Identification of Glaucoma Stages with Artificial Neural Networks Using Retinal Nerve Fibre Layer Analysis and Visual Field Parameters

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Abstract. For the diagnosis of glaucoma, we propose a system of Artificial Intelligence that employs Artificial Neural Networks (ANN) and integrates the analysis of the nerve fibres of the retina from the study with scanning laser polarimetry (NFAII;GDx), perimetry and clinical data. The present work shows an analysis of 106 eyes of 53 patients, in accordance with the stage of glaucomatous illness in which each eye was found. The groups defined include stage 0, which corresponds to normal eyes; stage 1, for ocular hypertension; 2, for early glaucoma; 3, for established glaucoma; 4, for advanced glaucoma and 5, for terminal glaucoma. The developed ANN is a multilayer perceptron provided with the Levenberg-Marquardt method. The learning was carried out with half of the data and with the training function of gradient descent w/momentum backpropagation and was checked by the diagnosis of a glaucoma expert ophthalmologist. The other half of the data served to evaluate the model of the neuronal network. A 100% correct classification of each eye in the corresponding stage of glaucoma has been achieved. Specificity and sensitivity are 100%. This method provides an efficient and accurate tool for the diagnosis of glaucoma in the stages of glaucomatous illness by means of AI techniques.

Keywords: Glaucoma Diagnosis, Bioinformatics, Artificial Neural Networks, Nerve Layer Analysis, Visual Field Parameters, Laser Polarimetry.

1 Introduction

Glaucoma is one of the principal causes of blindness in the world. It is an illness which has an asymptomatic form until advanced stages, thus early diagnosis represents an important objective to achieve with the aim that people who present glaucoma maintain the best visual acuity throughout life, thereby improving their quality of life [2], [14], [19].

In our study we contribute the inclusion of artificial intelligence and neuronal networks in the diverse systems of clinical exploration and autoperimetry and laser polarimetry [12], [13], with the objective of facilitating the adequate staging in a rapid and automatic way and thus to be able to act in the most adequate manner possible.

There are different methods available to the ophthalmologist to classify patients in different stages of glaucoma. To establish the different stages in clinical practice, the

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data of exploration and the degree of affectedness of the visual field (V.F.) are routinely employed. The application of Artificial Intelligence to Ophthalmology is relatively recent [4-7], [15], [16], [18], [25], orientated toward the analysis of the visual field.

More recently the analysis of the retinal nerve fibre layer (RNFL) by laser polarimetry has been included [2], [9-11], [21], [26]. All these diagnostic methods compose the criteria to be taken into account at the time of clinically classifying the stage of the glaucoma [22], [23].

Artificial Neural Networks owe their name to the parallelism in structure and function with the biological nervous system [14], [17], [24]. It consists of a group of neurones. Each neurone simultaneously receives various inputs from other neurones and adds them in accordance with the weights associated to each link, producing a response which depends on the level of inputs received and the weights associated to the links (see Figure 1).

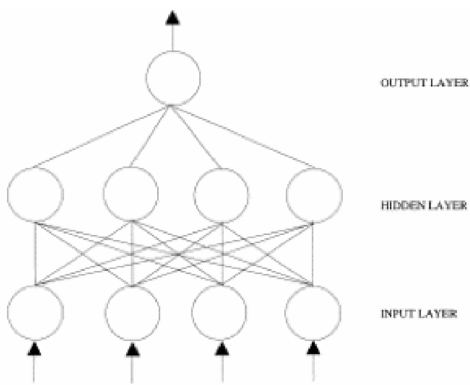

Fig. 1. ANN Model of a multilayer perceptron with one hidden layer

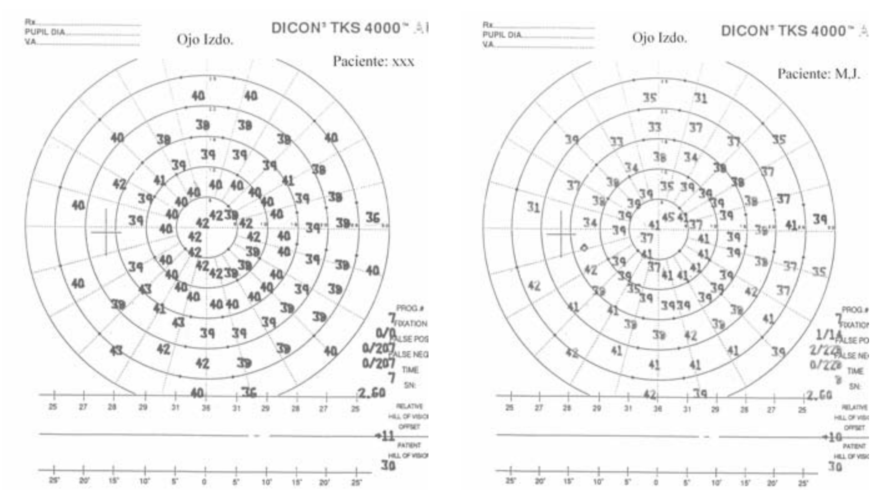

Fig. 2. Perimetry of a left eye of a normal patient (left image). Perimetry of a right eye of a patient with terminal glaucoma (right image).

