Identification of Diabetic Retinopathy in retinal fundus images using Convolutional Neural Networks

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***Abstract*—Diabetes retinopathy is one of the main causes of treatable vision impairments in the world. Its diagnosis requires experienced ophthalmologists to identify the presence of retinal lesions in the eye. This paper presents a Convolutional Neural Network (CNN) model for the identification and grading of Diabetic Retinopathy (DR) in retinal fundus images. A subset of 1,000 images of the Diabetic Retinopathy dataset available in Kaggle was used achieving 74.5% of accuracy. The presented CNN was developed in python using Keras framework and executed in the Kaggle server.**

Keywords—Diabetic Retinopathy, Convolutional Neural Networks, Medical imaging.

I. INTRODUCTION

Diabetes retinopathy (DS) is one of the main causes of vision impairment and blindness in the world. It is caused by a damage in the blood vessels inside the retina by high levels of blood sugar in the blood and high blood pressure. DS is a progressive eye disease associated with diabetes mellitus. By 2013 an estimated of 382 million people around the globe suffered DS, and by 2025 that number it is expected to increase up to 592 million. [1]

The evaluation of DR is made by the examination of retinal fundus photographs, that are taken with specialized fundus cameras. This evaluation is performed by ophthalmologists, who are trained to identify lesions in the eye. An early diagnosis of DR can prevent the progression of the DR, and therefore provide an effective treatment to the patient.

Significant studies have been conducted to develop automated methods that can detect DR from screening images. In this work, a Convolutional Neural Network model is proposed for detection and grading of DR.

This paper is organized as follows:

- Section II presents the biological inspiration of neural networks and the structure of different neural networks models used for medical imaging,
- Section III reviews related works conducted for the identification of DR in retinal fundus images,
- Section IV describes the dataset used for this paper,
- Section V explains the methodology used and the design of the solution,
- Section VI presents the results from the experiments,
- Section VII remarks the ethical issues related to the implementation of the designed solution,
- Section VIII discusses the results obtained and suggest future work and improvements.

II. BIOLOGICAL INSPIRATION OF ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are mathematical models inspired in human neurobiology. The structure of an ANN simulates the structure of the biological neural network.

The human brain contains an estimated of 100 billion nerve cells, also known as Neurons. Each neuron is interconnected within each other forming a network. The interneuron connection is called Synapse, and it's made between the Axons of the neurons, a branching fibre that serve as transmission line; and the Dendrites, branches that receive and transfer the signals to the nucleus of the neuron.

The communication between neurons is made by electrochemical impulses or spikes of voltage that are transmitted by one neuron to another when its incoming signals exceed a threshold. These same principles are simulated in ANN, that is composed by one or more processing units or nodes (neurons), and weighted connections between each other.

Each node has three sets of functions: multiplication, summation, and activation function. The dendrites are simulated by the Input vector. Each input value is multiplied by a weight value and summed up together. The result is passed to the activation function that will produce the final output of the ANN.

In general, there are three different classes of artificial neural network architectures:

A. Single-layer Feedforward Networks

In this architecture, the input layer is directly feed-forward to the output layer. Each input value is connected to every output node and multiplied by a series of weights. The sum of the product of the weighted inputs is calculated in each output node. If this value exceeds a threshold, the neuron fires an activated value, otherwise it takes the deactivated value.

B. Multi-layer Feedforward Networks

This architecture consists of an interconnection of two or more internal or 'hidden' layers between the input and the output layer. The function of the hidden layers is to extract relationships from the received input. The output values of each layer is calculated the same as in single-layer networks.

C. *Recurrent Networks*

In this architecture, the network transmits a feedback by connections from the outputs to the inputs. This allows the network to remember the information from the previous layers.

Automatic Diabetic Retinopathy detection has been widely addressed with neural networks models. Due to the architecture of Convolutional Neural Networks, they have been extensively proposed for the development of detection systems at image level.

A Convolutional Neural Network is a

III. Related Work

The first solutions on image processing of diabetic retinopathy can be categorized in Detection of lesions at pixel and image level; Detection of retinal vessels, to detect and measure the vessel diameter; Detection of retinal lesions, as micro aneurysms and haemorrhages; and Detection of abnormalities or irregular lesions, as ocular neoplasms and scars. With the use of neural networks the diagnosis can be made directly, without the need of manual annotations at pixel level. The suitability of CNN to extract relationships from images is widely used for image recognition.

