Glaucoma Detection Using Deep CNN And Adadelta Algorithms

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Abstract- *Glaucoma is one of the leading causes of blindness or vision impairment according to World Health Organization. It requires lot of expertise and practice to detect glaucoma from the retinal color fundus images. Certain types of glaucoma are referred as "Sneak thief of Sight" because there are usually no symptoms of the disease except for the loss of vision and pain at a very advanced stage of the disease. So, early detection during regular screening process can help in preventing vision loss.*

To make it scalable and efficient, various machine Learning models have been proposed over the years. Our study is aimed at analyzing the impact of various optimization algorithms and learning rates on training a pre-trained convolutional neural network model for detecting glaucoma from retinal color fundus images. Six different optimizers were studied with seven different learning rates. The Experimental results show that there is a significant impact in Loss and Accuracy of the model with different optimizers and at different learning rates.

Keywords- Glaucoma Detection, Deep Learning, Convolutional Neural Network, Glaucoma Prediction.

I. INTRODUCTION

Glaucoma is the first cause of irreversible blindness since it affects the eye's optic nerve. In most of the cases patients do not experience symptoms of vision loss until advanced stages. According to Mohammadi [1] and Jeyaraman [2], it is estimated that in developed countries, at least half of glaucoma patients feel no signals of the disease, which is expected to be worse in developing countries. In a study of glaucoma prevalence from worldwide published data [3], [4] found that by 2020, over 11.1 million people will be bilaterally blind from primary glaucoma. In [3] was also reported the increasing economical cost of treatment of glaucoma in advanced stages. In Colombia, the Ministry of Health and Social Security estimates that there is around 296,000 blind people for several causes, having glaucoma a prevalence of 3.9% in people over 40 years old in Bucaramanga. This gets worse by the fact that in the country, based on the population in 2011, there are 2 ophthalmologists for 100,000 patients.

The damage in the optic nerve is due to elevated pressure in the eye, which is caused by either overproduction of aqueous humour or by the blockage of the drainage system of this liquid. There is also evidence of the incidence of genetic family background in the appearance of the disease. There are several tests that can be performed in a patient with suspected glaucoma, such as tonometry to measure the eye's pressure, gonioscopy to see if angle is open or closed, optical coherence tomography (OCT) and funduscopy or fundus imaging to see the retina and the optic nerve as shown in Figure 1.

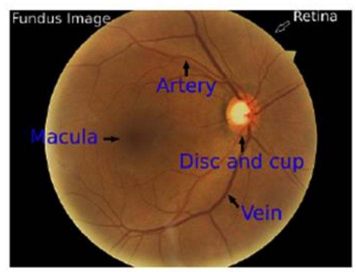
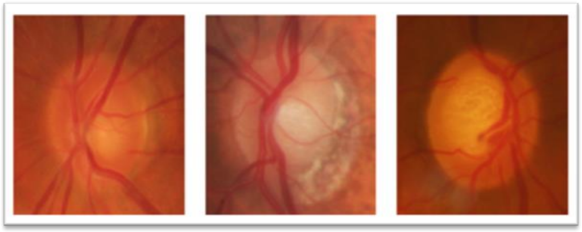


Figure 1.1: Fundus image and important parts of the eye.

The retinal fundus image is used to measure the thickness of the retinal nerve fiber layer (RNFL) to diagnose glaucoma. It is one of the noninvasive techniques most used by ophthalmologists. Its major advantage is that images can be taken easily for either healthy and nonhealthy retinas [5], it is also portable and not difficult to use for any health professional, specially in screening campaigns among population without access to health care services.

The thickness of the RNFL is calculated by measuring the proportion among the size of the optic nerve (named disc) and the size of the excavation inside the optic nerve produced by the increasing eye's pressure (named cup). This parameter is known as the Cup-to-Disc ratio (CDR). Figure 1.2 below show some stages of glaucoma.



(a) No glaucoma (b) Early glaucoma
(c) Advanced glaucoma
Figure 1.2: Sample normal, early and advanced glaucoma images.

In practice, what doctors do to determine if a patient has glaucoma or not, is to do a visual estimation of the CDR by observing the fundus image of both eyes of the patient. For the very well trained specialist this task can take around one to three minutes to give a diagnostic, however is prone to subjectivity. There is also the fact that it could be very demanding when this is done in screening campaigns where at the end, each specialist has hundreds of images to read. The CDR is calculated as follows,

CDR = area Cup/area Disc..................... (1)

If the CDR _ 0:6 it is glaucomatous, otherwise it is not. According to this, and as it was studied along the literature review, in order to do the automatic glaucoma detection, the first step is to obtain the segmentation of the disc and the cup as shown in Figure 1.2.

