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AI Based Early Childhood Glaucoma Risk Screening System Using Eye Image Analysis

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Abstract

This study describes an artificial intelligence-inspired, rule-based framework for early detection of risk of developing childhood glaucoma through analysis of the child's retina using colour fundus images. The system will first employ a series of pre-processing techniques on the input fundus image including conversion to greyscale format, noise reduction and contrast enhancement prior to finding the optic disc and optic cup in the images through use of a variety of image processing methods. From these two areas, the vertical Cup-to-disc ratio (CDR), which has been scientifically shown to be an important clinical measurement parameter for assessing the potential presence or future development of glaucoma, is calculated. The CDR calculation can be used to classify an individual as being at low, moderate or high risk of developing childhood glaucoma. The final implementation of the system will be as a web-based application where users can take a digital retinal image using a scanner or upload an existing image for analysis. Experimental results indicate that the designed system will yield quality results that are reliable and efficient for use as an initial screening procedure for childhood glaucoma. The system is also designed to be low-cost and readily accessible so that it can be used in a variety of possible clinical settings such as schools for children, rural healthcare clinics and within telemedicine environments to facilitate early detection of childhood glaucoma.

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1. Introduction

Glaucoma refers to multiple eye conditions that affect the eyes by causing progressive damage to the optic nerve, which is responsible for sending images from the retina to the brain. Glaucoma is a major contributor to irreversible blindness globally, and because of the often subtle or unnoticeable signs of glaucoma, finding it early can be particularly difficult in children. One of the most commonly used measures for assessing glaucoma is the cup/disk ratio (CDR), which measures the size of the optic cup in relation to that of the optic disk as seen in images obtained from patient's retinas. An increase in the size of the optic cup occurs in eyes that have glaucoma, resulting in a higher CDR. Therefore, the use of a CDR as an evaluation has great importance in the diagnosis process for glaucoma.

The traditional way that the CDR measurement is made is by using cameras (fundus cameras), optical coherence tomography (OCT) devices, or by trained professionals evaluating the retinal image. All these methods are typically expensive and often not readily available in many parts of the world. As a means of overcoming the shortcomings of these traditional methods, automated image analysis techniques can provide an attractive alternative. Utilizing methods for image preprocessing, segmentation, and rule-based analysis, images of the retina can be analyzed for their level of risk of having glaucoma, without having to rely on machine learning techniques or having access to a lot of data.

A comprehensive web-based, fully automated solution for childhood glaucoma screening has been developed that includes the capture or receipt of retinal (eye) images as well as enhancements for improving the quality of images captured; segmentation of the optic disc and optic cup areas; calculation of a vertical disc-to-cup ratio (CDR); and classification of the risk of developing childhood glaucoma. This fully automated web-based approach minimizes dependence on expert evaluation and specialized equipment; and also facilitates the rapid provision of a preliminary ophthalmological assessment, regardless of location or the availability of resources.

The development of the screening approach is intended to enable early identification of children at risk of developing glaucoma, thus enabling subsequent assessment and ongoing monitoring of children at risk of developing glaucoma, by automating the physical and personnel assessment activities typically associated with traditional glaucoma screenings. Since the approach is intended for use in settings such as schools, rural healthcare facilities, and telemedicine, the availability of an automated and low-cost assessment method further demonstrates a cost-effective approach for providing an assessment of the likelihood of children developing glaucoma and will ultimately enable the identification of children at risk for the development of glaucoma. The complete screening report will include the results of each screening activity, providing documentation of risk for subsequent follow-up and clinical decision-making. A Comparative illustration of retinal images can be seen in figure 1, the Cup-to-Disc ratio increases and the neuro retinal rim thins progressively with glaucoma severity.

