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Deep Convolutional Networks based on encoder-decoder architecture for automatic Optic Disc segmentation in retina images

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ABSTRACT

Currently, deep convolutional neural networks (CNNs), are the latest methods applied to modern computer vision research technology. There are numerous architectures attributed to convolutional neural networks, based on deep learning methods applied to modern computer vision technology some of which are used for image segmentation; such as Fully Convolutional Networks (FCN), U-net, and LinkNet. In the scope of this study, we focused on the architectures of convolutional neural networks in particular. We present this architecture, and how it can be used for Image Segmentation. The novel model is presented to an automatic segmentation of the Optic Disc from retinal images. We use the Indian Diabetic Retinopathy Image Dataset (IDRiD) as dataset, our proposed CNN model based on an encoder-decoder model, this concept was adopted from the U-net architecture. The idea consists to apply other encoder-decoder levels in order to get more feature maps. The model was implemented with keras in python. We also implement other models such as FCN and U-net to compare their results. A brief description of the proposed model, training with data augmentation, validation and predictions are given. In the end we conclude that adding some levels on original architecture achieves a better result. Finally, an overview is given of future usage of convolutional neural networks for image segmentation problems in medical imaging contexts and the challenges involved therein.

Key words: Convolutional Neural Networks; CNN Architecture; Deep Learning; Image Segmentation; Deep Network; Optic Disc Segmentation.

1. INTRODUCTION

Deep CNNs uses a modern technique for image segmentation, inspired by the visual system's structure itself. In particular, by the model proposed in [1] they have been applied to visual tasks since the late 1980's. In [2] the author proposes a self-organized neural network that has the ability of pattern recognition similar to a human being, called "neocognitron". It also possesses the ability of unsupervised learning. The author has led to developing the first convolutional neural networks. Using computational models based on local connectivities in cascade between neurons, and on hierarchically organized transformations of the image, found in Neocognitron[2]. A concept that describes when neurons with the same parameters are applied on patches of the previous layer at different locations, a form of translational invariance is acquired.

In 1998 Yann LeCun and his collaborators designed Convolutional Neural Networks employing the error gradient and attaining very good results in a variety of pattern recognition tasks[3], [20]. They have become the standard in many computer vision tasks, such as image classification, object detection [11],[12], image segmentation [9],[28],[14], and others. A Review article [5]that provides some examples of the most significant deep learning schemes used in computer vision problems. Examples include; Convolutional Neural Networks, Deep Boltzmann Machines, and Deep Belief Networks, and Stacked Denoising Autoencoders. Also, an account of their history, structure, advantages, and limitations is given; Followed by a description of their applications in various computer vision tasks, such as object detection, facial recognition, action and activity recognition, and human pose estimation.CNNs also are efficient for numerous problems like brain tumor classification [31] in medical imaging and speech recognition [32] task in natural language processing.

In CNNs, layers of convolution and subsampling consist of several "levels" of neurons, called feature maps, or channels. Each neuron of this layer is connected to a small section of the previous layer, called a receptive field. In the case of an image, a feature map is a two-dimensional array of neurons, or simply a matrix. Other measurements can be used if another kind of data is taken as an input, for example, audio data (one-dimensional array) or volume data (three-dimensional array) [5],[13].

Image segmentation is used to localize objects and contours within images, there are several techniques used for this process. Recently, the Deep Learning architecture is among the most modern of techniques used in image segmentation problems, in this section, we present some architectures of CNNs [1],[2],[3],[20]used in Deep Learning for image segmentation.

Image segmentation with CNNs [1],[2],[3],[20] involves feeding segments of an image as an input to a convolutional neural network, which labels the pixels. In CNNs the image will not be processed immediately, it is instead, scanned in sections using groupings of a few pixels such as (3,3) or (5,5) or others until all the pixels of the image are processed and mapped[3].

This paper presents a method for automatic Optic Disc(OD) segmentation in retina fundus Images based on CNNs encoder-decoder architecture. Several methods and techniques are used for OD segmentation, in [10] the authors present an OD contour detection of fundus images, by proceeding of elimination of vascular structure using vesselness filter and implicit region-based active contour model. Another method is detailed in [4] it consists of detecting the OD by using morphological and edge detection techniques followed by the Circular Hough Transform to obtain a circular OD boundary approximation, which requires a pixel located within the Optic Disc as initial information.