In [2] a 6-layer Convolutional Neural Network is used to detect DR in colour retinal fundus images. The images are downsized to 512x512 pixels and adjusted to increase the heterogeneity in the input data. A visualization layer is added at the end of the network to construct a heatmap to highlight the prognosis region in the input image. The model was evaluated on two external datasets, achieving an AUC of 93%.

In [3] a CNN is also proposed to recognize DR, age-related macular degeneration (AMD) and possible glaucoma. The performance of the model was evaluated with external data from multi-ethnic patients with diabetes and compared with the grading of two trained senior professionals with more than 5 years of experience in detecting DR. The authors report an AUC of 93% for DR detection.

In [4] the authors proposed a solution to create heatmaps to show which pixels in retinal fundus images are used to make the prediction and detection of lesions. They propose a CNN and an implementation of the o_O solution from M. Antony and S. Brüggemann scoring a 94.9% and 95.4% of performance for each model.

In [5] the authors demonstrate the effectiveness of transfer learning in dealing with limited amount of training data. A CNN model pre-trained with images in general was tested on a small dataset of Optical Coherence Tomography (OCT) images for diabetic macular oedema detection, and a chest x-ray dataset to diagnose paediatric pneumonia. The authors report an area under the ROC curve of 0.99, demonstrating the potential of a generalized platform for medical imaging.

In [6] a CNN is proposed for DR detection in retinal fundus images. The images were resized to 224x224 pixels, and undergone transformations for data augmentation. The proposed approach demonstrates that a good performance can be obtained using small images.

IV. Dataset Description

The dataset used for this study is the Diabetic Retinopathy Detection dataset retrieved from Kaggle[7] which contains a total of 35,126 high-resolution retinal colour fundus images from the left and right eye of patients with a variety of ethnicity, gender and age.

The images contained in the dataset were taken with different types of cameras and settings, which add considerable variation and noise to the images. See Fig. 3.

The images are labelled in 5 classes that represents the grade of the DR in the eye of the patient. The grading was provided by a clinician on the following scale:

TABLE I. Dataset Classes

Class	Description
0	No DR (healthy)
1	Mild
2	Moderate
3	Severe
4	Proliferative DR

Fig. 1. DR grading scale in dataset

The dataset is highly inbalanced, the class distribution is presented in Fig.2. To address this problem, a weighted class method was used. This method was used instead of the traditional approach of generating artificial images or oversampling, because of the limited computing resources. For the same reason, only a fraction of 1,000 images were used for the training and testing of the CNN model.

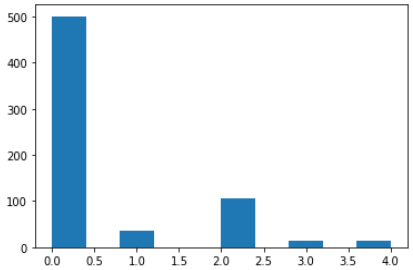

Fig. 2. Class distribution in dataset

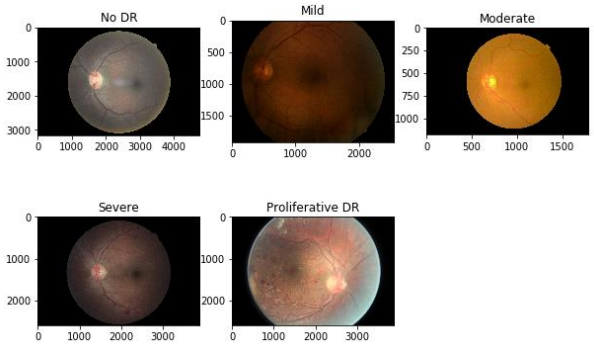

Fig. 3. Retinal images at each level of DR

V. Methodology

A. Data preprocessing

The images were resized to 512x512 pixels and rescaled by a factor of 255 to normalize them and reduce computation in the training phase.

80% of the sub-dataset of 1,000 images was designated for training and the remaining 20% for testing. A validation set was generated from 20% of the training set. This subset was artificially generated with a random variation in rotation, brightness, and horizontal and vertical flip. Fig. 4 shows a sample of the augmented data.