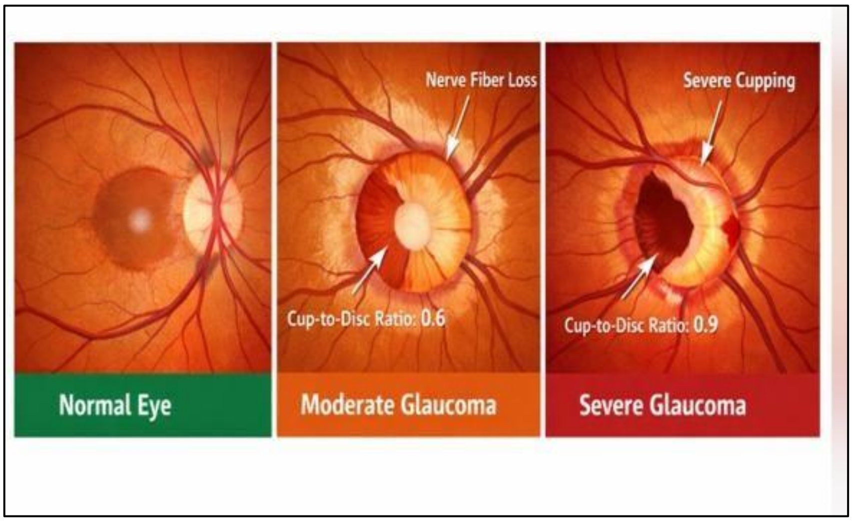

Figure 1. Comparative Illustration of Retinal Images

2. Related Works

Cheng et al. proposed the M-Net architecture proposed in this study aims to resolve OD and OC segmentation collectively within a single label. The M-Net consists mostly of multi-scale inputs, a U-shaped convolutional neural network (CNN), a side output and a loss function that supports multiple labels. The multi-scale input builds an image pyramid so that the model can learn multiple levels of the receptive field size [1]. Cheng, Jun et al. proposed the research provides a method to segment optic cups and optic discs using a super-pixel based classification system to help in the automatically screening for glaucoma. The method segments the optic disc from the superpixel segments in the image by first retrieving the intensity histograms and the centre-surround statistics from each superpixel. After storing this information about disc vs non-disc, the authors then calculated the reliability of each superpixel using a self-developed self-assessment reliability system. This reliability score indicates how confident the system is that the superpixel is an actual disc or cup. The researchers also added location information to aid in segmentation for the optic cup. The results with this method was evaluated using 650 images of enhancing segmented boundaries. The average error (overlap with true boundaries) of optic discs was 9.5%, while that for the optic cups was 24.1%. It was observed that overlapping error increases as reliability score decreases. This demonstrates that the self-assessment reliability score is useful in determining the quality of the segmented results. The segmented regions can be used to calculate the cup-to-disc ratio for glaucoma screening purposes, and the authors' method achieved 0.800 and 0.822 area under the ROC curve on two independent data sets respectively, which is better than all other methods tested [2].

O. Ronneberger et al. Our architecture contains a contractive pathway to acquire contextual information, as well parts within each of those sections used for localization (hence the term `symmetric'). Additionally, we demonstrate that the complete neural net can be trained from a bulk of training samples with little or additional input data and outperformed previous approaches (such as sliding window convolutional neural nets) in obtaining the best score throughout the International Society for Biological Imaging (ISBI) Challenges in Segmenting Neuronal Structures in Electron Microscopy Stacks [3]. S. Wang et al. proposed a lightweight, efficient segmentation network serves as the backbone for creating an entirely new patch-based output space adversarial learning framework (pOSAL) that jointly and robustly segments both optic disc (OD) and optic cup (OC) from disparate databases of fundus images. To enable the segmentation network to create accurate and smooth OD and OC segmentations, we insert into the framework a novel morphology-aware segmentation loss function that guides the network with respect to the unique shape characteristics found in the biology of the optic disc and optic cup [4]. H. Fu et al although the application of deep learning to medical imaging is relatively common, the evaluation of glaucoma has not been extensively studied in this manner due to the small number of datasets currently available for training. Additionally, without a standardized benchmark for evaluating current deep learning methodologies, it is challenging to objectively compare these methods. In order to address these challenges, we have established the Retinal Fundus Glaucoma Challenge, REFUGE (https://refuge.grand-challenge.org) in conjunction with MICCAI 2018. This paper presents an overview of each method and an analysis of the results obtained by each participant [5].

T. Walter et al. finding the optic disc is critical in our process. We use morphological filtering techniques in conjunction with the watershed transformation to find it. The algorithm was tested on a small image database using a human grader as a benchmark. This resulted in a mean sensitivity of 92.8% and a mean predictive value of 92.4% [6], [7]. A. Aquino et al. Morphology and edge detections is the methodology used to create a circular approximation of the OD boundary of the OD via the use of Circular Hough Transform methodology. The initial information required is that there is at least 1 pixel which exists within the OD boundary. In order to accomplish this an algorithm which uses a voting-type method to locate the OD is also proposed [8], [9]. K. He et al. this paper, they evaluated residual networks of up to 152 layers (8× deeper than VGG networks) on ImageNet and found that residual networks have a lower model complexity than VGG networks when compared on the basis of model size (number of parameters) as well as their performance (measured in terms of classification error). The best ensemble of residual networks achieved 3.57% classification error on the ImageNet test set; this ensemble won first place at the 2015 ILSVRC for the image classification challenge. We also evaluated how residual networks perform on CIFAR-10 when using 100 and 1000 layers. Understanding how depth affects a network's representation is critical for solving visual recognition problems [10].

