



Glaucoma Diagnosis by Fundus Images Using Deep Learning

M.Jagadeesan¹, G.Vairamuthu²,

P.Selvaraj¹, L.Muthu Venkatesh²

Department of Computer Applications

Kongu Engineering College,

Perundurai-638060, Erode, Tamil Nadu, India

Abstract—Glaucoma is the most common retinal disease, and it damages the eye by increasing intraocular pressure (IOP). Glaucoma will cause vision loss if it is not treated because it damages the Optic Nerve Head (ONH). An experienced ophthalmologist examines Glaucoma advancement on the retinal region of the eye. This method is very time consuming, and it takes longer to do it manually. As a result, this is a valid problem that can be addressed by using deep learning approaches to automatically diagnose glaucoma. Convolutional Neural Networks (CNNs) are a good choice for solving this problem because They can extract various amounts of info from a picture input, making it easier to see the difference between negative glaucomic and positive glaucomic images. In this research presents a glaucoma master framework for determining the Cup to Disc Ratio by segmenting the optic cup and disc (CDR). A combination of deep learning and an unique CNN is used to diagnose glaucoma in this study. In the proposed method uses two distinct CNN architectures to segment the Optic Cup (OC) and Optic Disc (OD) for a more accurate result (OD). This model was trained and tested using the DRISHTI – GS database, and it has an accuracy of 98 percent for optic disc segmentation and 97 percent for optic cup segmentation.

Keywords— *Resource Pooling, Rapid Elasticity, Heterogeneity, Lower Latency, Edge Location*

I. INTRODUCTION

Glaucoma is known as the "silent thief of sight" since it is the leading cause of visual loss in the globe. Glaucoma affects around 60 a million people on the planet, with the By 2020, the quantity is predicted to reach 79.6 million. Glaucoma can alter a framework of the eye's retinal components (Orlando, 2020). Glaucoma is produced by structural alterations in the ONH on the retina (Mvoulana et al., 2019). Glaucoma is a serious disease with the optic nerve that can lead to irreversible vision loss if not treated appropriately.

Pre-processing images,extraction of features, collection of features, distribution, and grouping are all part of the automated detection method. Pre-processing is the initial phase, and it entails eliminating noise and outliers from the image in order to enhance it. The pre-processing stage is an important element of the picture enhancement process since it removes any unneeded sections of the retina, improving accuracy. To pre-process data, many filters may be employed, including mean, median, and gaussian.

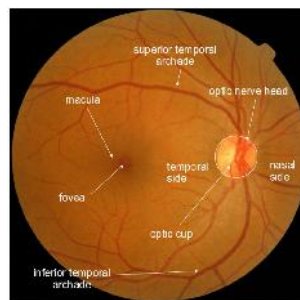


Figure 1.1: Fundus Image

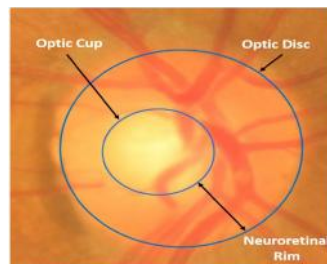


Figure 1.2: Optic Nerve

Based on current approaches, many strategies for detecting glaucoma using various retinal imaging modalities have been developed. The deep learning methodology will be used to diagnose glaucoma in the proposed method.

II. WORK CN CONNECTION

In ophthalmology, Previously, supervised deep learning methods have already been detailed in detail. The predominance of these studies, on the other hand, used large but private datasets to train their models. Fu et al. based on an ensemble of four distinct networks, suggested a disc-aware ensemble network, To arrive at the ultimate outcome, each of their guesses was combined. Haleem et al. suggested a RIFM-based technique for automated glaucoma identification, which extracts non-geometric (e.g., pattern, pixel appearance/intensity levels) and geometric (e.g., morphometric features) aspects from images. (SVM) A support vector machine algorithm The predictor were employed to classify these properties. Chai and his colleagues used computer sources that were well-aligned, rapid, and handy. Cloud computing has become a part of our everyday life.

