Detection of diabetic retinopathy based on a convolutional neural network using retinal fundus images

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Abstract. Diabetic retinopathy is one of the leading causes of blindness. Its damage is associated with the deterioration of blood vessels in retina. Progression of visual impairment may be cushioned or prevented if detected early, but diabetic retinopathy does not present symptoms prior to progressive loss of vision, and its late detection results in irreversible damages. Manual diagnosis is performed on retinal fundus images and requires experienced clinicians to detect and quantify the importance of several small details which makes this an exhaustive and time-consuming task. In this work, we attempt to develop a computer-assisted tool to classify medical images of the retina in order to diagnose diabetic retinopathy quickly and accurately. A neural network, with CNN architecture, identifies exudates, micro-aneurysms and hemorrhages in the retina image, by training with labeled samples provided by EyePACS, a free platform for retinopathy detection. The database consists of 35126 high-resolution retinal images taken under a variety of conditions. After training, the network shows a specificity of 93.65% and an accuracy of 83.68% on validation process.

Keywords: Diabetic retinopathy, Deep Learning, Convolutional Neural Network, Medical Image Classification.

1 Introduction

The recent success of convolutional neural network algorithms in natural imaging applications is due to the fact that it is inspired by the hierarchical organization of the human visual cortex, the use of database images on a scale of millions and the development of hardware (GPU) fast enough to process the training of millions of parameters. The results obtained have shown that in basic visual

tasks (from the point of view of human vision) these algorithms are capable of having a precision very close to that of a human. These facts have also allowed to open many possibilities in medical applications in different areas.
Although deep learning has reduced the time of analysis in medical imaging, including the diabetic retinopathy test, its computational cost far exceeds established previous methods. According to [1], prior algorithms to intensive use of convolutional neural networks can be categorized into 5 groups: preprocessing, location and segmentation of the optic disc, segmentation of the retinal vasculature, location of the macula and fovea, location and segmentation of pathologies of diabetic retinopathy. In [2], an automatic system for the detection of diabetic retinopathy was presented using fundus images extracting characteristics such as the area of blood vessels, area of microaneurysms and texture. The selected characteristics were trained using Naive Bayes to classify the disease in 3 states: Normal, Nonproliferative Diabetic Retinopathy (NPDR) and Proliferative Retinopathy. While [3] focuses on detecting changes in the retina that indicate diabetic retinopathy. Retinal images are first subjected to pre-processing techniques by color normalization and then image segmentation in order to detect blood vessels, microaneurysms, haemorrhages, the optic disc and lipid clusters. In that line, [4] presents a new algorithm for detecting blood vessels in the fundus images. The enhancement of the blood vessels in the image is carried out using a pretreatment stage, followed by transformations on curves which is applied to the equalized image. This improved image is used for removal of blood vessels. The estimation of the exudates is obtained from the blood vessels and the optical disc extracts from the image. The results show that the retinal images improved by this method have a better PSNR and the area of exudates shows the severity of the disease. By using an SVM classifier, [5] focuses on the automatic detection of diabetic retinopathy by detecting exudates in the background color of the retinal eye images and also classifies the severity of the lesions. [6] performs its work with the same classifier but using the sequential minimal optimization algorithm.
The works presented in [7] and [8] are among the first to solve the problem through neural networks, focusing on learning changes in blood vessels and lipid clusters. In [9], the authors classify different states of Diabetic Retinopathy (NPDR) and differentiate them from a healthy eye by analyzing fundus images. A feature extraction stage is performed and then use a multi-layer perceptron or "MLP algorithm" achieving 94.11% accuracy. More recently with the inclusion of CNN architectures, works like [10-12] have improved the learning ratios marked by other neural network architectures. In [10], is proposed the use of a deep neural network (DNN) by means of the use of auto-encoders to obtain an initialization model. Then they perform a supervised training using "random forest" for the detection of blood vessels in the fundus images. They obtained an accuracy of 93.27% and an area under the ROC curve of 0.9195. While [11] presents a method using deep learning to perform the detection of blood vessels in the fundus images. The structure or "ConvNet" that they propose is trained to segment the areas where the blood vessels of the areas that

do not contain them are located. Their experiments were carried out using the "DRIVE" database, obtaining an average accuracy of 94.7% and an area under the ROC curve of 0.9283. [12] propose a CNN approach to diagnosing diabetic retinopathy from digital fundus images and accurately classifying its severity. Developing a network with CNN architecture and data augmentation which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and haemorrhages on the retina and consequently provide a diagnosis automatically and without user input. By using a high-end graphics processor unit (GPU) on the publicly available Kaggle dataset and demonstrate outstanding results, particularly for a high-level classification task. On the data set of 80,000 images used its proposed CNN achieves a sensitivity of 95% and an accuracy of 75% on 5,000 validation images.

