Prevention of Diabetic Retinopathy through Convolutional Neural Networks

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***Abstract* — Today, eye problems represent a real dilemma that directly affects the quality of life of the person who suffers. However, many of these problems can be corrected in time. In this document, we propose software that can predict eye problems on time and that, through images, we can heal a large number of patients on time. The problem is that in many cases, when the damage is treated, the disease is already very advanced. Our contribution seeks to heal totally or partially, through recognition of images used for cases already recognized by eye problems. In our research, we find that a large part of the world's population gets to suffer from visual problems, starting in their forties. One way to predict visual damage is by evaluating the color in the retina and iris of the patient's eye. In conclusion, it is what is sought from our project.**

I. Introduction

Today, eye problems represent an important complex to the health and quality of life of people, however, every day, they keep appearing and it seems that few people know how to predict it. "The best defense is to have regular check-ups, because eye diseases do not always have symptoms. Early detection and early treatment can prevent blindness". [1]

"The increased incidence of eye diseases is multifactorial in origin since risk factors related to the individual, environment, and solar radiation contribute to their development. The retina absorbs millions of photons of ultraviolet and blue light, which cause greater phototoxicity and irreversible damage. [4] It is essential to study the pathogenesis of eye diseases and analyze the interaction of light with the eyes in depth. Eye disease prevention based on a personalized approach is critical to provide correct information, contribute to self-monitoring, and conduct a frequent medical follow-up. [6] Continuous development of technology in the field of ophthalmic optics offers new perspectives for prevention. The aim of this review is to provide an update on this topic that can be used for training medical students and primary care physicians.". [2]

Diabetic retinopathy

Diabetic retinopathy is a complication of diabetes, caused by high blood sugar levels damaging the back of the eye (retina). It can cause blindness if left undiagnosed and untreated. However, it usually takes several years for diabetic retinopathy to reach a stage where it could threaten your sight. [19]

Chronically high blood sugar from diabetes is associated with damage to the tiny blood vessels in the retina, leading to diabetic retinopathy. The retina detects light and converts it to signals sent through the optic nerve to the brain. Diabetic retinopathy can cause blood vessels in the retina to leak fluid or hemorrhage (bleed), distorting vision. In its most advanced stage, new abnormal blood vessels proliferate (increase in number) on the surface of the retina, which can lead to scarring and cell loss in the retina.

Diabetic retinopathy may progress through four stages:

Mild nonproliferative retinopathy. Small areas of balloon-like swelling in the retina's tiny blood vessels, called microaneurysms, occur at this earliest stage of the disease. These microaneurysms may leak fluid into the retina.

Moderate nonproliferative retinopathy. As the disease progresses, blood vessels that nourish the retina may swell and distort. They may also lose their ability to transport blood. Both conditions cause characteristic changes to the appearance of the retina and may contribute to DME.

Severe nonproliferative retinopathy. Many more blood vessels are blocked, depriving blood supply to areas of the retina. These areas secrete growth factors that signal the retina to grow new blood vessels.

Proliferative diabetic retinopathy (PDR). At this advanced stage, growth factors secreted by the retina trigger the proliferation of new blood vessels, which grow along the inside surface of the retina and into the vitreous gel, the fluid that fills the eye. The new blood vessels are fragile, which makes them more likely to leak and bleed. Accompanying scar tissue can contract and cause retinal detachment—the pulling away of the retina from underlying tissue, like wallpaper peeling away from a wall. Retinal detachment can lead to permanent vision loss [19].

III. Problem Statement

Although light is necessary and beneficial for numerous visual and non-visual functions, any optical beam is potentially harmful to the eyes if it is received and absorbed by the ocular tissues in sufficient quantity to cause photomechanical, photo thermal or photochemical reactions. [5]

A brief exposure to intense light can quickly cause mechanical or thermal damage to the eye, while moderate exposure over a long period of time can result in progressive biochemical changes that lead to cell death.

The specificity of the light spa Prevention and recognition of eye problems through Neural Networks
centrum, particularly ultraviolet rays and high visible light, are considered to be high-risk spectral bands for the anterior segment of the eye and for the retina progressively. [3]

The red end of the visible spectrum (even infrared) generates heat while photons of short lengths accelerate the aging process of the eye as they are accompanied by high energy photons. To maintain our biological balance and avoid seasonal affective disorders, some exposure to turquoise blue light, longer wavelengths is necessary. [3]

We need to reduce eye problems as fewer people as possible. Although there is still a lot to investigate about the validity and efficacy of commonly used screening methods and programs, studies are needed to monitor the costs and benefits, especially from the Primary Care setting, compared with not detecting visual defects, or that this screening be carried out by specialized personnel it seems reasonable to take advantage of the universality, equity and closeness of the Primary Care staff to detect anomalies in vision through health checks, especially at early ages, and derive them for its early treatment.