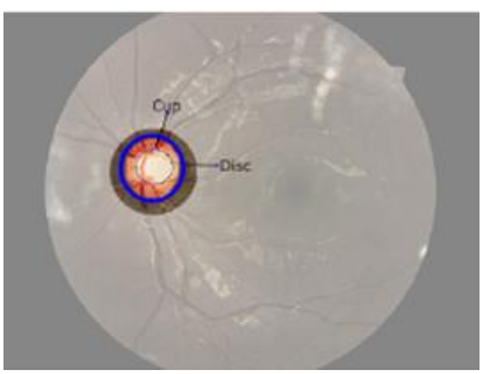


Figure 1.3: Disc and cup location.

Several works has been done for automatic glaucoma detection based on color fundus images [6], where the main difficulty is to provide an accurate estimation of the CDR. Anusorn et al [7] proposes a method for disc segmentation using edges detection. This method has problems if the eye has peripapillary atrophy which is a disease that alternates the edges of the disc. For segmenting the cup it uses as threshold one third of the highest grayscale intensity, however, the distance between the disc pixels and the cup pixels is not always the same, which makes difficult the segmentation among images taken from different persons. Another problem is to detect the cup edges when it is starting to grow in the early stages of the disease.

Dhumane and Patil [8] use super pixel segmentation to detect both disc and cup by means of a clustering algorithm, with a sensitivity of 88% and accuracy of 90.9%. It has a drawback when the excavation is growing in the nasal-temporal direction, since in that direction there is more presence of blood vessels that hide the cup. Ayub et al [9] propose the cup and disc segmentation using RGB and HSV color models and K-mean clustering. The method has 92% of accuracy, but they do not take into account the vascular system that goes throughout the disc which interferes with the precision of detecting the correct pixels that belong to the disc.

Nikam and Patil [10] implement the disc and cup segmentation with an ellipse fitting algorithm, where the fitting of the area is done by minimizing a distance cost function.

1.1 Materials and Methods

Glaucoma diagnosis in the clinical environment involves intraocular pressure measurement, visual-field testing or optic disk examination on fundus images. Even though intraocular pressure is an indication of glaucoma, its measurement is not an effective way of glaucoma diagnoses as some patients with glaucoma may have normal eye pressure. Visual-field testing, on the other hand, requires special equipment that some clinics may not have. The last method, optic disk examination, is more convenient than the other two and is more widely used by specialists for early glaucoma detection. Still, it bears the disadvantages that it is costly and time-consuming. The fact that there are millions of people around the world diagnosed with glaucoma led researchers to investigate the automatic detection of glaucoma. With the introduction of deep convolutional neural networks such as AlexNet [11], GoogLeNet [12], [13], VGG [14], ResNet [15] and DenseNet [16], researchers have attempted to use them for glaucoma diagnosis. Their research focused mainly on two areas. The first included using deep learning for feature extraction and the second involved the use of domain knowledge and medical features for detection.

Glaucoma is a progressive eye disease that damages our optic nerve [17]. It generally happens when fluid builds up in the front part of our eye. The pressure of the fluid inside the ordinary eye is 21mm Hg. The pressure in our eye increases with increase in fluid level causes damage in the optic nerves. The disease develops quickly and gradually and may lead to vision loss in both the eyes. But blindness from glaucoma can often be prevented with early estimation and treatment. When glaucoma develops, usually we don't have any symptoms in the beginning and the disease progresses inside [18]-[20]. In this way, glaucoma can steal our vision very gradually. Fortunately, early examine and treatment can help preserve our vision. Early detection, through regular and complete eye tests, is the key to protect our vision from damage caused by glaucoma. A complete eye checkup includes five general tests to detect glaucoma: Tonometry, Opthalmoscopy, Perimetry, Gonioscopy and Pachymetry.

Computing CDR [21] is another method to detect the glaucoma. The Cup to Disc ratio is the ratio of cup diameter to the disc diameter in the vertical position [22], [23]. There were many methods available for CDR assessment. CDR is calculated by comparing the segmented images of optic disc and optic cup with necessary modifications. Figure 1.3 shows the position of optic disc and location of optic cup in the eye.

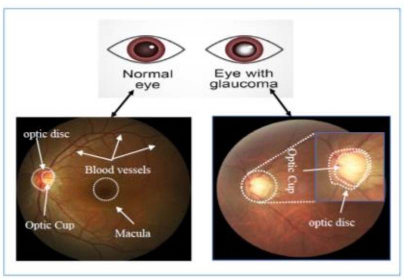


Figure 1.4: Optic disc and optic cup in eye.