2 Preprocesssing

Retinal images were provided by EyePACS [13], a free platform for retinopathy detection. The database consists of high-resolution retinal images taken under a variety of conditions. Both eyes images are provided to us for each patient. Each case is rated on a scale of 0 to 4, depending on the level of degeneration and these scales are used as labels in the algorithm. Fig. 1, shows the illumination variability and size in different images of the database.

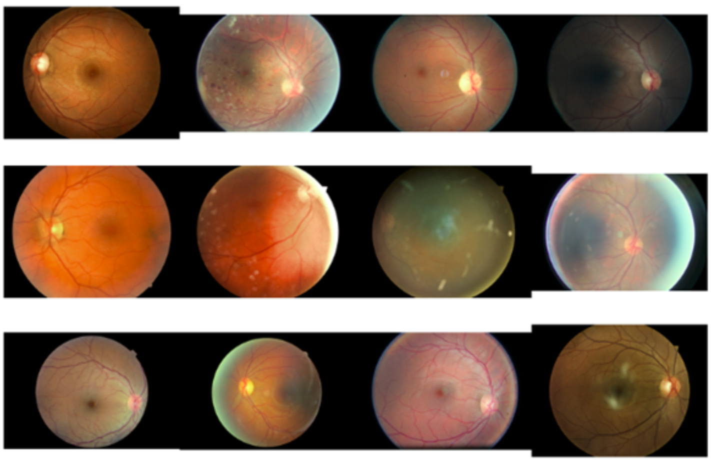

Fig. 1. Sample of the EyePACS image bank.

It can be noticed that the images in Fig. 1 are not standardized. In other words, each contains an non-regular black border, different aspect ratio, different lighting and different color average. In images pre-processing, each one was scaled by standardizing the size of the eyeball; then we 'subtract the color mean', and thus map the mean to gray (128). Finally, we re-scaled the image to 256x256. The results are shown in Fig. 2.

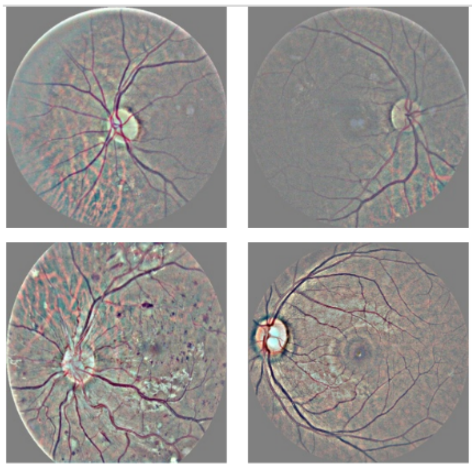

Fig. 2. Retinal fundus images after preprocessing.

We decided to separate the images into two sections: the right and the left eye. The same network model will be used in each section and thus, we achieve an specialized network type for the left eye and a similar network for the right eye. In a future work it is possible to make a fusion of these two networks using their fully connected layers. Another detail of the set of images is the class imbalance. So for that, it was decided to perform a binary classification. Table 1 shows the new division in classes.

Class	Name	Number of Images	Percentage
0	Healthy	25810	73.48%
1	Diseased	9316	26.52%

Table 1. Binary classification labels of the data.

The proportion between healthy and diseased cases is 2.74 to 1, respectively. We decided to use two versions of data set for the tests. The first has a ratio of 2.74 to 1, and the second has a ratio of 1 to 1 called 50/50. For this second version, we simply took all the diseased cases and the same number of healthy cases were chosen randomly. In both versions a data augmentation method was used, which consists on flips and take parts of the images. A probability of 50% was given for each image, If it gets positive, it is taken the 80% of the image in length and height from a random border inside. In a similar way was performed the flips

3 Neural Networks

Different configurations of neural networks architectures were tested, all based on convolutional networks. Table 2 shows the networks, number of layers and training mode.

Network	Distribution	Layers	Training Mode	Learning rate
Model_1	50/50	6	From scratch	0.01
Model_2	50/50	9	From scratch	0.01
VGG16	50/50	16	Pre-train	0.0001
VGG16noFC_1	50/50	15	Pre-train	0.0001
VGG16noFC_2	Original	15	Pre-train	0.0001

Table 2. Different neural network architectures

These models are inspired in the "Alex-net" model [14], they are convolutional layers followed by "max-polling" layers and finally by a set of fully connected layers. Moreover, all networks have a fixed momentum of 0.9, and the fully-connected layer has a dropout of 0.65, making it highly robust, but with low performance possibility in classification process.