III. Objectives

We seek to predict and prevent many eye problems in people. By means of a collection of images, we intend to detect such problems in time, by means of a software that recognizes malignant patterns in the corneas and in the iris of the patients. We look for it to be easy to acquire and reach both urban and rural locations. Since, in the latter cases, they are where a tool with that degree of utility is most required. We also seek a respectable and useful precision, that there is no disagreement or doubt about whether our final product works.

IV. State of the art:

The computer-assisted diagnosis of diabetic retinopathy has been explored in the past to reduce the burden of ophthalmologists and mitigate diagnostic inconsistencies among manual readers. [7] Automated methods to detect microaneurisms and reliably qualify fundoscopic images of patients with retinopathy Diabetics have been active areas of research in computer vision. [8] The first artificial neural networks explored the ability to classify patches of normal retina without blood vessels, normal retinas with blood vessels, pathological retinas with exudates and pathological retinas with microaneurysms. The accuracy of being able to detect microaneurysms compared to the normal patches of the retina was reported in 74%. [9]

Previous studies using various high and low digital image processing techniques have performed well in the identification of a specific feature in the detection of subtle diseases, such as the use of the top hat algorithm for the detection of microaneurysms. [10], [11], [12]. However, a variety of other characteristics, in addition to microaneurysms, are effective for the detection of diseases.

Additional methods of detection of microaneurysms and classification of DR involving k-NN [13], [14], support vector machines [15] and methods are integrated into sets [16] have been sensitivities and specificities within the range of 90% of use. of features and preprocessing algorithms.

Previous CNN studies [17], [18] for DR, the background images achieved sensitivities and specificities in the range of 90% for the normal classification categories at the moderate level versus the tombs in the largest private data sets of 80,000 to 120,000 images. However, precision measurements for the detection of four classes of DR, ie: without DR (R0), mild (R1), moderate (R2) and severe (R3) do not depend on the collection rates of classes classified according to the illness. While stages R0 and R3 are capable of achieving high sensitivity, the calculated recovery rates of R1 and R2 are often low. Experiments on data sets have become an early stage. In addition, the current accuracies for stages R1 and R2 are reported in 0% and 41%, respectively.

III. Underpinnings of our approach

A. Machine Learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.
The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly [21].

B. Deep Learning

Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans: learn by example. Deep learning is a key technology behind driverless cars, enabling them to recognize a stop sign, or to distinguish a pedestrian from a lamppost. It is the key to voice control in consumer devices like phones, tablets, TVs, and hands-free speakers. Deep learning is getting lots of attention lately and for good reason. It's achieving results that were not possible before [22].

C. TensorFlow

TensorFlow is an open source software library for numerical computation using data-flow graphs. It was originally developed by the Google Brain Team within Google's Machine Intelligence research organization for machine learning and deep neural networks research, but the system is general enough to be applicable in a wide variety of other domains as well. It reached version 1.0 in February 2017, and has continued rapid development, with 21,000+ commits thus far, many from outside contributors. This article introduces TensorFlow, its open source community and ecosystem, and highlights some interesting TensorFlow open sourced models [23].

D. Inception V3

Inception-v3 is trained for the ImageNet Large Visual Recognition Challenge using the data from 2012. This is a standard task in computer vision, where models try to classify images into 1,000 classes [24].

VI. Methodology:

In order to detect diabetic retinopathy in time, we have developed a software that analyzes photographs of healthy and diseased eyes and dictates which type corresponds to the two previously mentioned. Our model is based on image processing and CNN (Convolutional Neural Networks).

Our software consists of two classes calls "entrenar.py" and "predecir.py". These classes are necessary to carry out a full use of the software. They are programmed in Python. Both combine image processing and CNN to detect Diabetic Retinopathy. We have used a dataset of "good" images and "bad" images. The use of image processing techniques eliminates the human error margin. CNNs learn through patterns or examples. In a CNN, knowledge is not programmed directly, but is acquired through training, which adjusts its parameters of weight and size over time, to optimize its performance. [25]

The CNN architecture used in this software consists of artificial neurons interconnected and arranged in three layers (see Figure 1). The data enters through the "entry layer"; Each neuron in this layer contains the image of a retina in binary format and each of the binary images is represented in a one-dimensional matrix. In the training process, the synaptic weights of the connections between the neurons are modified. Once the training is completed, the result is received by a neuron in the output layer. This neuron indicates whether the image is good or bad.

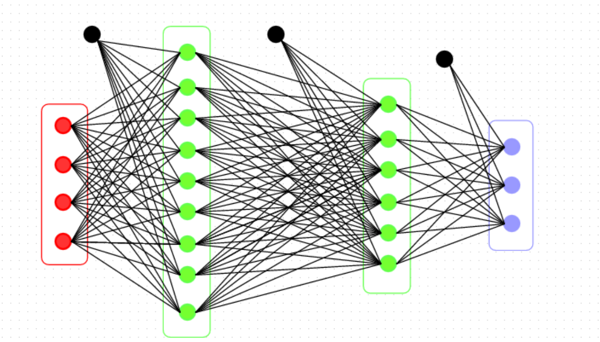

Fig.1 Structure of the convolutional neural network.