1.2 Optic Disc Segmentation

Optic disc segmentation is the fundamental and most important method in the detection of glaucoma. It is difficult to have one segmentation method to work well on all the retinal images. Therefore it is important to reduce the risk of failure by combining the results from several methods. In the proposed self assessed disc segmentation method [24], one result is chosen from the outputs of the three individual disc segmentation methods. Disc boundary is obtained from each individual methods and the self assessed score is calculated from these individual methods.

The self assessed score of these individual methods is used to obtain the most confidential output for the disc segmentation.

The method used is the Automatic segmentation method [25] which uses the circular Hough transform to detect the vessel boundaries from the image of the optic disc. The self assessed score is calculated as distance between the ending boundary points and the edge points of the images. The next method is the super pixel classification method [26] in which the super pixels are generated from the disc region of the eye. The self assessment score for this method is the difference between the raw boundary and its best fitted ellipse [26]. The disc boundary is detected by using elliptical Hough transform [27]. The self assessment segmentation score for this method is calculated as the number of edge points in last disc boundary. From the obtained scores, the best result is chosen as the optic disc boundary. Fig. 5 shows the localized and segmented optic disc. The self-assessed disc segmentation used selects one result based on the outputs from the above individual disc segmentation methods. Each individual method obtains a unique image for disc boundary and computes a self assessment score that reflects a confidence or reliability of its automated result. The self-assessed method determines the disc by applying the mentioned disc detection methods one by one until a confident output is obtained.

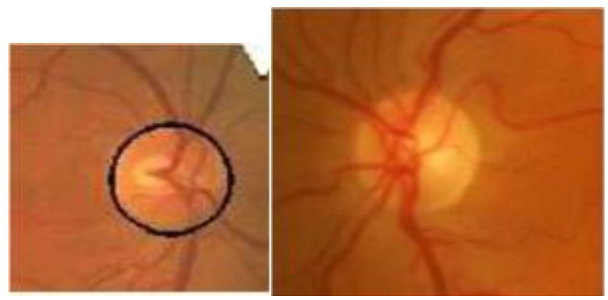


Figure 1.5: Localized disc (left) and Segmented Disc (right).

II. RELATED WORK

Several recent studies have used convolutional neural networks to classify glaucoma. Among them, Ahn et al. [35] investigated the performance of early and advanced glaucoma detection of fundus images with the help of a GoogLeNet Inception model and a newly created convolutional neural network model. Chen et al. [36] used deep learning, along with dropout and data augmentation techniques, to detect glaucoma on two fundus datasets. In [37], feature extractions of fundus images were done using convolutional neural networks and images were classified into normal and glaucomatous types using an SVM classifier. Fu et al. [38] proposed a disc aware ensemble network for automatic glaucoma screening by combining fundus image's deep hierarchical context and the local optic disc region. Li et al. [39] presented the performance of a deep learning algorithm to detect referable glaucomatous optic neuropathy on fundus images. In [40], fundus images of racially and ethnically diverse people and a few deep learning architectures were used to detect glaucomatous optic neuropathy. Shibata et al. [41] developed a deep learning algorithm to look for glaucoma on fundus images and compared the results to three ophthalmologists.

Orlando et al. [42] pre-trained convolutional neural networks on non-medical data to detect glaucoma on a fundus dataset. Sevastopol sky [43] utilized deep learning for automatic optic disc and cup segmentation of eye fundus images to classify glaucoma. A glaucoma detection system was developed in [44] to first extract the necessary features using convolutional networks and then most discriminative features were selected to be fed to softmax linear classifier to detect glaucoma on retinal fundus images. Asaoka et al. [45] used a deep feed-forward neural network classifier to distinguish between preperimetric glaucoma visual fields and healthy visual fields. Chakravarty [46] segmented optic disc-optic cup using a multi-task convolutional neural network to predict the existence of glaucoma in fundus images. In [47], domain knowledge and retinal fundus images were combined using a deep learning model to automatically diagnose glaucoma. Chen et al. [48] captured the discriminative features using a deep learning architecture to characterize patterns related to glaucoma. A curriculum learning method and a multi-stage deep learning model were used in [49] to diagnose glaucoma. In [50], glaucoma was detected using a multi-model deep learning framework that included a deep convolutional autoencoder and a traditional convolutional neural network classifier.

Rashmi Panda et al. [51] put forward an automated model for Retinal nerve fibre layer defect detection. As it is an early proof of glaucoma condition in fundus images. Early detection & prevention are ways to stop loss of vision. The new method performs detection in fundus images using patch characteristics driven RNN. Fundus images dataset is used to evaluate performance. This system obtains high RNFLD detection and accurate boundary localisation.