A CNN with two levels was created. The full picture was sent to the first CNN, which segmented the OD before passing it on the second. For classification, a sequence of CNN models was used in it , Then there's a completely linked layer. Pal et al. suggested a network with many models with a common encoder structure that included an auto associator and a CNN classifier. Zhao et al. used MRI to segment the optic disc. used a multi-task learning model with limited supervision. To identify glaucoma, Li et al. created a CNN with a technique for detecting attention. As a result of this process, the network focuses more on a certain portion of the image. The attention mechanism worked well, but ophthalmologists had to do a lot of labelling to train the network where to focus while analyzing the images.

In other investigations, researchers discovered that analysing glaucoma using a high quantity of retinal images that aren't labelled, which are more easily accessible than those that are labelled, gave positive findings. Sedai et al. Using two autoencoders, created a semi-supervised method for segmenting the OC. The photos with no labels are put into the first autoencoder, which learns the features. The second autoencoder leverages the first autoencoder's learned properties to diagnose glaucoma. They utilized a large private dataset to test their model. However, doctors exclusively look at the OC area when diagnosing glaucoma, despite the fact that the disease can damage any part of the retina. Becher et al. In three steps, the researchers accord a semi supervised super pixel by super pixel OD segmentation and OC decomposition method.

III. DIAGNOSING GLAUCOMA USING DEEP LEARNING

The bulk of modern glaucoma diagnostic procedures start with segmenting the area of interest, which may then be studied later to detect the illness. As a result, For these technologies to operate, human annotations and pre-processing activities are necessary. Furthermore, None of the past profound learning models took utilization of the colossal amount of non-labeled retinal pictures that are accessible simpler to come by than annotated ones. This study aims to employ deep convolutional neural networks (CNNs) to diagnose glaucoma from retinal pictures. The clinical assessment of novel glaucoma medications might benefit from these approaches. These algorithms can also be used to monitor the progression of glaucoma in the patients remotely and autonomously. In order to be employed in clinical practice, automated systems must be thoroughly examined on a regular basis. One of our objectives is to show that automated systems can diagnose glaucoma better than



human doctors, reducing the burden of ophthalmologists. If these systems are assessed different research organizations should be able to comparing their algorithms' performance utilizing combining distinct and publicly available datasets to create the same dataset. To compare automated systems to humans, data on the results of human specialists on the matching dataset should be made available.

Our earlier research established a semi-supervised learning approach for detecting glaucoma from fundus pictures, and this paper expands on that work. Using multiple available datasets, we compare the efficiency of three different comprehensive automated glaucoma classification systems to two human experts in this study.

In addition to fundus pictures, ophthalmologists generally evaluate other aspects while making a decision, nonetheless, in this research, Only the fundus photos were given to them in order to provide a reasonable contrast to the computerized procedure. supervised and semi-supervised training approaches are used in these systems, as well as other deep learning approaches.

A. TCNN: Transfer Convolutional Neural Network:

Transfer Convolutional Neural Network model that absorb and adapts glaucoma symptoms in the situation of detecting with a limited sample size glaucoma utilizing an off-the-shelf CNN.

B. SSCNN: Semi-supervised Convolutional Neural Network :

A paradigm for semi-supervised convolutional neural networks with self-education that a neural network is trained in two steps.

The TCNN model is used as a glaucoma diagnostic classifier in the initial step. The second step entails self-study technique that uses samples from the dataset that hasn't been labeled to enlarge the training set and enhance the CNN's pre-trained performance. The self-learning technique constructs a pseudo-label for each unlabeled sample by Choosing the highest-ranking class designation likelihood of being correct and accepting it as the true label.