3. Proposed Methodology

An AI-based Childhood Glaucoma Risk Screening System is devised with the ability to estimate the likelihood of glaucoma by examining images of children's retinal fundus. This system can assess retinal images through the use of either an image scanner/device in real-time or by manually uploading images from previous collections through use of a website interface. This describes a method for the achievement of the goals defined above. Initially the retinal image is acquired and adjusted to a standard resolution. The ultimate goal of this is to provide a good quality image by applying various preprocessing methods (e.g., removing noise, increasing contrast, and normalizing color). The next step is to process the image using computer vision technology to locate and extract the optic disc and optic cup regions. There are many different types of methods for defining boundaries for these two structures such as morphological operations and contour detection.

The Cup-to-Disc Ratio (CDR), defined as the vertical height of the optic cup divided by the vertical height of the optic disc, is a key variable used in determining risk for glaucoma.

After determining these measurements, values are classified into three risk categories (Low, Moderate, or High) relative to defined threshold levels. The overall architecture consists of four key processing modules; Image Acquisition, Image Processing, CDR Calculation, and Risk Classification as shown in figure 2. This will allow for a simple yet effective initial screening tool for use in schools, rural primary care centers, and via telemedicine applications amongst others.

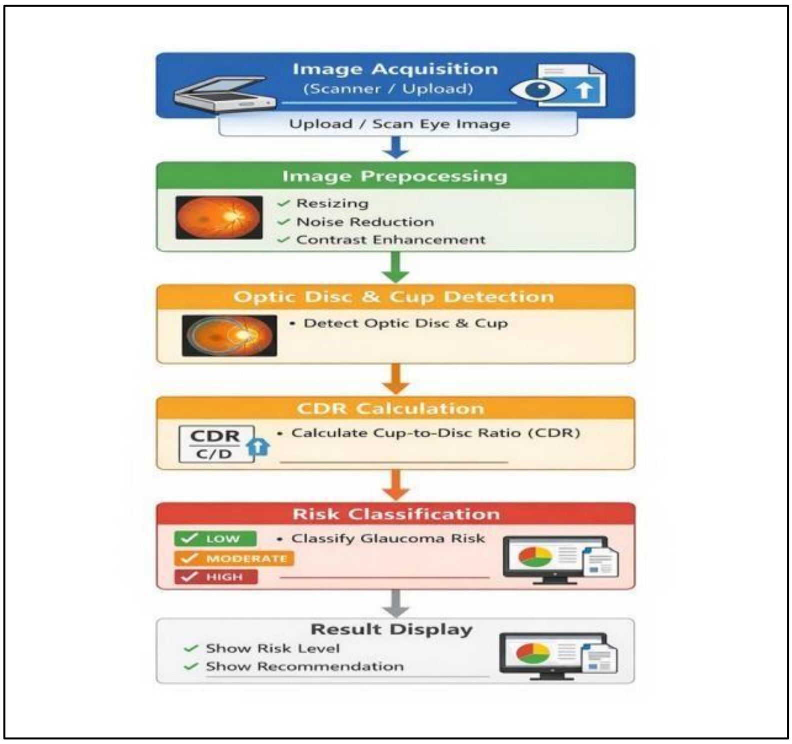

Figure 2. Overall Architecture of the Proposed Childhood Glaucoma Screening System

A comprehensive and user-friendly system for using the web to process retinal images using the Python and Flask programming languages. It makes use of OpenCV to carry out many of the basic image-processing operations that include filtering, segmentation, and extracting features. To provide an easy-to-use, interactive interface, the front end of the system uses standard web technologies of HTML, CSS, and JavaScript.

Retina images can be submitted to the system using either the web portal or a scanner or camera that is connected to the computer. Once an image is submitted to the system, the backend module of the web application will perform preprocessing, the detection of the optic disc/cup, and the calculation of the CDR.

