# AUTOMATED SOFT EXUDATES SEGMENTATION IN RETINAL IMAGES USING PATCH BASED UNET

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## ABSTRACT

Diabetic retinopathy is one of the intricate diseases which damages the retina of a diabetic patient. The eye vision can be lost in case of improper and late treatment. Automatic segmentation of lesions in a retina image is one of advance step for accurate & quick clinical diagnosis and computer based decision support systems. This paper presents a novel neural network model that detects lesions based on its characteristic in fundus images to treat diabetic retinopathy (DR).

First, we preprocessed to reduce image noise and done several data augmentations to make data variety more richer and distinct. After that, we segmented them using a model with Unet architecture and weighted cross entropy loss. According to results of segmentation, we found the sensitivity to be 77.916%, specificity 99.94%, and PPV 49.159%. Thus, the suggested DR diagnosis system clearly outperforms existing one by increasing true positives & reducing false positives in lesion segmentation, and hence it can be implemented to make an effective and efficient screening system for diabetic retinopathy.

***Index Terms*—** Image segmentation, Diabetic retinopathy[6][(
Deep Learning, ROC curve, Cross entropy

## 1. INTRODUCTION

Diabetic retinopathy is one of the most severe eye disease faced by people with diabetes. This is when high blood sugar levels induce harm to blood vessels in the retina. These damaged blood vessels can cease blood from passing through or swelling in eye which can hinder our vision. It consists of clinical diagnosis which requires detection of several retinal lesions like microaneurysms (MA), hemorrhages (HE), hard exudates (EX), and soft exudates (SE). Microaneurysms were described as circular, small, red dots while haemorrhages had dot like blot or flame. Soft exudates were defined as light white lesions with somewhat fluffy border while hard exudates were yellowish deposits of various shapes and size with relatively sharp margins.[7]

Fundus imaging has an influential role in diabetes diagnosis since occurrences of retinal lesions are common and consequences serious. Correct and early diagnosis of diabetic retinopathy is cost effective since consequences of deficient or late diagnosis are very severe and costly.

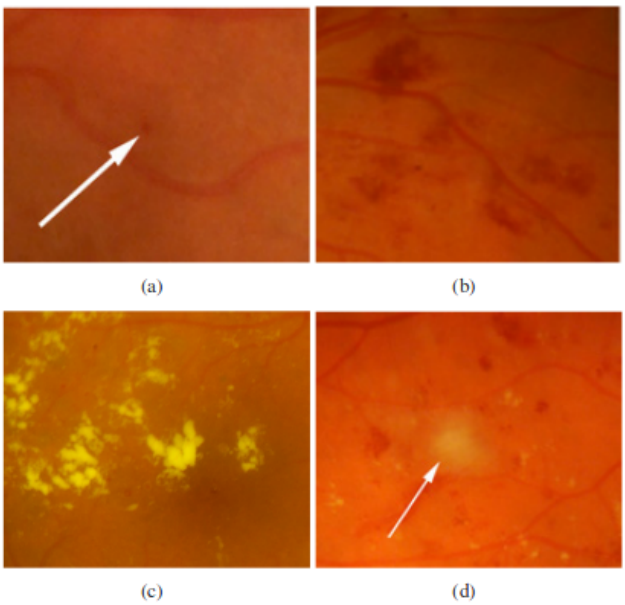
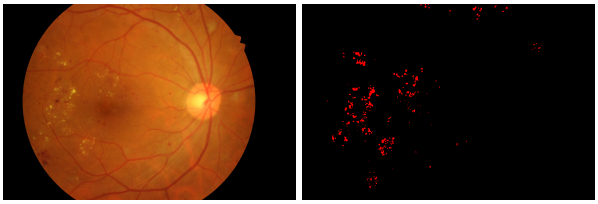



**Fig. 1**: Lesions in the eye fundus caused by the Diabetic Retinopathy: (a) Microaneurysm (b) Haemorrhages, (c) Hard Exudates, (d) Soft Exudates

Automatic screening for diabetic retinopathy can be done by using modern deep learning techniques with greater efficiency and lesser time. Computer-aided screening[7] also reduces the cost significantly as it does not require trained personnel. Diabetes has become one of the rapidly rising health threats worldwide & with growing numbers of diabetic patients, pressure on available infrastructure and resources increases so there is an urgent need for automatic system for screening. Over the years, Image segmentation is one of the most hot spot subject for image research community and hence continue to improve for better implementations in real life.

