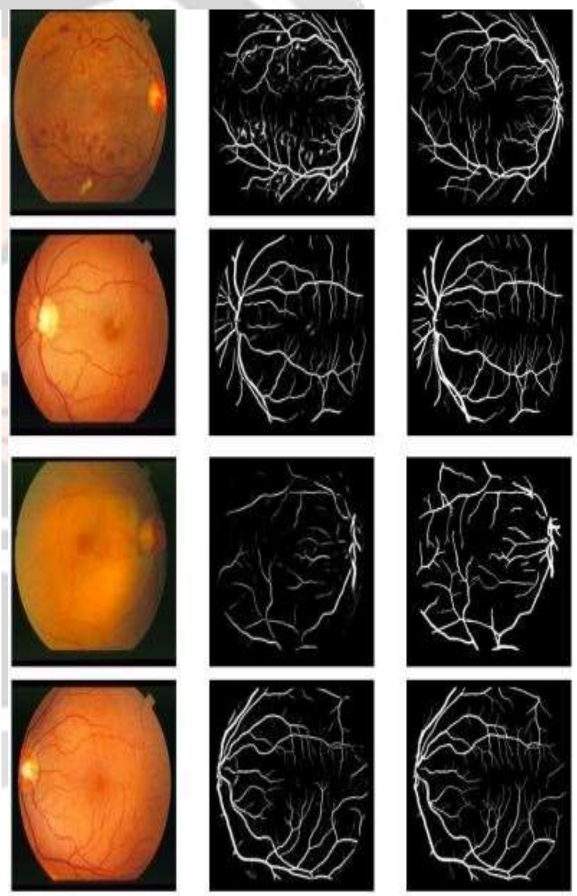

Fig -5: Tested output from an image in STARE Dataset

4. CONCLUSIONS

Retinal blood vessel segmentation has an important role in medical industry. There are many diseases that can be detected by segmenting retinal blood vessels. U-net is one of the retinal deep learning techniques which gave very good results. Based on this U-net other architectures are designed and all of them gave very decent results. All of them gave promising results. And some of them gave best results in terms of sensitivity and specificity when applied on DRIVE and STARE datasets.

5. REFERENCES

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