

Multi-dataset Training for Medical Image Segmentation as a Service

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Abstract: Deep Learning tools are widely used for medical image segmentation. The results produced by these techniques depend to a great extent on the data sets used to train the used network. Nowadays many cloud service providers offer the required resources to train networks and deploy deep learning networks. This makes the idea of segmentation as a cloud-based service attractive. In this paper we study the possibility of training, a generalized configurable, Keras U-Net to test the feasibility of training with images acquired, with specific instruments, to perform predictions on data from other instruments. We use, as our application example, the segmentation of Optic Disc and Cup which can be applied to glaucoma detection. We use two publicly available data sets (RIM-One V3 and DRISHTI) to train either independently or combining their data.

1 INTRODUCTION

1.1 Cloud based Segmentation

Segmentation is the process of automatic detection of limits within an image. In medical images we find a high variability both in the data sources and capture technologies used (X-ray, CT, MRI, PET, SPECT, endoscopy, etc.). Human anatomy also shows very significant variations.

Deep Learning methods are being increasingly used to process medical images (Litjens et al., 2017). The effectiveness of these systems is conditioned by the number and variety of the training images. If we want to implement cloud-based services, they will have to be trained with new data set samples periodically. These images will most probably come from different sources and, thus, we need to answer some significant questions: Should we train the networks specifically for images acquired with each of the available instruments? Is it possible to train a network with data from one instrument and make predictions for other different instruments? What happens if we train with combined data? It would be very difficult to implement a reliable image segmentation service without knowing the answer to these questions.

Several segmentation researchers (Sevastopolsky, 2017) (Al-Bander et al., 2018) have used several different data sets for their works, however, they always train and test with each of these data sets independently. In this paper we propose to compare this traditional method with a new approach where we preprocess and mix the data from several datasets and use it to create independent data sets for training and validation.

In this work we will use a generalized U-Net architecture as our training network, and study, as our example problem, the detection of the optical disc and cup in fundus images. However, the same techniques can be applied almost directly to the segmentation of 2D images in industrial applications, automatic driving, detection of people, etc.

1.2 Convolution / Deconvolution Networks

We will use a generalized U-Net (Ronneberger, Fischer, & Brox, 2015) as our example network as it is one of the most commonly used fully convolutional network (FCN) families for the segmentation of biomedical images.

The basic architecture of our network is shown in Fig. 1. The network consists of descending layers formed by two convolution layers with RELU

activation and dropout. The result of each layer is sub-sampled using a 2x2 max pool layer and used as input to the next layer. The 6th layer corresponds to the lowest level of the network and has a structure like the other descending layers. From this layer the data is oversampled by transposed convolution, merged with the output data of the corresponding downwards layer and applied to a block similar to those used in the descending layers. The last layer of the network is a convolution layer with a width equal to the number of classes to be segmented, which is just one in our case.

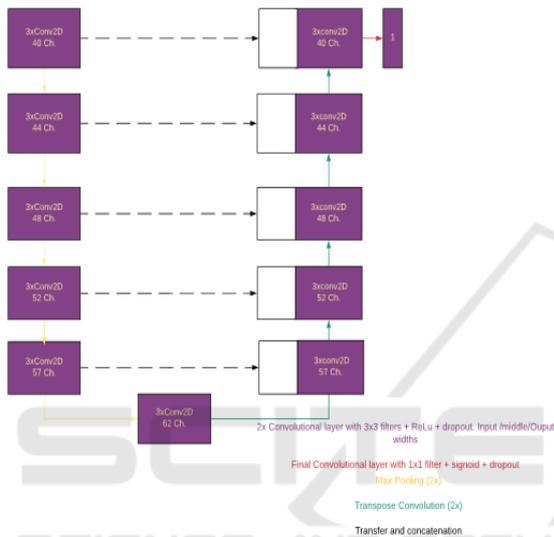


Figure 1: Proposed generalized U-Net Architecture.

We choose this specific architecture for our test as it has a moderate number of training parameters (near 1M), which allows us to train it using free GPU resources in the cloud and, when training with a single data set, produces results that are very similar to those obtained by other researchers.

1.3 Optical Disc and Cup

Glaucoma is a set of diseases that cause damage to the optic nerve in the back of the eye and can cause loss of vision. Glaucoma is one of the main causes of blindness and is estimated that it will affect around 80 million people worldwide by 2020.