C. SSCNN-DAE: Semi-supervised Convolutional Neural Network:

A convolutional denoising auto associator -based glaucoma classifier (CNN-DAE) extracts selective features and uses these characteristics to a supervised environment, train fully linked layers. manner as shown in Semi-supervised Convolutional Neural Network model with auto associator From unlabeled data, the CNN-DAE is utilized to get knowledge about selective characteristics of materials needed photos. the statistics for training the labelled set is a term that is used to describe a group of people generate maps with special features, which are then utilized completely linked layers to train in a direct manner until the figure is stable sufficient to depict fundus pictures. The constructed classifier is then assessed on the test dataset.

Our paper makes three important contributions:

- Using three learning algorithms depending on the availability of annotated data, we demonstrated Convolutional neural networks (CNNs) are three types of neural networks that may be used to identifying glaucoma using fundus pictures (semi-supervised, transfer, and monitored).
- To evaluate the performance of the offered models, we ran many tests using two datasets. When compared to the outcomes of two people who are experts, the model given shows that deep learning can outperform human experts in this task.
- Our 3 models are open source, allowing other academics and practitioners to readily construct high-performing disease diagnostic algorithms that can be developed using our methods on their datasets.

The finale of the paper to made laid out as follows: Section II introduces CNN's recommended models. In this section III, The experimental setup and datasets are explained, followed by the outcomes and commentary. In the end, Chapter IV brings the article to a close.



IV. DATABASE DESCRIPTION

The 101 fundus photographs in the DRISHTI-GS collection came from the Arvind Eye Hospital. There are 50 training photographs and 51 testing photos in all. In the picture samples of 40–80-year-old adults, Male and female photos were similarly gathered. All of the linked optic nerve head findings were carefully computed by four clinical professionals and are included in the database. An optic disc with a 30-degree field of vision and a resolution of 2896 X 1944 pixels is placed in the center of the picture to calculate the image ground truth values. Experienced clinical specialists obtain the median disc borders, optical cup, CDR value, and soft maps markers for the retinal image.

V. METHODOLOGY

The computation of CDR value is critical in this suggested approach for achieving more accurate findings in the identification of glaucoma, which is based on adequate OC and OD segmentation.

As an example, the fundus image with a resolution of 2896 X 1944px is used. After that, morphological techniques including CLAHE, erosion, and dilation (Contrast Limited Adaptive Histogram Equalization) are employed to increase the image's quality and contrast in the pre-processing stage. The characteristics of the pre-processed picture are recovered using the Watershed algorithm and the Sobel edge detection approach were used to localize the optic nerve region.

When the glaucoma detection zone has been found, it will be decreased to 512x512 pixels. Two separate CNN models were used to segment the retinal image and optical cup, each having 39 layers. Both models employ the cropped picture as an input, and the predicted mask is acquired from both ends.

Glaucoma is diagnosed using the cup-to-disc ratio, This is calculated using a retinal image cover and the optical cup mask as predicted. The sections below go through each block in detail.