Our proposed method based on CNNs, uses an encoder-decoder model like U-Net [17] architecture to perform the segmentation of OD on the IDRiDDataSet. The U-Net model is a convolutional neural network encoder-decoder based, that was developed for biomedical image segmentation [17]. It became the most popular architecture in the medical imaging community. In the following section, we outline our methodology, evaluate and compare different FCN based models, U-net and our proposed model.

2. METHOD

For confirmation purposes we made changes to the U-net based model. An encoder-decoder model is proposed to automatic Optic Disc(OD) segmentation in retina fundus Images. The architecture of our model is presented in Figure1. The main concept is applying additional levels to the original U-net architecture, in order to have more feature maps and get a better segmentation results, as shown in Figure 1: The input as RGB images from the retina datasets is used with the convolutional operation (1)[27] that to learn features from images.

Followed by max-pooling (2) operation defined as to encode network, then a deconvolution (3) [7], [8] operation is used to decode network, instead of simple up-sampling used in [17].

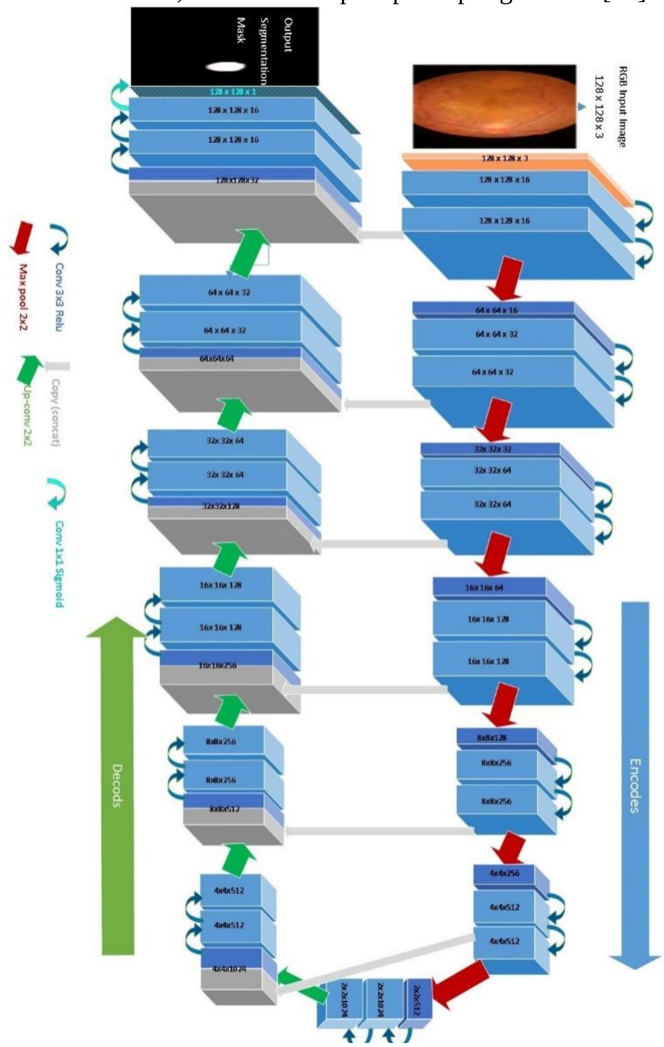

Figure 1: The proposed model based on encoder-decoder architecture for automatic Optic Disc segmentation in retina images dataset.

At every level we concatenate the output layer from each decode level to input layer after deconvolution operation. To avoid the network from overfitting we use the dropout layer concept for each convolutional operation. Finally, the fused features are used for the final to get the Optic Disc mask as output. An overview of automatic optic disc learning process is presented in Figure 2.

The convolution is defined in [27]as:

$$Y_j^l = f(\sum_{i \in M_j} w_{i,j}^l X_i^{l-1} + b_j^l) \qquad (1)$$

Where X_i^{l-1} is the input image, Y_j^l as output, $w_{i,j}^l$ and b_j^l are respectively weight and bias of the *j*filter in the *l* layerand *f* is the activation function.

