PREDICTION OF GLAUCOMA DISEASE USING DEEP LEARNING TECHNIQUES

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Abstract:

Glaucoma is a persistent, permanent eye disease that contributes to vision and quality of life loss. Within this paper we build a deep learning system for the automatic diagnosis of glaucoma with a Convolutionary neural network. Deep learning algorithms, such as CNNs, that infer a hierarchical representation of images to differentiate between glaucoma and NG trends of diagnostic decisions. The DL architecture proposed contains six learning strategies: four Convolutionary strata and two entirely linked layers. Strategies for drop-out and data rise were implemented to further enhance the treatment of glaucoma. Extensive validation of ORIGA and SCES databases is carried out. The findings show that the recipient's operating curve field under curve (AUC) is significantly higher than the state of the art algorithms in glaucoma identification at 0,831 and 0,887 in the two databases. The method may be used for the detection of glaucoma.

Keywords: Eye disease, deep learning, glaucoma, databases, CNN.

Introduction:

Glaucoma is one of the most popular blindness factors, and by 2020 nearly 80 million people are predicted to develop glaucoma [14]. The optic nerve is being increasingly weakened due to chronic eye disease which contributes to vision loss. Glaucoma is considered the invisible eye-thief, since the signs often appear while the condition becomes very progresses. While glaucoma cannot be healed, therapy will slow down its progression. This is very important to diagnose glaucoma early on the basis of successful images.

Digital fundus picture is one of the most common forms in which glaucoma is identified. DFI is a favored form of large-scale glaucoma screening because it is possible to achieve non-invasive DFIs appropriate for specific screening [1]. An automated device decides that there are any suspected symptoms of glaucoma found in a image in a glaucoma screening software. For further study, only certain photos that the machine finds suspicious are transferred to ophthalmologists.

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Glaucoma is mainly diagnosed by using patient records, intraocular pressure and field vision monitoring, along with an optical disk (OD) manual examination via ophthalmoscopy. OD is the location where the cell ganglion axons exit the eye and join the optic nerve from which photoreceptor sensory information is conveyed through the brain.

CDR is a significant concern among physicians of the systemic picture markers for glaucoma diagnosis [2][12][13]. However, clinical tests are complex for each image through manual recording of the cup and the disk, so it requires time to extract the disk and the cup directly into the fundus photos. With the extraction of the ROI, a smaller picture will be produced that takes far less time to process than with the segmentation of the disk and the cup [11,3]. In this post, we consider the ROI picture as the input of the proposed deep CNN.

In DFIs, the disease process is elusive and concealed for the diagnosis of glaucoma which varies from pictures from natural scenes. The descriptive function of picture scenes is linked to the identification of artifacts in clearly noticeable (e.g. shape, type or color) areas [5]. Nevertheless, even the experience and knowledge of the physician may detect symptoms of glaucoma disorder.

Deep learning (DL) is an important field of study that acquires discriminatory results. The DL design is composed of several linear and non-linear data transformations in order to generate theoretical and essentially functional depictions[15]. Deep learning architectures, which have been used widely lately for segmentation and classification of photos (CNNs) [15][9] are artificial neural networks. DL architectures are a development of multi-layer neural networks (NN) that require different design and training strategies for their competitiveness. Those involve spatial invariance, hierarchical awareness of features and scalability [14, 15]. The key focus in this report is to identify the specific features of glaucoma dependent on broad CNN.

Implementation on glaucoma disease prediction:

This paper is based on CNN, the latest profound learning architecture. The net of CNN comprises six weight-bearing layers are used: the first four are Convolutionary and the other two totally connected. The performance of the last completely linked layer for glaucoma prediction is given by a soft-max classifier. In our suggested learning system as in are used flexible standardization layers and overlapping layers. Our suggested glaucoma detection method succeeds in the sample diagnosis. With picture in the fundus is treated with our algorithm by clinicians and the expected labels as shown in fig (1.1)