4. Proposed Algorithm

Algorithm 1: Image Preprocessing and Noise Removal

Input: Retinal image I
Output: Enhanced image I_p
1: Read input image I
2: Convert image to grayscale
$I_g = Gray(I)$
3: Apply CLAHE for contrast enhancement
$I_c = CLAHE(I_g)$
4: Apply Gaussian Blur for noise reduction
$I_b = Gaussian(I_c)$
5: Normalize image intensity (optional)
$I_n = Normalize(I_b)$
6: Output preprocessed image I_p
7: End

Table 1. CDR Based Risk Classification

CDR Range	Risk Level
CDR < 0.5	Low Risk
0.5 ≤ CDR < 0.7	Medium Risk
CDR ≥ 0.7	High Risk

A CDR value is then analyzed against a set of threshold rules that allow users to assess their risk for glaucoma, as illustrates in Table 1. The final results and recommendations will be shown in the user interface, and the system provides automated documentation for each case by generating a report.

Algorithm 2: CDR-Based Glaucoma Risk Screening

Input: Optic cup and optic disc regions
Output: CDR value and risk level
1: Generate binary mask for optic disc (M_{disc})
2: Apply Otsu thresholding within disc region 3: Generate optic cup mask (M_{cup})
4: Compute vertical height of disc: $H_{disc} = y_{bottom\_disc} - y_{top\_disc}$
5: Compute vertical height of cup: $H_{cup} = y_{bottom\_cup} - y_{top\_cup}$
6: Calculate CDR:

$CDR = \frac{H_{cup}}{H_{disc}}$
7: If $CDR < 0.5$ then
$Risk = Low$
8: Else if $0.5 \leq CDR < 0.7$ then
$Risk = Medium$
9: Else
$Risk = High$
10: Display CDR and $Risk\ Level$
11: Store result in database with timestamp
12: End

The system can perform all of these procedures with minimal resources and can be deployed on a typical home computer and have access to the Internet, which allows it to be implemented in low-resource settings.

5. Techniques Used in the Proposed System

The childhood glaucoma risk screening system intends to utilize a set of imaging processing & analytical techniques to identify the structural components of the retina for the purpose of determining the likelihood of developing glaucoma. Each component of the system enhances image quality, isolates critical sections of the images, determines specific measurements of those critical sections, and accurately classifies the likelihood of developing glaucoma. Table 2 summarizes the specific techniques applied at each stage.

Table 2. Techniques Applied in the Proposed System

Stage	Technique Used
Image Enhancement	CLAHE
Noise Reduction	Gaussian Blur
Optic Disc Detection	Hough Circle Transform
Cup Segmentation	Otsu Thresholding
Feature Extraction	Vertical Cup-to-Disc Ratio
Classification	Rule-Based Risk Classification

The first step in this process includes applying CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve the contrast of the original retinal image so that the optic disc and cup can be visualized more clearly. A Gaussian blur is then performed on the image to reduce noise and smooth out the image for more precise identification of the structures within. The optic disc will be identified using the Hough circle transform and the optic cup will be segmented from the background using Otsu's thresholding method. The vertical cup-to-disc ratio is calculated in order to derive a measurement that will assist in determining whether or not there is a likelihood that a person will develop glaucoma. Based on this vertical cup-to-disc ratio, the system will classify an individual into one of three categories (Low, Medium, or High) based on specific thresholds established for the classification of people into these two categories.

6. Results and Discussion

An assessment was carried out using 747 retinal fundus images to evaluate the proposed childhood glaucoma risk screening system. These 747 images are classified as 199 normal; 548 images have characteristics of glaucoma. The system first preprocessed the image, detected the optic disc, segmented the optic cup, and calculated the vertical cup-to-disc ratio (CDR). A total of 91 screening sessions were performed using a web-based interface; 62 were performed using the real-time webcam capture process and 29 were performed using uploaded retinal images. Table 3 presents the distribution of glaucoma risk levels based on CDR computations:

Table 3. Screening Results

Risk Level	Number of Cases
Low Risk	44
Medium Risk	15
High Risk	32

The results of the experiment highlight the ability of the system to classify samples into distinct risk categories according to the experiment design using 91 samples. This demonstrates the reliability of the system to classify images into distinct risk categories based on CDR. The figure 3 shows the image upload interface of proposed work. Images taken from enlarged opticcupped eyes were assigned a Moderate or High risk level indicating a true positive, while normal eyes were detected as Low risk level consistently, as demonstrated in figure 4.