Kavita Choudhary et al. [52] presented a paper with the aim of detection of glaucoma at early stages using cross-validation algorithm. Authors analysed symptoms prevailing in persons & computed & generalised those symptoms to reach conclusive evidence. It was found that measures such as blood pressure, Age, Sugar level, & myopia were combined for various datasets are related to changes of a person suffering from glaucoma. Authors in their study have done an analysis of glaucoma disease by Classification method such as cross-validation algorithm & split validation algorithm. The outcome reveals that patients who have high blood pressure, high sugar level, myopia & with the family history of this disease can suffer from glaucoma. It is also observed that the patients with age more than 50 have higher chances of glaucoma.

Seong Jae Kim et al. [53] in this paper studied and attempted to design machine learning models that have robust power of predicting& interpretability for glaucoma diagnosis based on RNFL thickness & visual field. Different features were collected after examination of RNFL thickness & visual field. Authors used 4 machine learning algorithms like C5.0, random forest, SVM & K- nearest neighbour to design a glaucoma prediction model. Learning models are constructed using training dataset & their performance was evaluated by using validation data set. Finally, the authors observed that the random forest model gives the best performance & remaining other models show similar accuracy.

Shwetha C. Shetty et al. [54] disused and analysed that Glaucoma is an ocular disorder and its identification includes measuring the shapes and also the optic cup sizes. Pre-processing of data is then clustered using K-means clustering, which is used for segmenting the optic curves. It is again executed to find its various dimensions. Since the fractional dimension is used to determining the various dimension of non-regular identities, the authors presented a new method for detection of glaucoma using method of the perimeter for the fractional analysis. The outcome reveals the new approach is accurate in detecting glaucoma.

Liuli et al. [55] in this paper presented attention-based convolutional neural network for detecting glaucoma, known as AGCNN. Approaches which were proposed in the past for automatic detection system based on fundus images are insufficient to remove high redundancy, which may lead to reduced reliability & accuracy of detection. To overcome this shortcoming, the newly proposed method establishes a large-scale data set, which includes fundus images labelled as (+) ve or (–) ve. The attention maps of some images are taken from ophthalmologists through a simulated experiment. Then a new AGCNN structure is constructed which includes a subnet, a pathological area localisation subnet and a glaucoma classification subnet. Experiment on LAG database& other available datasets reveals that the proposed method gives a detection performance superior to previous models.

Jin Mo Ahn et al. [56] here, they have presented a method for the detection of the glaucoma disease which utilises fundus photography and uses deep learning. The author discussed that advanced & early glaucoma both could be correctly identified using machine learning along with fundus images. Dataset of 1,542 images was used and divided into training, validation & test datasets. The newly put forward model that is trained using CNN is more effective and accurate in the detection of early glaucoma.

Annan Li et al. [57] suggest that automatic detection of disease is important for retinal image analysis. When studied and compared with segmentation based approaches, it is found that image classification based approaches perform better. But challenges are always there due to improper sample, effective features and also shape variations of the optic disc. To overcome these, a new classification based model for detection of glaucoma is put forward by authors in these papers, in which deep convolutional networks are used to represent visual appearance, holistic & local characteristics are combined to reduce or remove misalignment.

Ali Serener et al. [58] discussed Open-angle glaucoma as it is one of the basic kinds of disease & slowly, a person tends to lose his sight. Diagnosis of this disease manually by experts is possible, but it either takes a huge time or cost. Authors in this paper presented a method for the detection of both early & advanced glaucoma automatically. ‘ResNet-50’ & ‘GoogLeNet’ deep CNN algorithms are trained & tuned using transfer learning. It is found that ‘GoogLeNet’ mode l is better than ‘ResNet-50’ for detecting both early & advanced glaucoma in the eye of the patient.

Ramin Daneshvar et al. [59] analysed that baseline OCT measures predict VF progression in patients with suspicious or established glaucoma & also authors compared performance with semi quantitative optic disc measures. It is observed that baseline pRNFL & macular OCT parameters can be used for checking the risk of glaucoma progression in future. People abnormal OCT findings require better care to prevent progression of functional damage.

Guangzhou et al. [60] presented a model for the detection of glaucoma within the patients by making the use of the open-angle for glaucoma that is based on the 3-D data colour images. Various fundus pictures as input provide the CNN architecture. After getting output from every CNN model, the outputs have been combined. And the random forest method is used for the classification of the fundus pictures. This classification is done with healthy and glaucoma infected eyes. At the result obtained for the AUC is of .96.