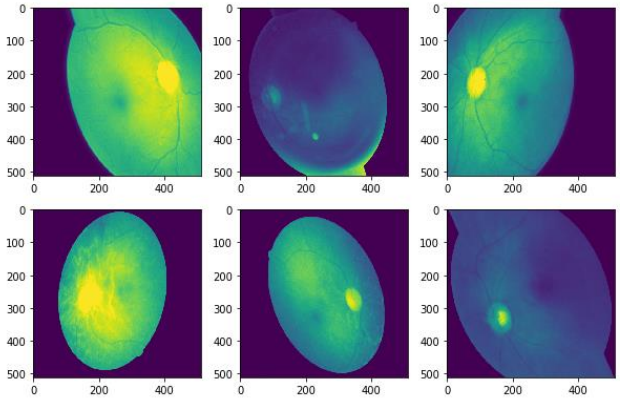

Fig. 4. Generated images for the validation set

The resulting dataset was composed by 670 images for training, 133 for validation and 330 for testing.

B. Convolutional Neural Network

Several CNN architectures were evaluated in the experiments, using different kernel ranges, convolutional layers and filter size. The final architecture of the CNN is presented in table II.

TABLE II. CNN Architecture

Output Shape	Description
512 x 512 x 3	Input
512 x 512 x 16	9x9 Convolution, 16 filters
256 x 256 x 16	Max-pooling
256 x 256 x 32	7x7 Convolution, 32 filters
128 x 128 x 32	Max-pooling
128 x 128 x 64	5x5 Convolution, 64 filters
64 x 64 x 64	Max-pooling
64 x 64 x 128	3x3 Convolution, 128 filters
32 x 32 x 128	Max-pooling
131072	Flatten fully connected
512	Fully connected
5	Softmax

Fig. 5. Convolutional Neural Network (CNN) architecture used.

The network was trained using Stochastic Gradient Descent as optimizer with Nesterov Momentum, because of its fast convergence [8]. A max-pooling filter was used after each convolutional layer to reduce the input dimensionality.

To reduce overfitting, Dropout was used in the fully-connected layer [9]. Batch normalization was used after each convolutional layer to reduce the amount of hidden units and speed up the training.

Softmax activation function with categorical cross-entropy loss was used in the last fully-connected layer to compute the probabilities for each class label.

The training and testing set was divided in batch size of 32. Although it is confirmed that a larger batch size contributes to achieve a higher accuracy [10], the limitations in the computing resources was a constraint to increase this size. The final results were obtained from a total of 20 epoch with 32 steps each.

VI. Results

The final CNN model scored an accuracy of 76.4% and a validation loss of 0.75.

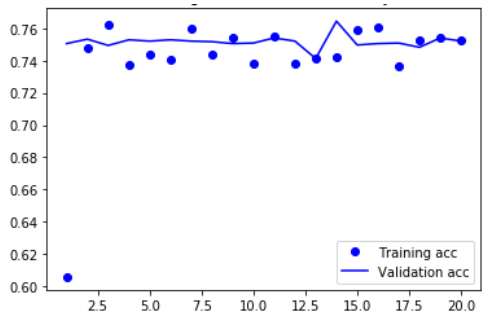

Fig. 6. Training and Validation Accuracy

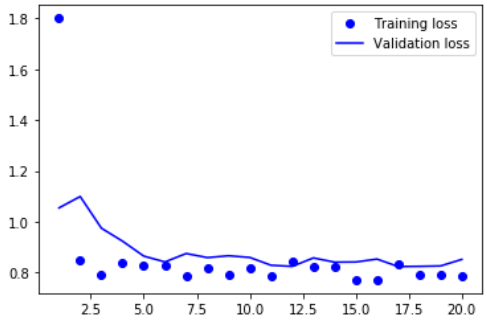

Fig. 7. Training and Validation Loss

As the above graph indicates, the

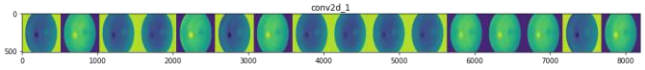

Fig. 8. First layer activations

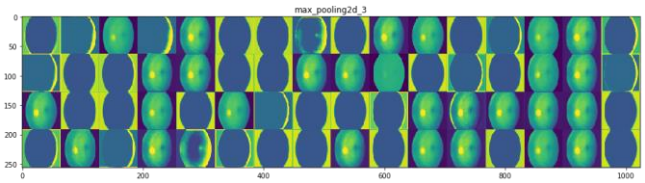

Fig. 9. Last layer activations

VII. Ethical considerations

The implementation of automated systems for diagnosis of diseases has the potential of improve the healthcare industry in overall. More Accurate and reliable AI systems can be developed as more data is being generated and collected. These systems could minimize the time for diagnosis and provide a clinical interpretation with the same precision as the human expert. Although these stated benefits, considerable risks should be addressed, as a failure in a correct interpretation can put the patient's safety at risk.

VIII. Conclusion

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