## 2. PRE-PROCESSING OF RETINAL IMAGES

The training dataset contains 143 fundus images and its soft exudates masks. Each image is of size (Width * Height) of (4288 * 2848). Out of all 143 images, 26 images has soft exudates lesions while others do not. An example of fundus image and its lesion mask is shown below. Images of diabetic retinopathy are very few and the area containing soft exudates lesions in the fundus image is very low as compared to total area of the image. So in order to increase the quantity of retinal images and reduce the negative segments, we have divided the images in various small patches. To maintain a balance in the training data, we have reduced the number of non-lesion patches to make it equal to the number of lesion patches we were able to extract. We have created a two type of patches of size (512* 512) pixels & (1024*1024) and slide it with stride of 256 & 512 pixels respectively as done in the case of convolution filters. As data for soft exudates is very less and they have very few lesions in the mask, so we were getting a less number patches but after inclusion of patches of size(1024*1024) in resized form of 512*512, we have increased quantity as well as quality of information in the data.



(a) Fundus Image (b) Lesion Mask

**Fig. 2**: Retinal Fundus and mask

We have slided with stride of 256 pixels which gives us overlapping patches and hence enables us to capture the surrounding context of lesions that are halved by one patch but those lesions will be fully included with its surroundings in the next patch. Hence, overlapping patches of stride 256 gives better results than distinct patches of stride 512. For the training data of Microaneurysms, this patch extraction algorithm produced 1638 patches from the available 143 images.

To increase the diversity in our data, we have included several augmentations like random left-right flip, random up-down flip, random brightness and hue changes etc. This technique of randomly mirroring and jittering the images helps us to increase variations in our data and make our model more robust and efficient to unseen images.

## 3. LESION SEGMENTATION TECHNIQUE

The architecture used in the model is Unet[10] which includes a shrinking path to capture context of surrounding and a symmetric expanding path that enables accurate localization. This is an example of Unet architecture shown above here:

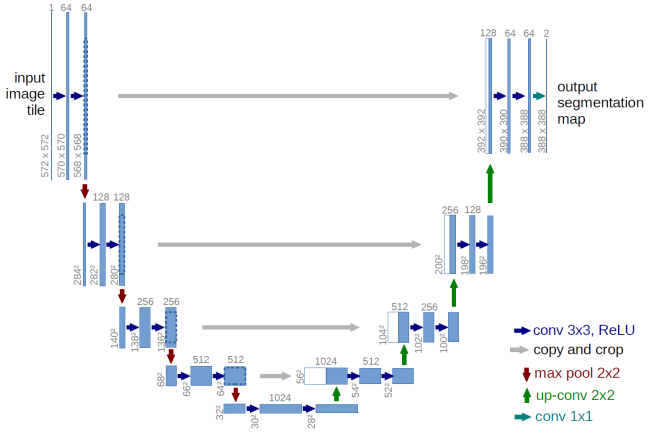



**Fig. 3**: U-net architecture (example for 32x32 pixels in the lowest resolution).

We improve and extend this architecture such that it works with very few training images and produce more accurate lesion masks.[10] The fundamental idea is to supplement a usual contracting network by successive layers, where upsampling operators replaces pooling operators. Hence, these layers enhance the resolution of the output image. For localisation, high resolution features from the contracting layers are added in upsampled output. A successive convolution layer can then learn to yield a more precise result.

The network architecture consists of a contracting path (left side) and an expansive path (right side). The contracting path includes the standard structure of a convolutional network & the iterated application of two 3x3 convolutions. Each contracting layer is followed by batch normalisation[9] and then activation function as rectified linear unit (ReLU). It also consists of a 2x2 max pooling operation with stride 2 for downsampling[10]. We started with 16 feature channels of 512*512 patch image and at each downsampling step we double the number of feature channels till 1024 feature channels. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 up-convolution that halves the number of feature channels. In expansive path the upsampling output is concatenated with the corresponding feature map [10]from the contracting path, and two 3x3 convolutions, each followed by a batch normalisation layer & ReLU. At the final layer a 1x1 convolution is used to map each 16-component feature vector to the desired number of classes.[8]

In the model, we have used pixelwise weighted binary cross entropy as loss function. In this, weightage given to losses of lesion and non lesion pixels is in the ratio 1:1. we have given more weightage to lesion pixels than normal as they are very less in area. We dont want to miss any lesion in the image so more weightage is given to them. The optimum weightage was chosen after iterating over several other weights. We train by Adam Optimizer with an initial learn-

ing rate of 1e-4, and exponential decay rates for 1st and 2nd moment estimates as 0.9 and 0.999 respectively. We used a batch size of 8 for 100 epochs.