Juan Carrillo et al. [61] the authors have provided the glaucoma detection method as the glaucoma is the irreversible cure of eyes. They have provided a tool for computing the glaucoma symptoms in eyes. They have used this tool for the detection, and the detection is observed by the sizes of the cup and the disc. Also, they have used the fundus images for the evaluation.

III. PROPOSED WORK

Our Firstly,

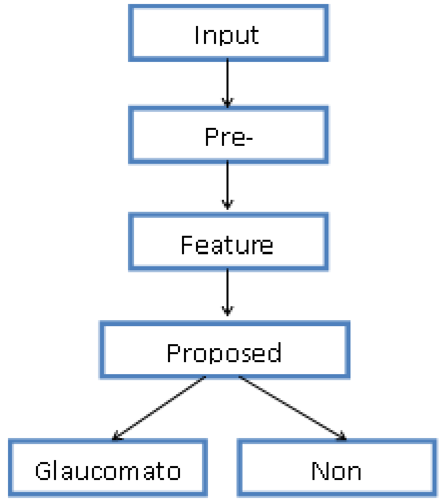


Figure 4.1: Proposed Model.

The first step of preprocessing was to manually crop the retinal images around the Optic Nerve Head (ONH). As it was proven, glaucoma affects only the ONH region and its surroundings. Therefore, we reduced the area of interest only to the ONH and its surroundings by manually cropping the images.

The next step was to normalize (the pixels’ value was reduced to a value between 0 and 1) and standardize the cropped images. In order to simulate a bigger dataset, the image augmentation technique was applied. Data augmentation is mostly applied in the medical imaging field, where there is often not enough data available.

Using Python Libraries Keras, TensorFlow, a sequential model was created with a pre-trained VGG16 model and all the layers are frozen in order to enable transfer learning. It also helps in preventing the weights being modified resulting in reduced training time. In addition, a final Dense layer with SoftMax activation is added to form a fully connected layer whose output will be a probability in the range of 0 and 1, which in our case will indicate the class of our fundus images.

We chose six different optimizers Stochastic Gradient Descent (SGD), Adadelta, Adam, RMSprop, Adagrad and Nadam with seven different learning rates (0.0005, 0.0001, 0.005, 0.001, 0.05, 0.01, 0.1)

The batch size is set to 32 and Epoch is set to 25 for training the same model in Fig 2.1 with the above-mentioned optimizers and learning rates. The loss function used is “Binary Cross Entropy” since the model is a binary classifier. ‘Accuracy’ is the performance metric for evaluating the model.

A Random Normal initializer is used to initialise weights. Bias is initialised to zero. The seed is set to zero for all the models to get same sequence of numbers across trials. The Test Data is used as the validation data set to validate the models. Loss and accuracy against epochs are documented and plotted using ‘matplotlib’ library.

Optimizers:

Stochastic Gradient Descent: Stochastic gradient descent is a variation to the gradient descent algorithm in which the updates are made to the coefficient after each training instance, instead of updating at the end of batch of instances. The learning will be much faster and the randomness of training data will be ensured.

Adagrad: It is one of the gradient descent algorithms which adapts learning rate and is highly suitable for sparse data since it considers low learning rates for frequently occurring parameters and high learning rates for infrequent parameters. It takes a subset of training data and update the weight by computing the gradient and squared error.

RMS Prop: RMS Prop computes the learning rate with an exponential average of squared gradients. Similar to Adagrad it takes a subset of training data and compute the gradient and squared error along with decay rate and then update the weights.

Adam: It is one of the most efficient algorithms which computes learning rate for each parameter. It takes into account both the exponentially decaying average of gradients and squared gradients which is the first moment and second moment. Both gradient and squared gradient are computed and biased towards zero and weights are updated by bias corrected gradients and squared gradients. Combination of momentum and RMS prop.

Adadelta: It is a stronger extension of Adagrad. It adapts learning rate based on moving window of gradient updates instead of considering all the past gradients. It enables continuous learning even after many updates.

Nadam: It incorporates Nesterov accelerated gradient with Adam. It is beneficial for noisy gradients and for gradients with high curvatures. With Nadam, the learning process is accelerated by summing up the exponential decay of moving averages for the previous and current gradient.

IV. RESULTS WORK

The classification performance can be evaluated in terms of accuracy. Accuracy explains correctly classified instances of the symptoms with respect to heart disease.

Classifier	Accuracy (in %)
Simple Neural Network	84.11
Residual Network (ResNet 50)	89.91
Proposed Model	**92.17**

Table 6.1: Performance evaluation based on Accuracy.

AS we can see from above results, Proposed DeepCNN Classifier is performing better as it has highest test accuracy.

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