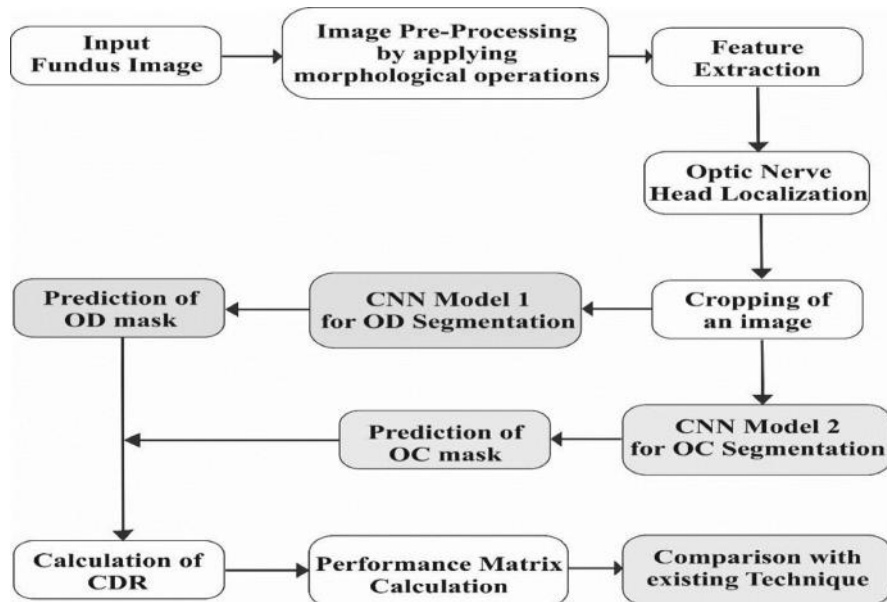


Figure 2: System Work Flow

A. Pre-Processing

The e-processing of a photograph is an important step in the diagnosis of fundus photographs. Noises of pepper and salt, as well as white gaussian noise, had the largest impact on fundus images. The ophthalmologist's diagnosis of the condition



relies heavily on the reduction of noise from these pictures. Gaussian noise in fundus images is reduced using the Gaussian filter. This picture does not include distinct channels for the RGB (Red, Blue, and Green) components. To the following phase, the whole set of merged channels is transmitted.

B. Dilation and Erosion

Two of the most important structural mathematics approaches for the purpose of picture improvement are dilation and erosion.

The retina imaging, veins will be visible. grow lighter as a result of the dilation, and extra pixels will be added to the input image's borders.

Dilation fills the interior spaces between pixels, therefore double the dilation process enhances the image even more. In the erosion process, the same structural element that was utilized in the dilatation phase will be utilized. Erosion aids in the creation of pictures that are clean and the difference of photos borders. If the delay occurs twice, the erosion occurs twice as well.

C. Contrast Limited Adaptive Histogram Equalization (CLAHE) technique

The CLAHE performs well in picture improvement when compared to regular Histogram Equalization (HE) and adaptive Histogram Equalization (AHE). This assists in the contrast improvement of low-contrast photographs, especially medical photos. In this situation, the visual contrast is addressed by reducing the contrast. When the noise is more noticeable, we can reduce the contrast by applying standard histogram equalization to increase the noise. As a result, Following the application of CLAHE to the HE, expected outcomes will take place expected. When the variance is compared to the input picture value of severity to the required level of strength, the CLAHE is determined. Histograms will be used to depict the outcome. The histogram's level reflects the image's contrast. The slop and clip limits functions will take place used to change the image's contrast.

Traditional normalization of histograms separates the picture into many sub-regions, with application bilinear interpolation to each one separately. The changing noise in different areas causes a challenge after combining all of the regions. To address this issue, the CLAHE is used to reduce contrast enhancement. A pixel is mapped with its four neighbors and aggregated into a single area using bilinear interpolation. Filters and CLAHE work together to assist eliminate noise from fundus RGB pictures, as a consequence of which the image is better and denoised. The fovea, macula, and Head of the visual cortex are all located in the retinal area in the eye. In order to identify glaucoma, the optic nerve head must be located. As a result, by finding the brightest portion of the image, the CLAHE will be utilized to segment the optic nerve head.

D. Shape detection

The Edge Histogram Descriptor (EHD) is a tool that may be used to determine the shape of a picture. Five distinct sorts of shapes are used to depict the area of a picture. These five picture kinds encompass a vast variety of possibilities. The picture is subdivided into 4x4 parts, which are known as sub-images. Each of the 16 blocks that make up the sub-images forms a histogram. The margins of each section are separated into five categories. The edges include straight, diagonal, 135-degree diagonally, 45-degree non - parallel, and asymmetrical edges.

VI. FEATURE EXTRACTION

Using Edge Detection by Sobel algorithms and Watershed algorithms, the recommended approach collects edge and contour form features. It is easier to locate the OD and OC by decreasing the characteristics of margins and curves. The cropped region will then be fed into the recommended model for segmenting the retinal image and the optical location of the cup.

A. Sobel edge detection

An image processing approach for finding the borders of a given input picture is edge detection. This approach may be used to extract data as well as segment the selected locale. The accurate translation of the OD and OC lines will be drawn for identify glaucoma diagnosis. As a consequence, the Sobel Edge Detection technique will be used to retrieve the edges information. There are other edge detection approaches, including Canny, Prewitt, Roberts, and fuzzy logic, but the Sobel approach is the most commonly used. It demonstrates how well the image's pixels represent the edges.