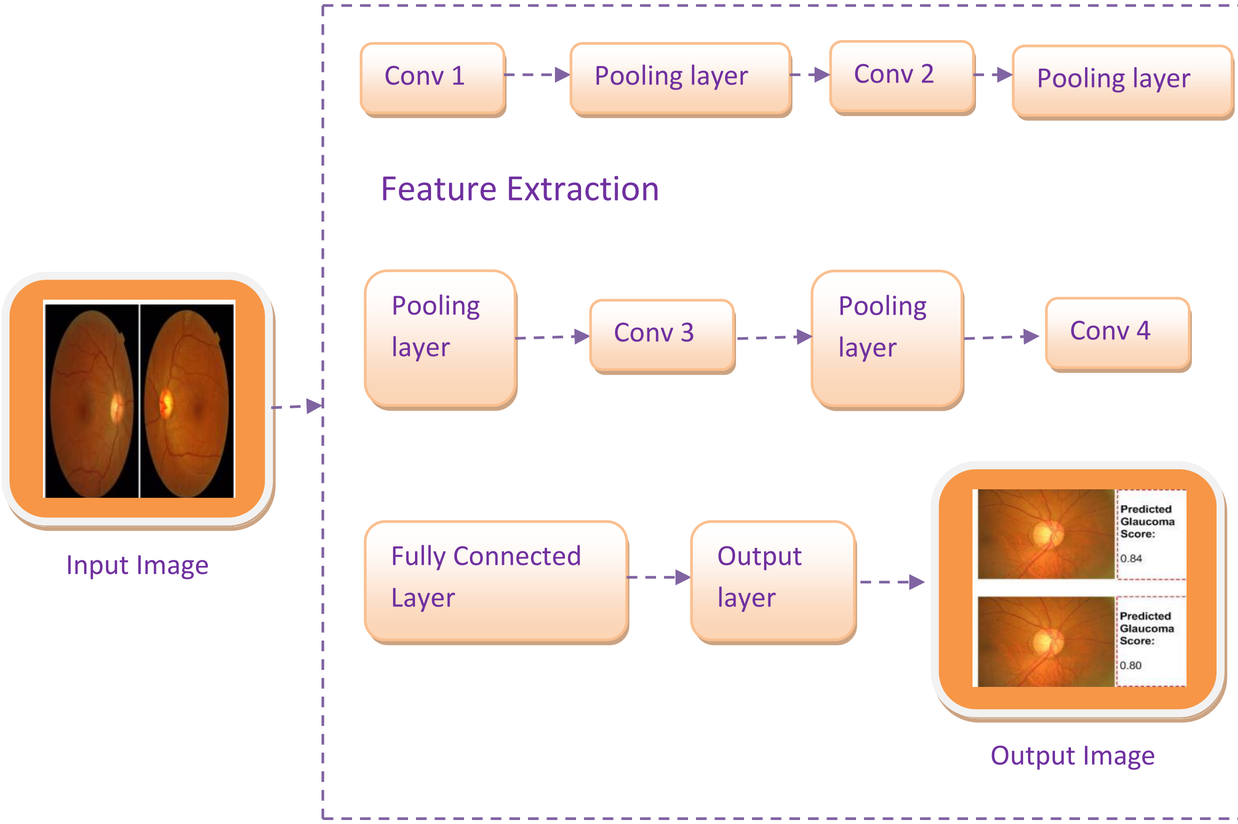

Fig (1.1) Structure diagram for glaucoma prediction using deep CNN algorithm

Convolution steps:

Based on patches randomly sampled in an image, innovative layers are used in most instances to learn small feature detectors. By comparing the feature detector with the map, a function in the picture may be calculated at certain locations. Let us define H(n)(n)(1) and H(n) as the input/output of the n-th layer of CNN. From H (0) to the 2D reference image patch and H(N), the last layer of N will be supplied. Let M(n) I and M(n) O be the input size and output map; respectively, the input size and output map are the n sheet. The n-th layer input and output maps are denoted as Q (n) I and Q (n) O. Since n-th is the (n jusqu'1)-th resulting rank, Q(n) I = Q(n) O and M(n) I = M(n) O. While the product of the n-th line is the layer input. Let H(n)j be the output character-map n-th layer jth.

Max-pooling layers:

The CNN pooling layers add up the statistics of a feature through an picture field. A collection of units divided by pixels consists of a grid of pools that outline a size-first neighborhood based at the pooling point. We get typical neighborhood pooling when p = s. If p < s, we get overlapping bundles that could help to solve overfilling. The max-pooling layers in our learning model are focused on both the reaction-normalizing layers as seen in Fig.1.1.

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Classification of glaucoma disease:

Throughout the previous ARGALI approach [8], the representation of retinal fundus is separated into grids, where the optic nerve head is positioned and the grid is identified, which is the most possible choice. In retinal fundus picture, with proper definition of ROI, we are taking the algorithm [3 «] to correctly identify the ROI in the retinal fundus image to improve the estimation and increase the output of glaucoma detection.

