Digital Retinal Images For Vessel Extraction

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***Abstract*— Retinal Images and it's information is used to diagnose the possible retinal diseases such as diabetic retinopathy. However, due to non linear radiance and variance in modalities, the dissimilarity between blood vessels and background is very small. This problem embeds a need to perform some operations to segment blood vessels from it's retinal images and improves the segmentation accuracy.In this study, we are using the modified convolutional neural network (CNN) architecture named as Fully Dense UNet (FD-UNet) using for the segmentation of retinal blood vessels from their respective images .**

***Index Terms*—Image reconstruction, image augmentation, Dense U-net, Retinal blood vessels, biomedical imaging**

I. INTRODUCTION

Feature segmentation is an important problem in image processing when there is contrast between the background and the feature. With the help of Computer vision we can perform segmentation by taking this problem as a binary classification problem. The growing application of Computer vision has enable the bio medical science community to optimize diagnostic process and visualisation. Ophthalmology has benefited greatly from it which until few months ago depends heavily on visually oriented tasks.

The Retina is the innermost part of the eye. In recent years, much research has been made into developing an automatic diagnostic system to cope up with diseases like Diabetic retinopathy. Retinal images analysis, it's segmentation and inspection of it's features like length, width, tortuosity serves as significant indicators for analysing the presence of retinopathic diseases.

The manual grading of the images, low contrast and analysing is having high time complexity and requires alot of mental concentration. Hence, the need for software tools that can segment the blood vessels from it's retinal images for various studies.

In the last decade, a lot of research has been made for developing algorithms for blood vessel segmentation. The database is provided by DRIVE database. In this paper, we will apply Dense U-net Model for Vessel Segmentation task of retinal images. We will use separate techniques to leverage the small test like batch normalization, applying Leaky Relu and changing Dense Layer. Due to this, we achieved an accuracy of 98.18% on all images. This paper described below as , part 1 gives the Introduction of the research work, part 2 gives the related work. part 3 tells the Methodology we propose to solve the problem. part 4 gives the results and discussions about the work and we conclude the paper with Conclusions and Acknowledgement. The dataset consists of training set and ground truth set and the resulting images are set to compare with the ground truth image for loss evaluation and training.

II. Related work:

Image segmentation is basically the segmentation of some specific features from an image, here we are working on blood vessel segmentation. The purpose of doing image segmentation is to have proper vision over blood vessels for doing diagnostic retinopathy. Olaf Ronneberger, Philipp Fischer, and Thomas Brox have done previous work by publishing the study that shows different results on leaverging U-net model, their model has achieved an accuracy of 92.13% consisting of 23 convolutional layers.They have also used data augmentation for model learning the wanted invariance and robustness properties. A model called Retina U-net was also developed by group of students in Zhejiang University(paper [2]) on top of U-net structure and got accuracy of 97.90%.However,we modify the conv2d layer to dense block and reduced the number of layers from 23 to 10 and finally got better result. This method however do not achieve very good results when performing on larger epochs and on images with a high number of exudates.

III METHODOLOGY

3.1 Dataset:

The public available DRIVE database has is there to perform research studies for segmentation purpose and regarding blood vessels from Retinal images.. Our Dataset has been obtained from a screening program in Netherlands.The 40 images are taken randomly from a group of 400 diabetic patients from the age 20 to 85 years. Out of that 40 images, 33 people do not show any signs of damage or diseases but 7 do show signs of diabetic retinopathy. For this purpose, the segmentation process is required to better study the ophthamology and concerned patients. There are 40 images in total and we have 20 images for training and 20 for testing purpose.