For the diagnosis of glaucoma, we propose a system of Artificial Intelligence that employs Artificial Neural Networks and integrates, jointly, the analysis of the nerve fibres of the retina from the study with scanning laser polarimetry (NFAII;GDx), perimetry and clinical data.

2 Patients and Methods

The present work shows an analysis of 106 eyes of 53 patients, in accordance with the stage of glaucomatous illness in which each eye was found. The groups defined include stage 0, which corresponds to normal eyes; stage 1, for ocular hypertension; 2, for early glaucoma; 3, for established glaucoma; 4, for advanced glaucoma and 5, for terminal glaucoma. The developed ANN is a 16-30-1 multilayer perceptron provided with the Levenberg-Marquardt method [13], [17], [24].

To classify the eyes in groups, besides studying IOP (Goldmann tonometry) and the ophthalmoscopic study of the optic disc by means of biometry using Volk aspheric lens [14], [19]. Dicon TKS 4000 autoperimetry (Figure 2) has been used for the analysis of the visual field and laser polarimetry for the measurement of the thickness of the layer of retinal nerve fibres using the NFA-II, GDX fibre analyser (Figures 3 and 4).

The used ANN is a multilayer perceptron with backpropagation with a hidden layer. The input layer consists of 16 neurones, the hidden layer has 30 neurones and the output layer is a single neurone. The input neurones receive the values of 16 input variables and the output neurone obtains the value of the output variable that corresponds with the stage of the glaucoma for each eye. The definition of the 16 variables of input of the neuronal network consists of:

- **AGE.** Age of the patient.
- **CHAMBER.** Depth of the anterior chamber of the ocular globe.
- **IOP.** Intraocular pressure—expressed in millimetres of mercury.
- **OPTIC DISC.** Cup-to-disc ratio. If the result was less than 0.4, 0 was assigned; if between 0.4-0.5, 1 was assigned; if between 0.5-0.6, 2 was assigned and if between 0.7-0.9, 3 was assigned.
- **FIXATION.** Fixation losses by the patient from all those performed during the autoperimetry testing of visual field examination.
- **NS, TS, NI, TI.** Average of the values of the visual field in the superior nasal, superior temporal, inferior nasal and inferior temporal quadrant, respectively.
- **MEAN.** Mean of all the values of the visual field.
- **NORMAL DEVIATION SUPERIOR, INFERIOR, TEMPORAL, NASAL.** Difference of the thickness of the nerve fibre layer employing the GDX programme in the superior, inferior, temporal and nasal quadrant, respectively, for our patient compared with the normal patient of the same race and age.
- **NUMBER.** Experimental number extracted from all the values on acquiring an image employing NFA-II, GDX.
- **MEAN THICKNESS.** Mean of the thickness of all the pixels of the image; utilising the 65,536 points in an image considered valid.

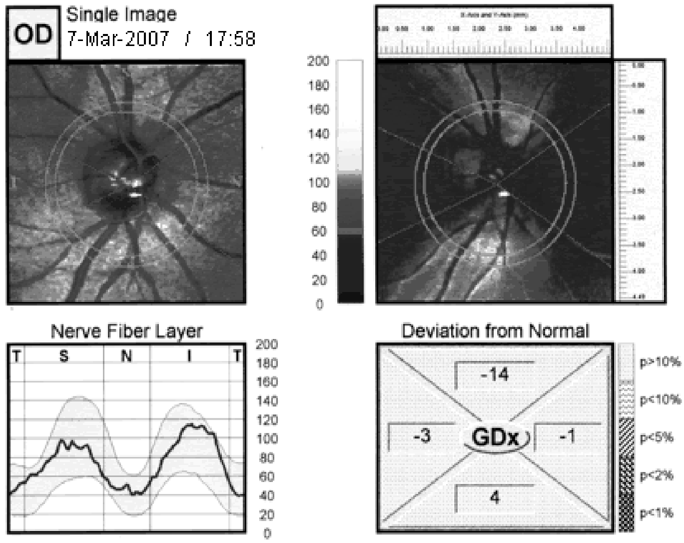

Fig. 3. Analysis with laser polarimetry for the measurement of the thickness of the layer of retinal nerve fibres using the NFA-II, GDX fibres analyser for a normal patient