The max pooling operation as defined in [29]:

$$y_i = max_{N\times N}\left(x_i^{n\times n}\, u(n,n)\right) \qquad (2)$$

Where $u(n,n)$ is the window function applied to the input. The deconvolution defined in [7], [8] as:

$$y'^{c}_{1} = \sum_{k=1}^{K_1} z_{k,1} \otimes f_{k,1}^{c} \qquad (3)$$

Wherey' is the deconvolutional layer with c color channels formed by convolving 2D feature maps $z_{k,1}$ with $f_{k,1}^{c}$filters and$\otimes$ is the 2D convolution operator.

As shown in Figure 2 the process for automaticoptic disc segmentation is divided into three main stages:

The first stage consists of preparing the data by reading it from datasets, we resize the dataset from 4288 x 2848 to 128 x 128 pixels, then a pre-process is applied to images and labels with data augmentation techniques [25], [21]included in Keras image pre-processing, in our case we use the following operations; rotation by 45, width and Height shifting 0.1, shear intensity 0.15, zoom 0.1, horizontal and vertical flip, then a constant fill mode is applied.

In the second stage, we create and build the different models of network architectures implemented for our experiment with Keras, then the network is invoked to learning party. In [30] the author has applied a deep CNNs architecture for Optic Disc detection, in his experiment he gets a better result with 500 training epochs. We also opt for the choice of 500 epochs to train our model, for each epoch the loss function is calculated, at the end of this stage history loss function is saved as a .CSV file for scatter presentation and analysis.

Finally, in the third stage we save the learned network as an hdf5 file for prediction usage and visual presentation of results. In next section we expose our experiments with dataset description and network implementation.

3. EXPERIMENTS

3.1 DataSets

We use a Database for Diabetic Retinopathy, called the Indian Diabetic Retinopathy Image Dataset IDRiD[23], this is the first database representative of an Indian population. It constitutes typical diabetic retinopathy lesions and normal retinal structures annotated at a pixel level. The dataset provides information on the disease severity of diabetic retinopathy, and diabetic macular edema for each image. This makes it perfect for development and evaluation of image analysis algorithms for early detection of diabetic retinopathy, this dataset was available as a part of "Diabetic Retinopathy: Segmentation and Grading Challenge" organized in conjunction with IEEE International Symposium on Biomedical Imaging (ISBI-2018), Washington D.C. The IDRiD dataset, is a new publicly available retinal fundus image database consisting of 516 images categorized into three parts: A. Segmentation, B. Disease Grading and C. Localization. For this experiment we focused on the Optic Disc labeled images, located in "A. Segmentation" directory. The training set of Optic Disc contains 54 images with mask labels, and the testing set contains 27 images with mask labels. Figure 3 presents sample images and segmentations of Optic Disc.

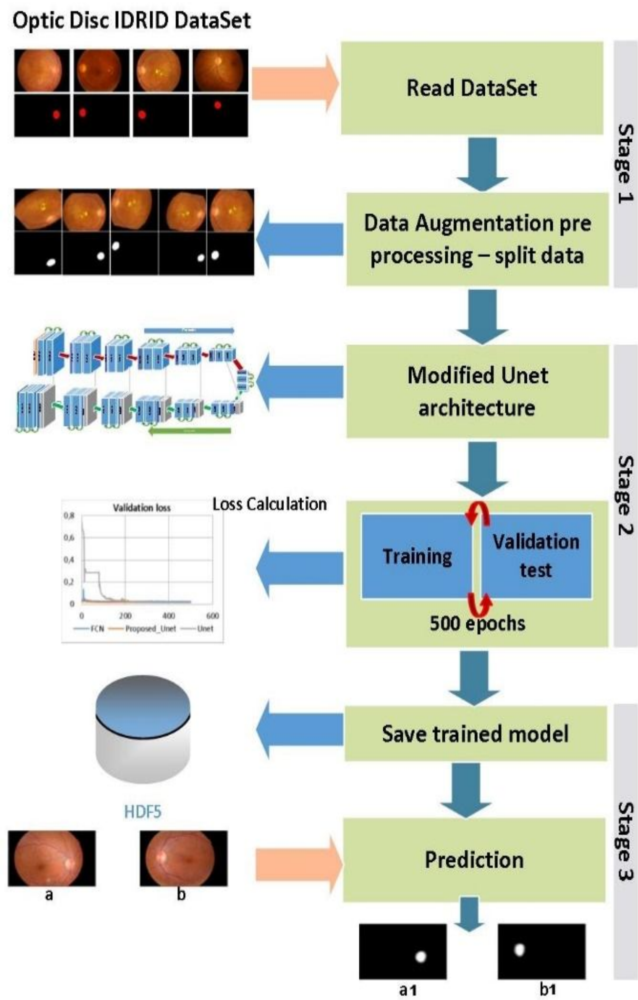

Figure 2: The overview of learning process for automatic Optic Disc segmentation.