Only when the disease progresses, with a significant loss of peripheral vision, the symptoms that may lead to total blindness begin to be noticed. Early detection is, thus, essential.

Many risk factors are associated with glaucoma but intraocular hypertension (IH) is the most widely accepted.

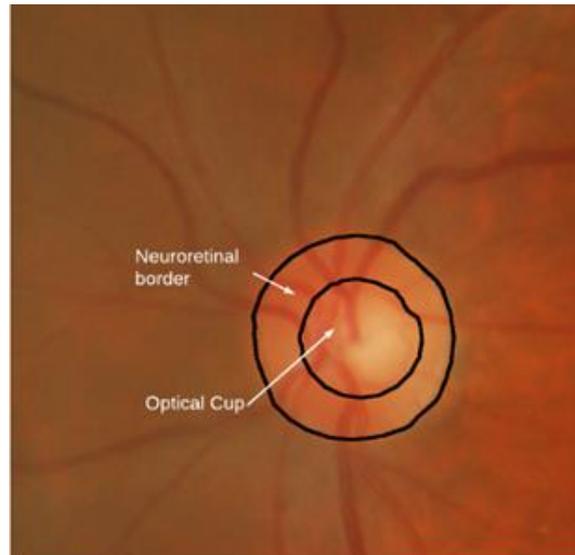


Figure 2: Neuroretinal border and Cup.

IH can cause irreversible damage to the optic nerve or optic disc (OD). The OD is the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together. It is also the entry point for the major blood vessels that supply the retina and it corresponds to a small blind spot in the retina. The optic disc can be visualized by various techniques such as color fundus photography. The OD is divided into two regions as shown in Fig. 3: a peripheral zone called the neuroretinal border and a white central region called the optic cup (OC).

Glaucoma produces pathological cupping of the optic disc. As glaucoma advances, the cup enlarges until it occupies most of the disc area. The ratio of the diameter of OC to OD is known as CDR and is a well-established indicator for the diagnosis of glaucoma [9]. Therefore, the correct determination of this diameters is key to the correct calculation of the CDR. Human segmentation of OD and OC is a slow and error prone process. Thus, automated segmentation is attractive as, in many cases, it can be more objective and faster than humans.

Several approaches have been proposed for fundus image OD/OC segmentation. The existing methods for automated OD and OC segmentation in background images can be classified into three main categories (Thakur & Juneja, 2018): templates based on form matching and traditional machine learning based on random forests, support vector machines, K-means, etc. (e.g. (Kim, Cho, & Oh, 2017)), active contours and deformable models (e.g. (Mary et al., 2015)), and more recently, deep learning-based methods (e.g. (Zilly, Buhmann, & Mahapatra, 2017),(Al-Bander et al., 2018)).

The aim of this paper is to study the influence of the dataset selection on the results. We will use a segmentation approach based on (Sevastopolsky, 2017) but with significant modifications to make it flexible and suitable for cloud-based implementation.

2 MATERIALS AND METHODS

For this work we used the Google Collaboratory iPython development environment. The environment has very good support for Keras for implementing and training networks on GPUs in Google cloud. Our network is based on (Sevastopolsky, 2017) but with very significant modifications:

- We use a different dual image generator and use it for both training and testing.

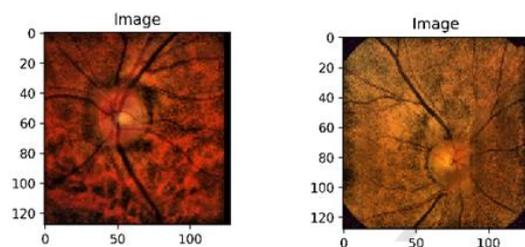


Figure 3: Disc images from RIM and DRISHTI datasets.

- We use a parameterizable recursive U-net model which allows us to easily change many parameters necessary to compare different implementations of U-Net.

- We use 120 image batches for both training and testing and train for 15 epochs using 150 training steps and 30 testing steps per epoch. We use an Adam optimizer algorithm in most cases with a 0.00075 learning rate. These values have proven suitable for training in U-Net architectures and provide good results with reasonable training times.

