Diabetic Retinopathy Detection through Image Analysis Using Deep Convolutional Neural Networks

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Introduction

Diabetic Retinopathy (DR) is a leading disabling chronic disease and one of the main causes of blindness and visual impairment in developed countries for diabetic patients. Studies reported that 90% of the cases can be prevented through early detection and treatment [?]. Eye screening through retinal images is used by physicians to detect the lesions related with this disease.

The DR disease is standardly classified [?] in the next fixe classes:

0. - No apparent retinopathy
1. - Mild Non-Proliferative Diabetic Retinopathy (NPDR)
2. - Moderate NPDR
3. - Severe NPDR
4. - Proliferative DR

In this paper we propose an automated classification of retinal images into these 4 classes using Deep Learning techniques.

Figure 1: Image samples of the five different DR severity classes sorted from 0 (left) to 4 (right)

Methodology

Evaluation function

The performance of the classification model is measured using the quadratic weighted kappa (QWK) index. See equation 1.

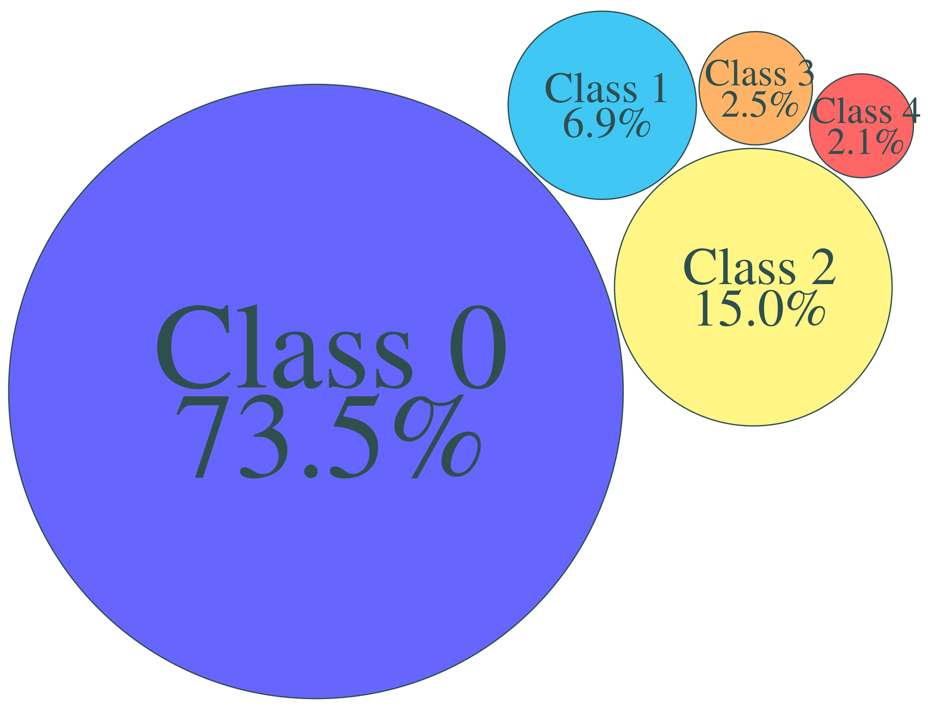
$$\kappa = 1 - \frac{\sum_{i=1}^{C}\sum_{j=1}^{C}\omega_{i,j}O_{i,j}}{\sum_{i=1}^{C}\sum_{j=1}^{C}\omega_{i,j}E_{i,j}} \quad \text{where} \quad \omega_{i,j} = \frac{(i-j)^2}{(C-1)^2} \tag{1}$$

The interpretation of kappa values can be done using the guide of table 1.

Table 1: Table Interpretation of kappa, after Landis and Koch (1977)

Kappa	Strength of agreement
<0.20	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.00	Very good

The Data



Training and Testing procedure

Logarithmic loss function is used for optimization. Leaky ReLU[?] is used as activation function. In all layers a batch normalization [?] is applied before the activation function. Dropout [?] (p=0.5) is performed before the final classification layer. A random initialization based in the Kaiming&He approach[?] is used for all the networks.

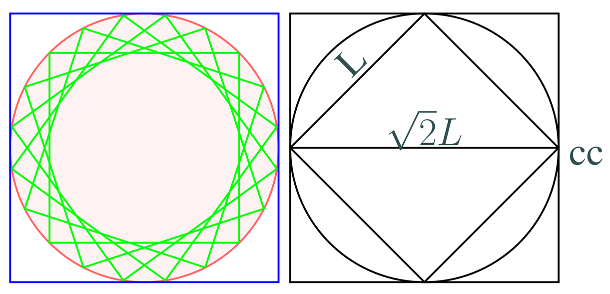
All models are optimized using stochastic gradient descent with Nesterov momentum. All the high resolution images are resized to the fixed input network size before training. For every epoch, a data augmentation technique based on cropping, rotation, mirroring and brightness & contrast correction is applied.

At test time five 72°rotated evaluations are averaged to get the class classification of every image (see figure 2).

Combining the information coming from both eyes (eq.2), we can improve the classification scores.

$$\begin{aligned} P_L &= P(Left|Right)P(Right) \\ P_R &= P(Right|Left)P(Left) \end{aligned} \tag{2}$$

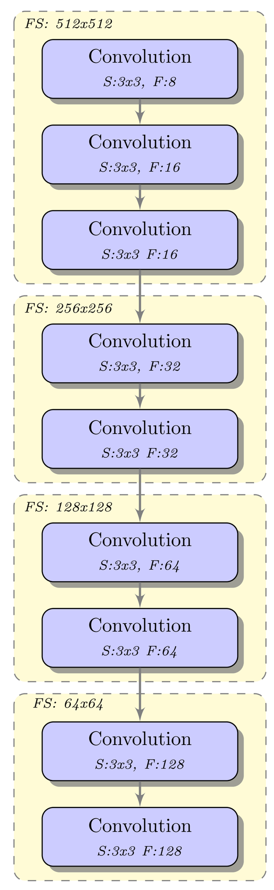
Figure 2: Ensemble used at test time and geometric relationship between crop and image size

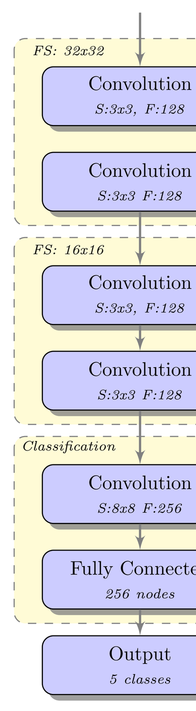


Results

In table ?? are shown the best results obtained from the use of different input sizes.

In table ?? we show the architecture of the best performing network.





Conclusions

In this paper is shown that deep learning techniques are a promising technique for solving medical imaging problems like the diabetic retinopathy detection. Having enough data this method is able to perform near human level expertise achieving κ values of 0.752 not far from the κ achieved by human experts, around 0.80.

Forthcoming Research

Future work will be centered on testing higher resolution input images, newer schemes such as residual networks, the use of alternative cost functions that encode the prior information of the ordering of the classes and more elaborated methods for combining the information coming from both eyes.

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