The output results were the probability corresponding to each pixel to be a lesion pixel. So after taking a certain threshold, we got the lesion mask for each image. This optimum threshold is chosen from FROC curve at which true positive rate is maximum without compromising on false positive rate. All models are trained and tested with Tensorflow on a single NVIDIA GTX 1080 GPU.

## 4. PERFORMANCE EVALUATION OF LESION SEGMENTATION

Intensity image with particular abnormality segmented as foreground and rest part of an image as background. Methods used for lesion segmentation of diabetic retinopathy are evaluated by using sensitivity, specificity, positive predictive value[9] and finally, the detection performance are summarized using Free Response Operating Characteristic (FROC) curves. Sensitivity is the percentage of actual lesion area classified as lesion in the predicted mask and specificity is the percentage of actual normal retinal area classified as normal(not lesion) in predicted mask. PPV is the percentage of predicted lesion area which is actual lesion area. The FROC curve is created by plotting the true positive rate (TPR) against the false positive (FP) area per image at various threshold settings.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$PPV = \frac{TP}{TP + FP}$$

Sensitivity, specificity and PPV can be calculated as where TP is the area of actual lesions found as lesions in predicted mask , TN is the area of not lesions found as not lesions, FP is the area of not lesions found as lesions (false positives) and FN is the area of actual lesions found as not lesions (false negatives).

## 5. RESULTS

The output results are the probability corresponding to each pixel to be a lesion pixel. So after taking a certain threshold, we got the lesion mask for each image. This optimum threshold is chosen from FROC curve at which true positive rate is maximum without compromising on false positive rate. All models are trained and tested with Tensorflow on a single NVIDIA GTX 1080 GPU. After training the model and tuning its parameter, we have segmented almost all the lesions with exact size and shape at precise locations. These are the sensitivity, specificity and PPV value:

**Table 1**: Evaluation Metrics

| | |
|---|---|
| Sensitivity | 0.77916 |
| Specificity | 0.99942 |
| Positive Predictive Value | 0.49159 |

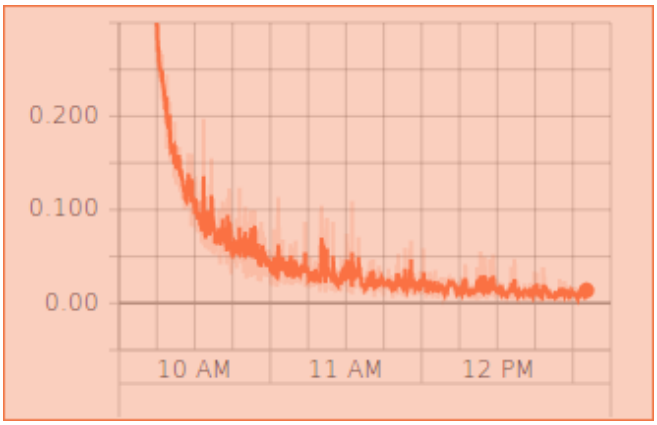



**Fig. 4**: Binary Cross Entropy loss plotted against training time

The loss function was continuously decreasing as we further train over epochs. This is the FROC curve which helps us to find the optimum threshold for making the mask.

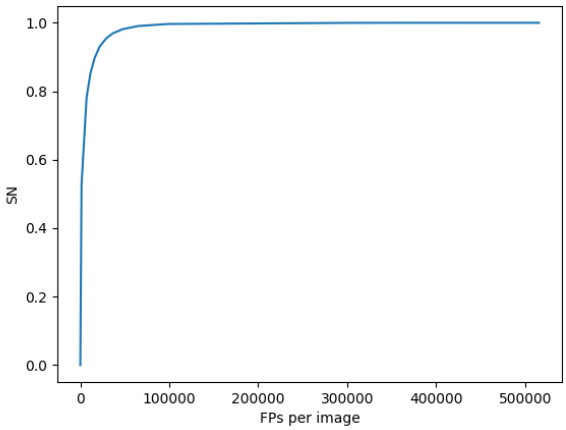



**Fig. 5**: FROC Curve: SN plotted against average FP area per image

## 6. CONCLUSION

This paper proposed a novel method for automated lesion detection in fundus images. To develop this robust lesion segmentation model, we have done data augmentation and provided the small patches of image instead of single large image. After training the model and hyper parameter tuning, we

have detected almost all the lesions with correct shape and size at precise locations. Hence, the proposed lesion segmentation technique will significantly helps ophthalmologists for initial DR diagnosis.

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