Models 1 and 2 were trained from scratch. By testing of said model it was analyzed the capacity of a convolutional network to learn the corresponding filters to classify the data. When trained from scratch, the networks must learn basic filtering such as edge detection or corners in their first layers. A pre-trained network already contains such filters, so the models VGG16, VGG16noFC_1 and VGG16noFC_2 are based on the model VGG-net [15] already trained in the ImageNet database [16]. The two latter ones allows the network to re-adjust the filters according to the data used, resulting in a more robust result. Also, they dont have two Fully Connected Layers, but they have just one.

From the first four networks, VGG16noFC_1 has a good performance, so we decide to use a similar network, but this time using the Original distribution. To equilibrate this difference, we use Class Weight, which consists in assign a weight in the cost function of the data depending on the class. As we talked before, the distribution was from 2.74 to 1, so the weight assigned are 1 to the healthy Cases and 2.74 for the diseased ones. Furthermore, we assign it a decay of 0.00005. This new network is called VGG16noFC_2.

4 Results

After performing the tests to configure the hyperparameters of each network in Table 2, we obtained the following results.

Network	Epochs	Accuracy	Sensitivity	Specificity
Model_1	45	63.6%	-	-
Model_2	91	66.4%	-	-
VGG16	80	74.3%	62%	86%
VGG16noFC_1	75	72.70%	68%	77.60%
VGG16noFC_2	80	83.68%	54.47%	93.65%

Table 3. Results of the training in the test set.

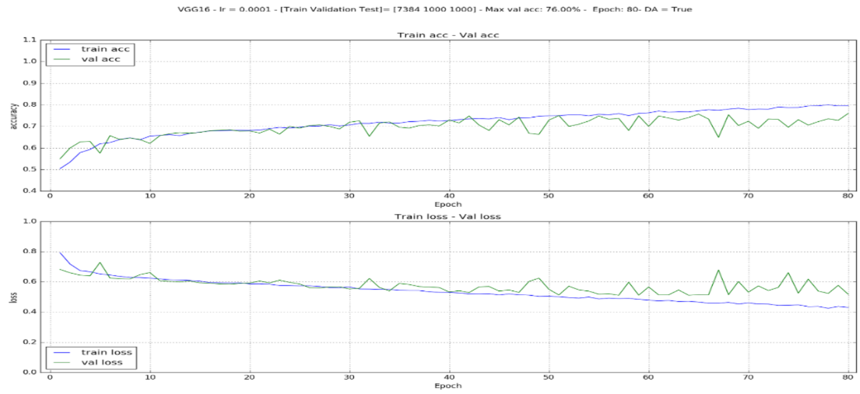

Fig. 3. Epochs vs Accuracy and Loss Function for VGG16.

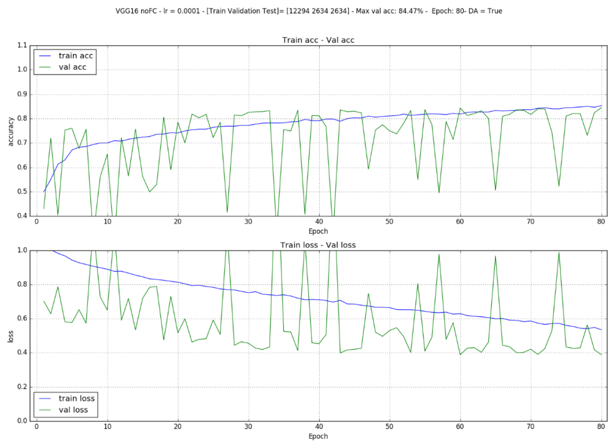

Fig. 4. Epochs vs Accuracy and Loss Function for VGG16noFC_2.

In Fig. 4, we can see that the network VGG16noFC$_2$ is highly noised and not uniform in the test set, although in the training set, it has a continuous and non-noise graphics. So it can be deduced that it has a low value of sensitivity, and a high value of specificity, which can be verified in table 3. As we can see in Fig. 3, the graphics generated in the train set are continuous and they dont have noise, and in contrast, the test graphics has little noise, but it isnt so high. In Table 3 we can see that, although it is 9 points in percentage accuracy below from VGG16noFC$_2$, it is not so highly sensible as it. We can see it in the sensitivity value of 62% in contrast with the 54.47%.

5 Conclusions and Future Work

In this work, we have implemented the most efficient CNN architectures to detect diabetic retinopathy, beginning with a pre-processing stage that included the normalization of the saturation values of each figure, as well as normalization of measurements and elimination of noise. The second stage included training by applying various values of hyperparameters and data distributions. At the end, a 93.65% efficiency in specificity and 83.68% accuracy were obtained in VGG16noFC$_2$ but just 54.47% in sensitivity. Which means that true positive rate is lower than true negative rate. These results leave a possibility of using work as an effective method of discarding the disease in the future. For future work, we will seek to expand the retina imaging database, make a fusion of the two networks (right and left eye) using their fully connected layers as well as improve the network architecture and develop cost functions that fit the database model more closely.

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