3.2 MODEL:

The proposed segmentation method is summarized in Fig. 1. It consists of a sequence of steps namely, Convolution 2D layer, batch normalisation Max pooling, image generation and morphological processing for enhancing features. Each of these steps is detailed in the following section

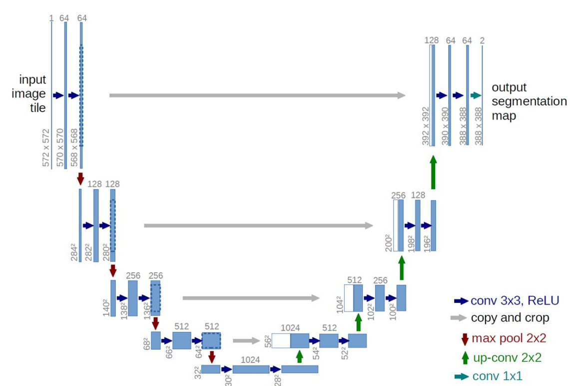

Fig 3.2 U-net architecture containing filters from 32x32 to 512x512

3.3 Convolution 2D

This Convo2D is used for working with the digital images.The image is represented as 2D matrix and a convolution operation is performed with smaller matrix.That small matrix is called as 2D Kernel The U-net model uses Convolution 2D operation for the processing of image for extraction of features. In our model, we are using 10 convolution 2D layers with the filter size varying as 32x32, 64x64,128x128,256x256 and 512x512.

3.4 Batch Normalisation

We are processing the images in batches. As we know different features have different characteristics.That's why we are performing batch normalisation to speed up the process. In our model, this step is implemented because we are processing the input images on batches. After applying the convolution 2d function, we are normalizing the last layer outputs by using the mean normalization

3.5 Max pooling 2D

Max pooling is the process of sub-sampling for the purpose of feature extraction.We down-sample the 2D matrix which is coming as input and br reducing its dimensions extracting the features. We have used Max pooling with every convolution 2D layer with the 3*3 convo and using the stride factor of 5 doing the downsampling.We are moving from64*64 to 512*512 Thus going down by factor of 2.

3.6 DenseBlock:

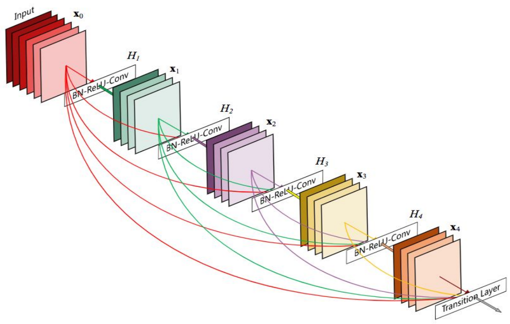

Fig 3.6.1 The five layer dense block having growth rate of 4. Every layer consider the features of all previous layers.

In DenseNet,we basically uses the growth factor which decides for feature consideration of how many previous layers for extracting new features. In our model, we have used denseNet because it removes the vanishing-gradient problem, makes strong the feature movement, lets feature reuse, and it's made to decrease the number of parameters For the feature of segmentation, recent studies shows that dense convolutional networks proves to be best.

3.7 Training

Our model is trained on 40 images which is 20 images on training and 20 images validation on NVIDIA tesla GPU. The information about training.
Number of Epochs: 100
Batch size: 20
Patch size: 96x96
Max filter : 512x512.

IV. Experimental Results.

We empirically demonstrate Dense U-Net's effectiveness on several hyper parameters and compare our all results , and also with other architectures and implementations. After training on DRIVE dataset, our results are as follows.

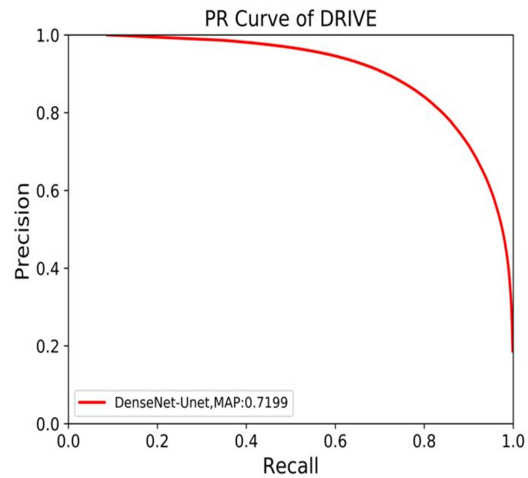

Fig 4.1 PR curve on DenseNet-Unet Map: 0.7199

Precision-Recall is the factor that depicts the successful prediction in the highly imbalanced classes. In information retrieval, precision shows how relevant are the results and recall is the measure of how much of the relevant results are true.