Figure 3(a)

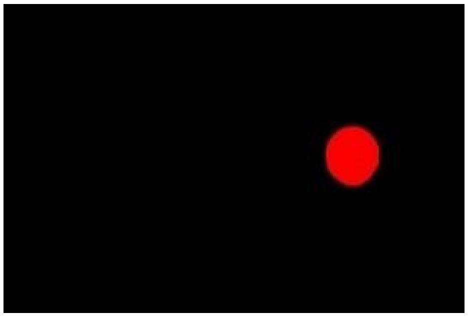

Figure 4(b)

Figure 5(c)

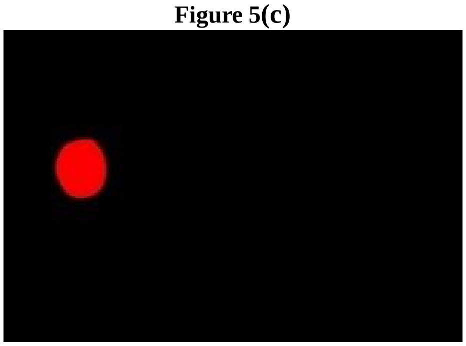

Figure 6(d)

Figure 7: Retinal photograph and Optic Disc annotations:(a,c) sample fundus image from the presented dataset; (b,d)sample optic disc label mask.

In the next section we describe the network architecture and implementation of models used in this experiments.

3.2 Network Architecture with Implementation

We present some CNNs network architecture used in Deep Learning. Thereafter an overview of used and implemented models for this paper is given:

Fully Convolutional Networks (FCNs) [16], use convolutional layers to process varying input sizes and can work more quickly. The output layer has a large receptive field and dimensions are similar or the same to that of the image, while the number of channels constitute the number of classes to predict. The convolutional layers can efficiently classify every pixel to get the context of the image for each object, including their location in the image.

U-Net[17]is a convolutional neural network that was developed for biomedical image segmentation [17]. It came the most popular architecture in the medical imaging community.

The network architecture, having an Encoder that extracts spatial features from the image, and a Decoder that constructs the segmentation map from the encoded features. The Encoder follows the typical formation of a convolutional network. It involves a sequence of two 3 x 3 convolution operations, followed by a max-pooling [29] operation with a pooling size of 2 x 2 and stride of 2. This sequence is repeated four times, and after each down-sampling, the number of filters in the convolutional layers is doubled. At the end, a progression of two 3 x 3 convolution operations connects the Encoder to the Decoder, succeed by one 1 x 1 convolution for output segmentation map.

Other architectures of convolutional network such as AlexNet[11],VGGNet[15], GoogLeNet[18], and ResNet[19] were appeared in ImageNet competition as winner respectively in 2012, 2013, 2014 and 2016. Although there are other architectures that we do not belong in this paper.

The proposed model based on U-net [17]architecture. The model consists of adding convolution operations, a tow level of 2x2 max pooling until obtaining at the end of max pooling operations a pixels extracted features, then some up-convolution operations, the final layer a 1x1 up-convolution is used to map each 16-component feature vector to the number of classes, in our case the output segmentation contains the Optic Disc mask prediction. Our model is bigger than original with 10 other convolutional layers as showed in Figure 1.

In [17]the author has been sing the mode called “valid” with no padding, that consists of a simple reduction in dimension from borders due to the convolutional layer, in our case we use the mode “same” the results in padding the input such that the output has the same length as the original input. The use of padding in the convolution layer involved reduction of spatial information, in [24] the authors studies the impact of padding scheme with AlexNet-based architecture on Faster R-CNN for vehicle detection, also the authors propose same-padding and valid-padding scheme to improve the performance compared with the original AlexNet configuration.

The parameters used in our experiments are described, for each convolutional layer of the network we use “he normal” as kernel initializer and Rectified Linear Unit[22] “Relu” (4) as activation function, except the final layer we use “glorot normal” (5) as kernel initializer and “Sigmoid” (6)[22] to map feature and get predicted mask. We choose the Adam for optimizer with default parameters, the network was trained by minimizing the binary cross-entropy (7) for loss calculation and maximizing "accuracy" for metrics.