Within the[3] method, the bright border, which requires identifying the trim circles center and trim radius, is reduced or omitted by a preprocessing phase. The product collected is tested at a fixed resolution of 256 instead 256. After achieving ROI Finally, from each pixel, the mean value of all pixels in the disc picture is deduced to minimize the impact of the lighting discrepancy between frames.

Data augmentation:

We use data augmentation for artificially extending the dataset with mark protection transformations and dropout for configuration combination to solve the over fitting of image images.

If we maximize info, our network would be significantly overcrowded. Data increase is the production of horizontal reflections and translations of image[11,16]. The explanation for the improvement in data during the training period is the recovery of the Random 224 patches and their horizontal reflections from 256 images and the checking of our network in these derived patches. The CNN forecasts at the time of analysis by eliminating 5 224 € 224 patches, plus 4 angle patches and center patches, and combining the soft max layer predictions of the network on these 10 patches. A multi-view analysis (MVT) should be described as this research tool.

Dataset used:

For this research, we follow the same circumstances of glaucoma treatment experiments [7], such that similarities are made simpler. The ORIGA data collection is made up of 166 glaucoma and 4820photos of regular fundus, including specific glaucoma diagnosis. The SCES data collection contains 1672 pictures of a fundus, and 46 are examples of glaucoma.

Result and discussion:

To validate the efficacy of our deep CNN in glaucoma diagnostic accuracy, we compare the CNN predictions with a state-of-the-art reconstruction-based approach [7].We have the same setting [7] for ORIGA dataset. A random collection of 97 images from the total 648 photos is provided in the training package, and the remaining 548 photos are checked.

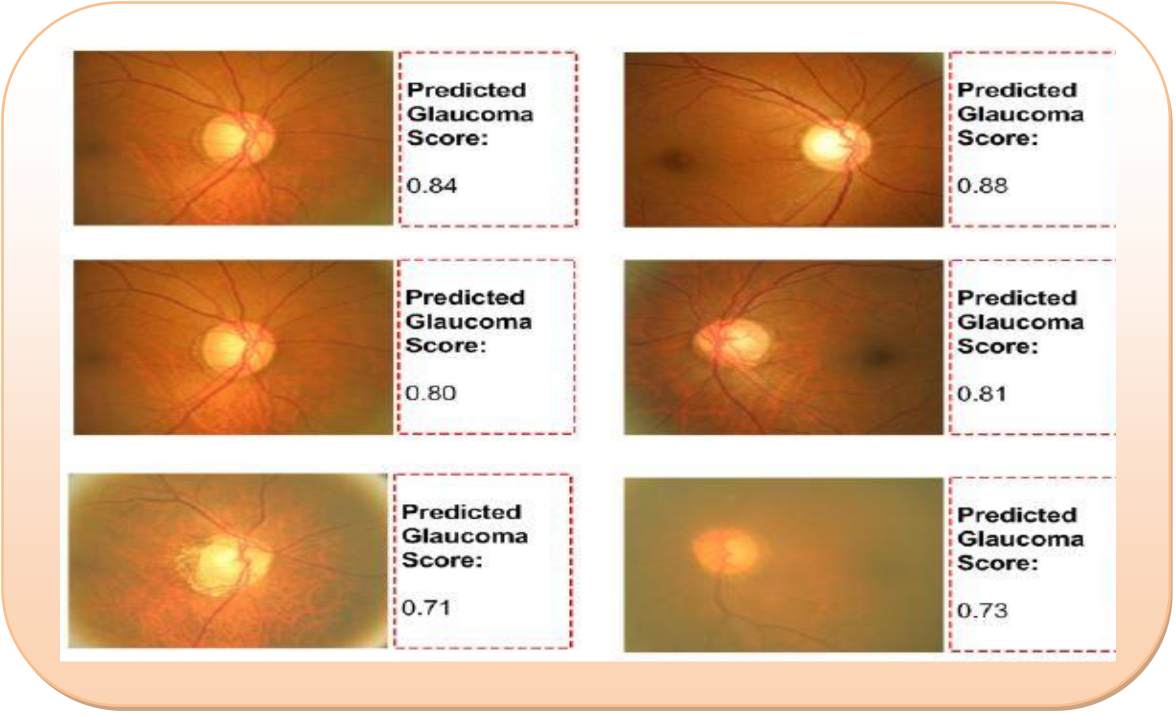

Fig (1.2) Prediction results for glaucoma disease using deep CNN

We use 652 ORIGA images for testing for SCES datasets and the total 1672 SCES images is the test results. The AUC values of our ORIGA and SCES system are respectively 0:842 and 0:867. The AUC figures are 0:873 and 0:870, respectively, for the modified reconstruction process. Moreover, Fig. 2 brings our proposed algorithm six sample tests. 2 The clinicians and the forecast labels with probabilities of our algorithm diagnose each fundus picture. Although the third row has bad picture clarity, the glaucoma is still observed in our system and reveals its solidity and stability.