The vector values of the dots from the outside, which vary progressively light to bright, are used. As a result, the vascular borders are easily pulled from the disc and cup.

B. Watershed algorithm

Most people use the watershed approach to segment photos, however it may also be used to extract features. In the suggested technique, this algorithm is employed to extract the contour form.

The Object borders and edges would be clearly distinguishable between OD and OC obtained based on the result. The whole picture is initially split in the form of discrete collection of sections in this segmentation method, each having its unique contour shapes. Super pixels are created by grouping the pixels in each zone together. By considering the entire image as a surface, In the map, the 'watershed lines' & 'catchment basins' picture may be detected. It constructs the areas by giving dusky pixels a weak value & bright pixels a large value. The three primary algorithms that this technique employs are the Gradient method, Marker Controlled Distance Transform Approach. The cropped image is utilized as the starting point for the OD and OC border extraction techniques.

VII. CROPPING

After you've found the disc component on the picture, you may move on to the next step, The image's leftover portion will also be reduced in size to the needed dimensions. The scale of the supplied image is 2896 x1944 pixels, 512x512 pixels will be chopped to be used in future processing, As input photographs, only cropped photos will be used. While there is a chance that data will be lost as a result of this, eliminating regions that aren't essential for glaucoma diagnosis will speed up calculation and increase disc and cup segmentation accuracy.

A. Proposed segmentation methodology using modified CNN

In this method proposes segmenting the OD and OC for glaucoma detection using a modern edition of the Convolutional Neural Network. Improve the accuracy of the segmentation method, two different CNN models are used. In both the OD and OC segmentation procedures, the number of layers used was the same. The entire fundus image, with a size of 2300 X 1600 pixels, is not available as a source of information to the CNN model that is used to image retraining. To reduce the execution time, the CNN model is fed a clipped image component with a dimension of 128×128 in the vicinity of the optic disc.

By applying multiple filters to two sets of data, the convolution layer is utilized to create a future map. The maximum values from the clusters in the max-pooling layer are selected, It is possible to reduce the picture size.

Down sampling trains CNN to focus on the most critical activation sites, minimizing feature map duplication and enabling for quicker, less memory-intensive training. Up sampling is a technique for recovering data that has been lost.

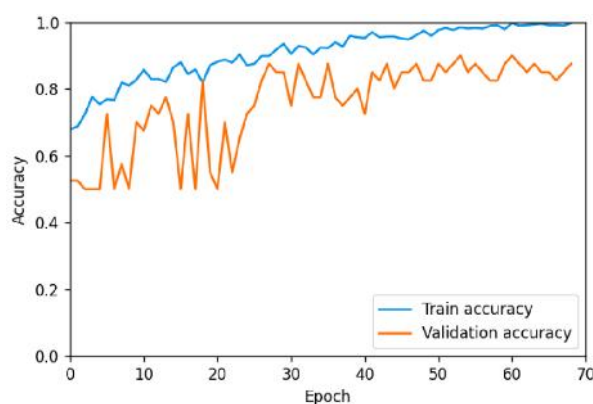


Figure 3 Train-validation accuracy graph

VIII. CONCLUSION

Using fundus photographs, a generic deep learning approach was developed to detect glaucoma. Inception V3 and ResNet50 are two deep learning architectures used in the algorithm. Five separate datasets are utilized to train and test this model, four for training and one for testing. Prior study has concentrated on just either one or two variables.

This approach perfects the information throughout training and validation.

To guarantee that's it compatible with any information

When compared to earlier studies, the results demonstrate that the ResNet50 model is 98 percent of the time equivalent or better. For AUC accuracy, the Inception V3 algorithm is equivalent or better 97 percent of the time, prediction accuracy is equivalent or superior. It is always equal to or better than the competition.

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