Step 1: Defining the training conditions of our neural network.

Our dataset, is conformed with half of good images and the other half with bad images This percentage is used to balance training and increase the likelihood of true positives and true negatives We define that, the images are always read in a resolution of 100 x 100, since this way we avoid variants in the sizes of the images.

```
#Epocas
epocas = 10#Iteraciones
altura,longitud = 100, 100#HacerTodasLasImagenesConDimensionesAsi
batch_size = 32#ImagenesAMandarEnCadaPaso
pasos = 100#pasosencadaepoca
pasos_validacion = 200#Verquesisirve
filtrosConv1 = 32#Filtrosencadaconvolucion
filtrosConv2 = 64#Filtrosencadaconvolucions
tamano_filtro1 = (3,3)
tamano_filtro2 = (2,2)
tamano_pool = (2,2)
clases = 2
lr = 0.0005
```

As we can see, we use 10 iterations of 100 steps each, that is 1000 layers. Then, we define what we have already mentioned, the dimensions it will take in each image in order to avoid errors in each image by the variance of its size. Then, in the first convolution, we define 32 filters, in the second 64. This is for you to improve your precision exponentially.

We define the sizes of them and then, we specify that we will use two classes (good and bad). To finish this section, we add the "learning rate", to declare the level of learning.

Step 2: Preprocessing images.

Digital image processing is the set of techniques that are applied to digital images with the aim of improving the quality or facilitating the search for information.

In this part we made a set of techniques encompassed within them preprocessing of images whose fundamental objective was to obtain, from a source image, a result that would be more appropriate to determine a retina with or without diabetic retinopathy.

```
#Preprcesamientodeimagenes

entrenamiento_dataGen = ImageDataGenerator(rescale=1./255,
shear_range=0.3,
zoom_range=0.3,
horizontal_flip=True)

validacion_dataGen = ImageDataGenerator(
rescale=1./255)

imagen_entrenamiento = entrenamiento_dataGen.flow_from_directory(
data_entrenamiento,
target_size=(altura,longitud),
batch_size=batch_size,
class_mode='categorical')

imagen_validacion = validacion_dataGen.flow_from_directory(
data_validacion,
target_size=(altura,longitud),
batch_size=batch_size,
class_mode='categorical')
```

We define our variable and rescale the image, we write our parameters. As the range and zoom of cut, in addition to rotate horizontally. We declare another variable, now validation and we did the same. Then, we take the sample image of our directory, and we expose the corresponding parameters, establishing the mode of our class as categorical. The same is done with the validation.

Step 3: Creation of CNN Network.

```
dir = './modelo/'

if not os.path.exists(dir):
    os.mkdir(dir)
cnn.save('./modelo/modelo.h5')
cnn.save_weights('./modelo/pesos.h5')
```

Finally, we import the generated model and this is how our training was carried out.

VII. Experimental Results

We managed to get an accuracy above 98% and we managed to make our software able to discern between good and bad class.

```
Epoch 7/10
100/100 [==============================] - 193s 2s/step - loss: 0.0439 - acc: 0.9863 -
val_loss: 0.0134 - val_acc: 1.0000
Epoch 8/10
100/100 [==============================] - 194s 2s/step - loss: 0.0390 - acc: 0.9882 -
val_loss: 0.0277 - val_acc: 0.9913
Epoch 9/10
100/100 [==============================] - 196s 2s/step - loss: 0.0225 - acc: 0.9941 -
val_loss: 0.1782 - val_acc: 0.9204
Epoch 10/10
100/100 [==============================] - 208s 2s/step - loss: 0.0372 - acc: 0.9859 -
val_loss: 0.0397 - val_acc: 0.9824

In [6]:
```

```
In [3]: runfile('C:/Users/INSPIRON/Desktop/dataset-20190426T214415Z-001/dataset/
predecir.py', wdir='C:/Users/INSPIRON/Desktop/dataset-20190426T214415Z-001/dataset')
good

In [4]:
Terminal de IPython    Historial de comandos
ermisos: RW    Fin de línea: CRLF    Codificación: ASCII    Línea: 28    Columna: 18    Memoria: 8
```

VIII. Conclusions and Future Work

We conclude this article by presenting software that is able to recognize when an eye presents Diabetic Retinopathy, using Convolutional Neural Networks and images of healthy eyes and infected eyes for training.

However, the Retinopathy presents phases, our future work is to make a software that indicates the phase in which the eye is, thus avoiding a greater contamination of it and giving an adequate treatment to the disease and the patient. Also, we know that there are people with low resources and we want this software to be within their reach.

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