- We have tested several generalized U-Net configurations and finally decided to use the lightweight configuration shown in Fig.1

Regarding the datasets we use publicly available RIM-ONE v3 and DRISHTI datasets. RIM ONE-v3 (Fumero, Alayón, Sanchez, Sigut, & Gonzalez-Hernandez, 2011), from the MIAG group of the University of La Laguna (Spain), consists of 159 fundus images which have been labelled by expert ophthalmologists for both disc and cup. DRISHTI-GS (Sivaswamy, Krishnadas, Joshi, Jain, & Tabish, 2014), from Aravind Eye hospital, Madurai, India consists of 101 fundus images also labelled for disc and cup.

The code we use for both OD and OC segmentation is the same and the only difference is the loading and pre-processing of images and masks.

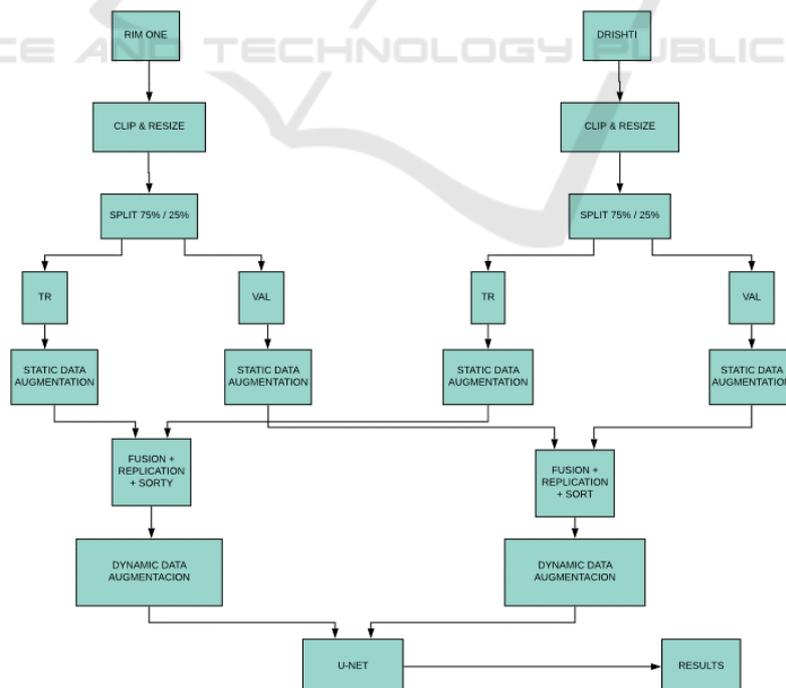


Figure 4: Multi-dataset-based training approach. For single dataset fusion step is not needed.

As already mentioned, our final objective is to perform disc and cup detection as a service in the cloud and, for this purpose, it is necessary that we are independent, as much as possible, from the specific characteristics of the captured image. As an example, in Fig. 3 we can see that images coming from the three different datasets have very different characteristics.

Our approaches for disc and cup segmentation are very similar. Fig. 5 shows the methodology used for cup segmentation when using a mixed dataset for training and validation (Zoph et al., 2019). When we train with either RIM-ONE or DRISHTI we use the same approach without the fusion step.

Originally, we start by clipping and resizing the original images in the datasets. When we segment the disc, we remove a 10% border in all the edges of the image to reduce black borders in the images. When we segment the cup, we select the area that contains the disc plus an additional 10% from the original images. After clipping we resize the images to 128x128 pixels and perform a clip limited contrast equalization.

After the equalization we do data set splitting. For each dataset we use 75% of the images for training and 25% for validation. It is essential to split the datasets before performing any data augmentation to ensure that the training and validation sets are completely independent from each other. After splitting we perform, for each used dataset, static data augmentation by creating images with modified brightness and different adaptive contrast parameters.

When we train with a mixed dataset after the static data augmentation, we do the fusion of the data from the different datasets. This process is done independently for the training and validation dataset. In the fusion process we perform data replication and shuffling so that we provide longer vectors as input for our dynamic image generators. The image generators do data augmentation by performing random rotations, shifting, zooming and flipping on the extended fused dataset images.

As one of the main glaucoma indicators is the CDR, i.e. the relation between the OD and the OC diameters we introduce a new parameter RRP -Radii Ratio parameter- which is the relation between the radius of the predicted segmented disc and the radius of the correct disc. We estimate the radii as the square root of the segmented area divided by pi.

Apart from the mean Dice coefficient over the validation data set we use an additional quality parameter that is the percentage of the images where the estimated radius error is less than 10%.