Our suggested glaucoma detection method succeeds in the sample diagnosis. Picture in the fundus is treated with our algorithm by clinicians and the expected labels as shown in fig (1.2). We use the area under the receiver curve in this study to assess the efficacy of the diagnosis of glaucoma. As seen in Fig (1.3), the ROC is defined as a curve showing the equilibrium between the true positive rate and the true negative rate.

In our proposed deep learning design, we use dropout in the two completely linked layers. Dropout entails the output of a secret neuron being set to zero with a likelihood of 0:5[10]. If the nerves are disabled in CNN, they are not active in forward movement and are not part of a back movement. In the experiments, both neurons are included but their output is weighted by 0:5.The first and second Convolutionary layers in the proposed profound learning architecture obey response-normalization stages.

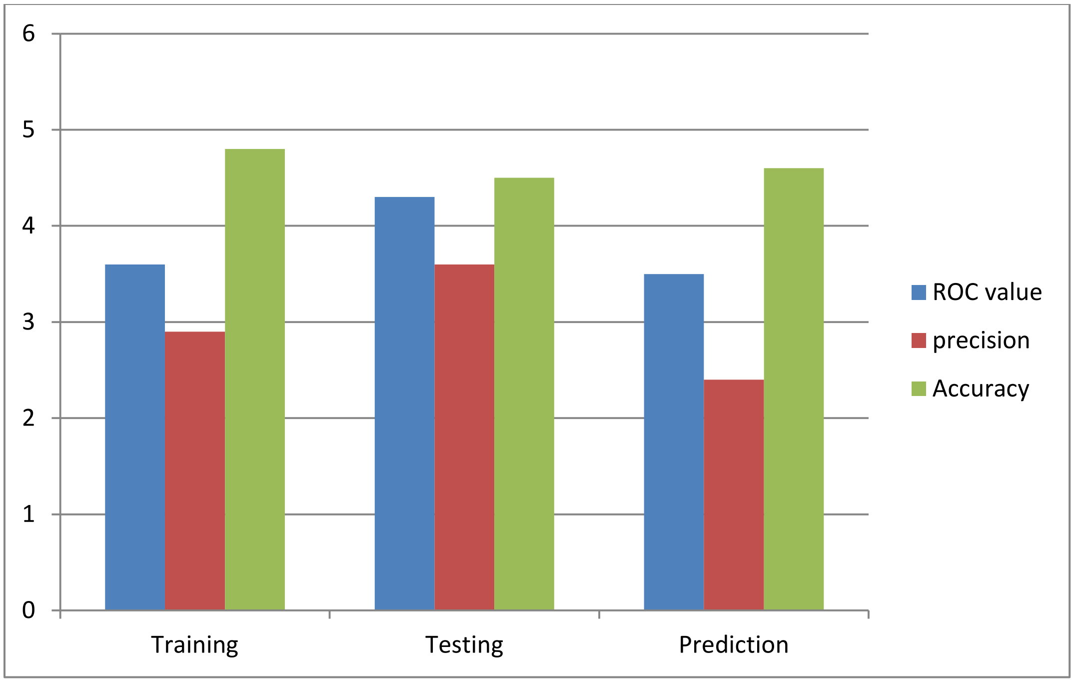

Fig (1.3) classification results on glaucoma disease using deep CNN

Conclusion:

This paper provides a DL System for identifying glaucoma focused on deep CNN, which describes the unequal traits that help describe the secret manifestations of glaucoma. The DL framework consists of six levels: four levels of convolution, and two layers of relation. We often follow response-normalization layers and overlap-pooling layers in order to reduce the issue of over fitting. The proposed DL architecture also adopts with the goal of further enhancing efficiency, dropout and data increase strategies. We implement solution standardization layers and overlapping pooling layers to reduce the overlapping issue. In the planned deep CNN, discontinuation and data raise approaches are used to raise the output better. Our study on CNN-based DL design is planned to expand to other detections of eye diseases in future work.

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