1. The Reluactivation function is defined on [22] as:

$$f\left(x_{i,j,c}\right) = max\left(w_c x_{i,j}, 0\right) \quad (4)$$

where $x_{i,j}$ is the input pixel at index (i,j), and c is color channels ; when value is less than 0 it's become 0 otherwise it keeps its value.

2. The glorotnormaldefined in [6] as:

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_j+n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j+n_{j+1}}}\right] \qquad (5)$$

when W is a layer and U[-a,a] is a uniform distribution in the interval (-a, a) and n is the size of the previous layer(the numberof columns of *W*).

3. The Sigmoid activation function is defined in [22]as:

$$f(x) = \frac{1}{(1+exp(-x))} \qquad (6)$$

where x is the input and *f*the activation function.

4. The binary cross entropy as defined in [26]:

$$-\frac{1}{N}\sum_{i=1}^{N}\left[y_i \times \log\left(h_\theta(x_i)\right) - (1-y_i) \times \log(1 - h_\theta(x_i))\right] (7)$$

where N is the number of training samples, $y_i$is the target label for training samplei, x_i input for training samplei,and$h_\theta$is the model with neural network weights θ.
In the next section we will shed lights on the evaluation and the analysis of the method used in this experiment.

4. EVALUATION

We evaluate the performance of the proposed model on IDRiD dataset, they are 54 OD images labeled. Due to the small size of our dataset we can improve the performance of the model by augmenting the data we already have, to do this, we use the data augmentation [25],[21] techniques by applying transformations to generate additional samples. Deep learning frameworks usually have some built-in data augmentation utilities, we use the class Image Data Generator included in Keras Image Preprocessing, it generates batches of tensor image data with real-time data augmentation. The dataset was randomly divided as follows; 5% for visual presentation, the rest 95% was automatically split with data augmentation techniques as 60% for training, and 40% for validation.

5. ANALYSIS

In this section we discuss and analyze the performance of our proposed model, evaluated on IDRID dataset by validation loss calculation, based on binary cross-entropy loss function and visual observation. Figure 4 displays the final segmentation results in tow retina images for implemented models FCN, U-net, and proposed model: (a) present tow RGB retina images, we draw contours of segmentation results in original image, (b) present the mask annotation, (c) the segmentation result of our proposed model, (d) the segmentation of origin U-net and (e) the segmentation of FCN architecture.

We observe that the visual segmentation of U-net and proposed architecture models gives better results when approaching to the annotated label compared to FCN.
Table 1 shows the results obtained by loss function on the validation step for all implemented models.