Contrast enhancement via CLAHE and noise reduction via Gaussian blurring improved the visibility of retinal structures leading to improved accuracy in identifying the optic disc and cup locations. Hough Circle Transform effectively narrowed the location of the optic disc, while Otsu's Threshold provided an accurate segmentation of the optic cup. Thus, the automated computation of cup-to-disc ratio (CDR) eliminated bias in human observers and consistently classified risk.

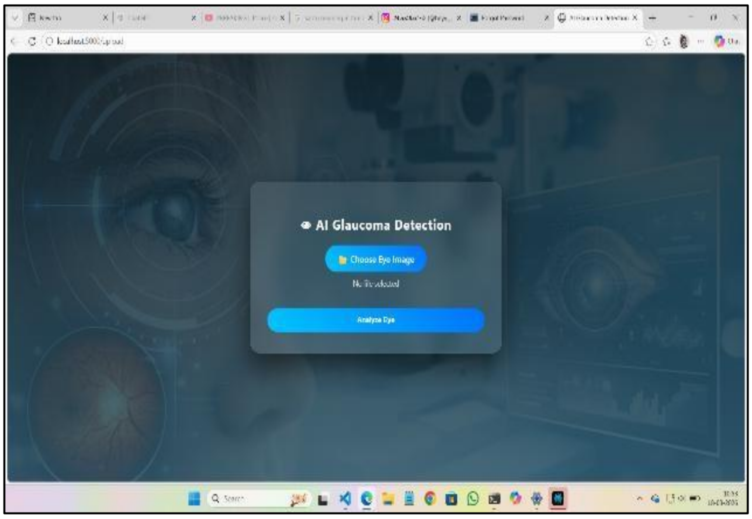

Figure 3. Upload Section

Figure 4. CDR Value Generated from Eye Image

Overall, the results demonstrate that the proposed system can serve as a reliable, fast, and accessible tool for preliminary glaucoma risk screening, particularly in schools, rural healthcare centers, and telemedicine applications where specialized ophthalmic resources are limited.

The evaluation of the proposed screening system for childhood glaucoma showed that it was effective as a preliminary diagnostic tool. The preprocessing stage (i.e., enhancing the contrast of retinal images through the Contrast Limited Adaptive Histogram Equalization (CLAHE) process and reducing noise through Gaussian Blur) yielded substantially improved clarity of the retinal images for reliable determination of the optic disc and optic cup regions. The Hough Circle Transform identified the optic disc location consistently, while thresholding based on the Otsu method successfully located the optic cup for accurate vertical cup-to-disk ratios to be measured.

The CDR values that were calculated were determined to be an adequate measure for classification of glaucoma risk. Larger optic cups produced higher CDR measurements and could be classified accordingly as Moderate or High risk glaucoma, with normal images being classified as Low risk. As well, the automated method reduced the amount of time required for processing and eliminated the variability associated with human subjective observation, and provided consistent and reliable results in screening. In addition, being web-based allows users to conduct screenings remotely via webcam capture or upload of images, thus proving to be a viable option for telemedicine and those in resource-limited settings.

Overall, the system offers an efficient, accessible, and cost-effective method for assessing glaucoma risk in young children. Although it is intended for preliminary screening only, it will assist healthcare providers with prioritizing cases to be evaluated by further clinical evaluation.

7. Conclusion and Future Work

This article describes a rule-based, AI-inspired identification system to enable screening for childhood glaucoma from retinal images. This system does this through preprocessing, identification of the optic disc and cup, and calculation of the vertical Cup-to-Disc Ratio (CDR) to assess risk categories of Low, Medium, or High. By utilizing 747 retinal images, this study demonstrates that this system can reliably distinguish between all risk categories. By automating CDR measurement and classification, the amount of observer variability is reduced; therefore, speeding up the process of screening. The web-based interface of the system is also capable of real-time analysis with the assistance of webcams or by uploading retinal images. Therefore, it is readily applicable in schools, rural clinics, and tele-healthcare. This system provides a cost-effective and non-invasive tool for early screening of childhood glaucoma and will assist healthcare professionals with identifying children who are at risk of developing childhood glaucoma and will allow for timely interventions to be made. Some improvements that can be made to the system may include improving the accuracy of segmentation through more advanced techniques; enlarging the size of the training data to test on children with an even greater variety of conditions; and including additional retinal characteristics to describe the optic nerve head structure and vascular patterns. Further enhancements such as providing mobile-compatible systems, utilizing the processing power of the cloud for the image processing, and integrating with healthcare record systems will help to add to the scalability of the system allowing for wider usage which will assist in the prevention of loss of vision in children.

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