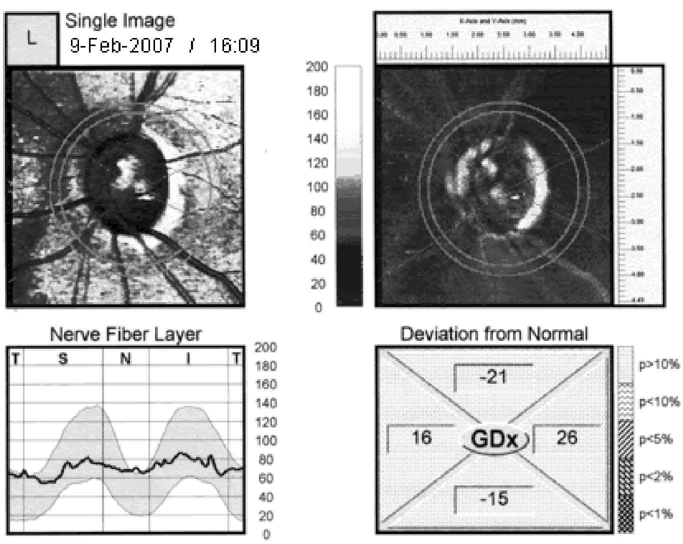

Fig. 4. Analysis with laser polarimetry for the measurement of the thickness of the layer of retinal nerve fibres using the NFA-II, GDX fibres analyser for a glaucomatous patient with stage 5 glaucoma

3 Results

The implementation of the neural network model has been carried out by means of the scientific computation platform *Matlab*, using the toolbox of *Neural Networks*. Once the model had been defined, half the data were randomly employed to train the ANN. The learning was carried out using half of the data from the study, in accordance with the diagnosis of an ophthalmologist, expert in glaucoma. The evolution of the process of learning is shown in Figure 5.

Finally, with the model of the ANN trained, the other half of the data were used to evaluate the yield of the model utilised. The learning was carried out with half of the data and with the training function of gradient descent w/momentum backpropagation and was checked by the diagnosis of an ophthalmologist, expert in glaucoma.

The model of neuronal network has been evaluated from the other half of the data. A 100% correct classification of each eye in the corresponding stage of glaucoma has been achieved. Therefore, the specificity and sensitivity are 100%.

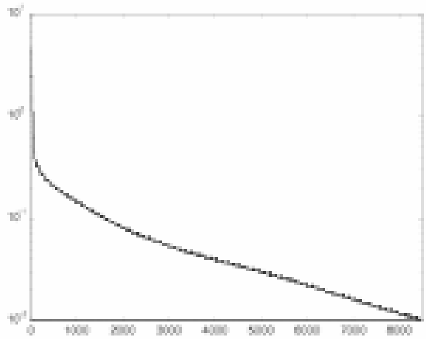

Fig. 5. Training evolution of our proposed neural network model

4 Discussion

Neuronal networks have been applied to evaluation of visual fields for the diagnosis of glaucoma and have compared favourably with the clinical evaluation made by clinical specialists [2], [6], [7]. The design of these networks is similar to that employed in this study [4], [5]. Nevertheless, the recent use of laser polarimetry in clinical exploration to the study of retinal nerve fibre layer thickness has increased the parameters available for performing a diagnosis and assigning a degree of affectedness of glaucoma.

In our study we have integrated both data obtained with polarimetry and algorithms originating from the exploration of the visual field by autoperimetry. The approach of this study differs basically from previous works in the inputs. The data utilised do not originate from only the parameters of visual field analyser. The neuronal network elaborated in this study is set up to process 16 input variables, which include those data extracted from the clinical exploration itself, such as optic disc appearance, from autoperimetry and laser polarimetry. This neuronal network therefore analyses the degree of affectedness, both structural and functional, achieving the assignment of each case to the group corresponding to the stage of the glaucomatous illness. The high specificity and sensitivity obtained make this network superior to the expert systems and to other neuronal networks with similar architecture but with algorithms originating only from visual field examination [16-18].

In the future the definition of more exact and specific indices for incipient glaucomas or the prediction of the possibility that an ocular hypertension could evolve towards glaucoma will make the neuronal networks with this model an essential tool in clinical practice for early diagnosis and treatment of glaucoma.

This method provides an efficient and accurate tool for the diagnosis of glaucoma in the stage of glaucomatous illness by means of AI techniques. Further implementation for this model will include more algorithms and quantitative data obtained from new objective functional and structural tests.

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