PR curve is the curve between precision and recall. Greater the area under the curve shows both high recall and high precision. High score for both shows that our model is classifying the vessel pixels and non vessels pixel accurately. Having the confusion matrix we can have:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

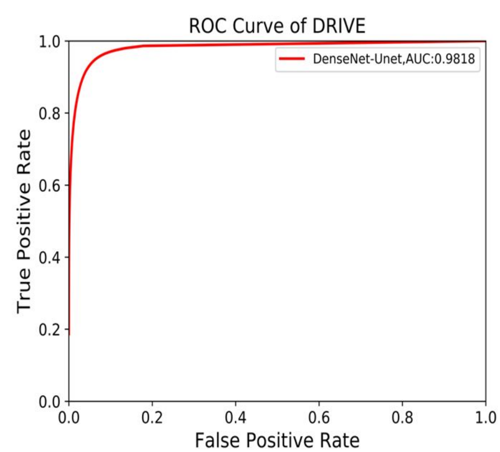

Fig 4.2 The ROC Curve: Value- 0.9818

When there is classification task, we can use AUC-ROC Curve with surety.It is the important evaluation factor for checking model’s performance.
AUC is the measure of how the classifier is capable of separating.It depicts how the model is capable of doing accurate separation between classes.
Higher AUC, we can say better is the model is predicting at 0 and 1.
The ROC curve value is 0.9818 which depicts that our model is 98.18% capable of distinguishing between classes correctly.

Methods	AUC ROC on DRIVE
Liskpwski	0.9790
Retina-Unet	0.9790
VesselNet	0.9841
THIS Model	**0.9818**

Table 4.1 AUC ROC curve of Different models

This our model is capable of distinguishing between the classes accurately by the factor .9818.which is somewhat lagging behind the already work done by Xing ChenCong.But the results are quite satisfying and we will be looking for future possibilities of improving our model so that we can achieve more better segmentation results.

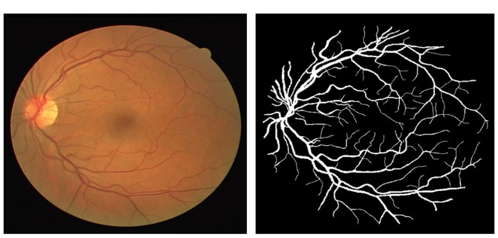

Fig 4.2(a) The Original Retinal Image (b) The Ground Truth Image

The colorful image is the original image and it has been cropped around the FOV(45 degree) and is compressed in JPEG format.

Where as Ground Truth image is the manual segmentation of the given image by the experienced experts to compare the segmentation results of the model.

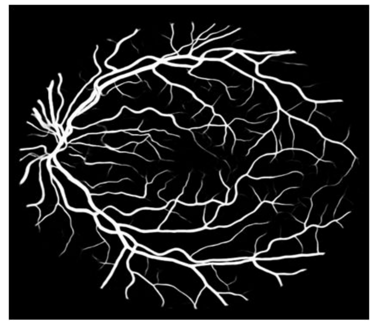

Fig 4.4. The Resulting Image

The image above is our resulted image which is on average 98.18% accurate compared to ground truth.

V. Conclusion:

The performance of this segmentation model for the retinal image for each subtask is comparable with the retina-Unet@github but not able to beat VesselNet@github whose highest accuracy is 98.41% where as our best result got was 98.18%. As a future work, we will consider doing hyper-parameter tuning and try different convolutional 2D layers. Second, Attention based Unet and DeepLab-v3+ are also worth to try.

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VII. References:

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