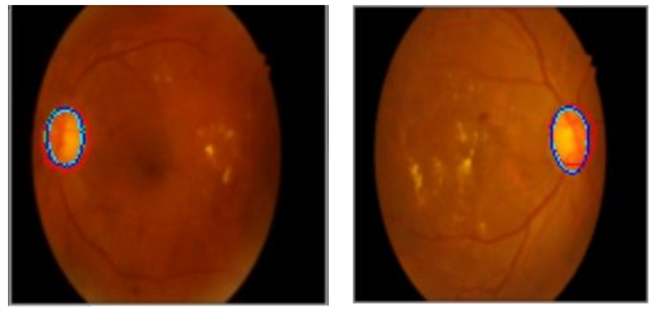

Figure 4(a) : Retina image ; contours:FCN, Unet, Proposed modelLabel

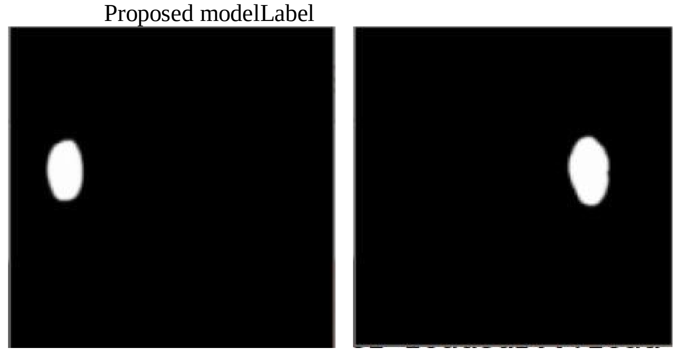

Figure 4(b): Manuel label mask

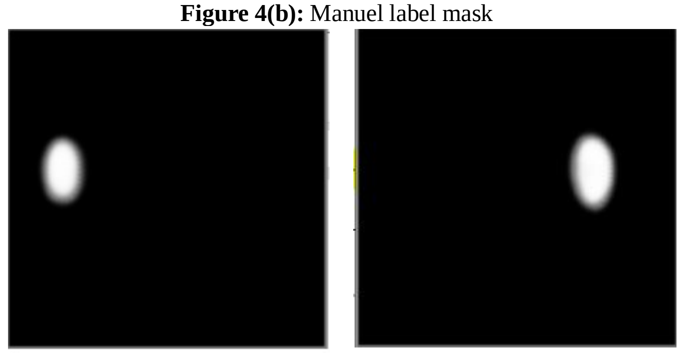

Figure 4(c): Our proposed model Predict

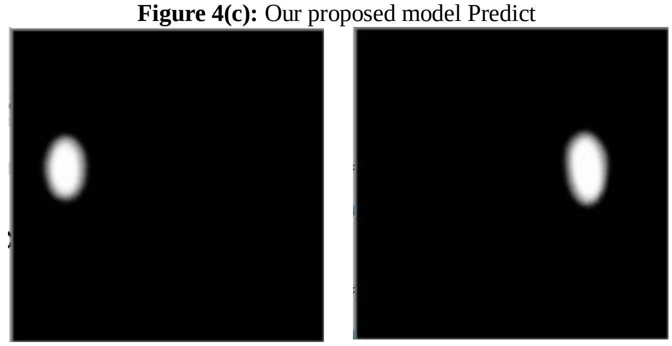

Figure 4(d) : Unet Predict

Figure 4(e): FCN Predict

Figure 8: The segmentation results in tow retina images from FCN, Unet and proposed model trained models with 500 epochs on IDRID datasets.

We observe that the segmentation of U-net and proposed model architectures gives better results when approaching the manual annotated label compared to FCN.

Figure 5 shows the results obtained by loss function on the validation step for all models.

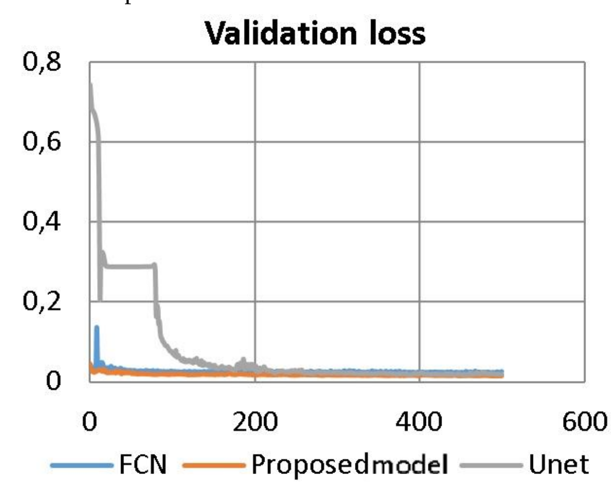

Figure 9: Scatter plot of history training for loss function.

Table 1: The binary cross-entropy loss function result for first, middle and last epoch

Epoch	FCN	Proposed model	Unet
1	**0,0434**	0,0440	0,7433
250	0,0237	**0,0166**	0,0272
500	0,0249	**0,0140**	0,0183

The scatter plot with smooth lines in Figure5 present the comparison of loss function for the different networks architectures training to 500 epochs. The binary cross-entropy loss function is presented respectively by blue color for FCN, red for Proposed model and gray for origin U-net. As shown in Figure 5 we get a better result with our proposed model applied to IDRiD dataset.

Table 1 shows the compared values of loss function get from first, middle and last epochs for all implemented models, we notice that we get the best result with our proposed model.

6. CONCLUSION

This document presents an encoder-decoder model for automatic Optic Disc segmentation in retina images. We Compare the proposed network model with the origin U-net and FCN, we obtain an effective semantic segmentation of Optic Disc. Our proposed model has achieved better results on Optic disc than the basic U-net network on IDRiD dataset, we demonstrate that adding some levels to the network can also through a better result.

The future work is to further generalize our improvements to other deep segmentation models, optimize and evaluate them on more Data Sets.

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