3 RESULTS

In Table I we show the Dice coefficients for the Disc and Cup segmentation for three different training scenarios:

- We train using 75% of the DRISHTI dataset and we validate with the remaining DRISHTI and with the RIM ONE validation data set.
- We train using 75% of RIM ONE the dataset and we validate with the remaining RIM ONE and with the DRISHTI validation data set.
- We train with 75% of a combined data set and validate with the rest of the combined data set.

We can see in the table that when training with DRISHTI we get very reasonable results when testing with images from the same dataset with a Dice coefficient above 0.98 for both OD and OC segmentation. However, if we validate this network with the RIM ONE data set result fall below 0.50.

A very similar situation happens if we train with the RIM ONE data sets. If we validate with the RIM ONE test data, we get Dice coefficients that are above 0.96 but this value falls below 0.66 when we test with DRISHTI data.

If we train with a combined data set, we get results that are more stable when testing with both datasets. For OD segmentation we get a 0.96 Dice value for DRISHTI and a 0.87 for RIM ONE. In the case of OC segmentation these values fall to 0.94 and 0.82.

Table 1: Dice coefficient for OC and OD.

Author	Disc DRI	Disc RIM	Cup DRI	Cup RIM
(Zilly et al., 2017)	0.97	-	0.87	-
(Zilly et al., 2017)	0.95	0.90	0.83	0.69
(Sevastopolsky, 2017)	-	0.94	-	0.82
(Shankaranarayan a, Ram, Mitra, & Sivaprakasam, 2017)	-	0.98	-	0.94
Drishiti Trained	0.98	0.50	0.98	0.42
RIM Trained	0.66	0.97	0.61	0.96
Multi-dataset	0.96	0.87	0.94	0.82

In table I we have also included results from other papers that have studied the OD/OC segmentation problem using Deep Learning based approaches and training with, at least, one of the datasets that we use.

In all these cases the researchers have trained and tested independently with the different datasets.

Even though our network is very light when we train with a single dataset, we get similar results to those obtained by other researchers. For DRISHTI dataset training we obtained a Dice coefficient of 0.98 for both OD and OC segmentation. This compares favourably with 0.97 and 0.87 (Zilly et al., 2017). When training with RIM ONE we obtain 0.97 for OD and 0.96 for OC. This also compares well with 0.98 and 0.94 (Shankaranarayana et al., 2017).

The most important result from table I comes from the data that is not available in other studies, i.e., when we train with a dataset and use the network with data captured with another source, we get poor prediction result.

Table I also shows that when we train with a combined dataset the network performs well doing predictions from both datasets.

In Table II we show the percentage of the predictions that estimate the radius with an error below 10%. This data is clinically very relevant as the ratio between the cup and disc radii, i.e., the CDR, is directly related to glaucoma.

When we train with a specific dataset, almost all the radii for the testing data from the same dataset are predicted with less than 10% error. However, the radii prediction for the other dataset are much worse and, in some case, we never get errors below 10%. As can be seen in the table this situation improves very significantly when we train with a mixed dataset.

Table 2: Images with less than 10% radius error.

	Disc DRI	Disc RIM	Cup DRI	Cup RIM
Drishti Trained	100	38	100	0
RIM ONE Trained	62	100	0	95
Multi-dataset	100	82	100	54

4 CONCLUSIONS AND FUTURE WORK

We have been able to show that by using data from different data sets, doing adequate image pre-processing and performing very significant data augmentation, both statically and dynamically, we have been able to perform cup and disc segmentation getting results with a performance that is equivalent

to that obtained by other authors using a single dataset for evaluation and testing. This is, at least, a first approach at the possibility of running this type of segmentations as a service on the cloud.

We have also introduced a new clinically significant parameter (Radii Ratio parameter- RRP) that is very useful to estimate the accuracy of the CDR.

We have shown that a very deep lightweight U-Net derivative can perform as well as other heavier less deeper alternatives for OD/OC segmentation.

This work has shown the advantages of using a dataset that combines data from different sources using aggressive data augmentation. Much work is necessary to improve the commercial viability of this type of service. In this work we have trained with a mixed dataset but, in real life, we would have to start training with the available data and do retraining as more and more image data from different sources becomes available. It would be necessary to adequately study the behaviour of this type of trained network with existing and new datasets.

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