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EARLY DIAGNOSIS OF GLAUCOMA BY OPTIC DISC AND OPTIC CUP SEGMENTATION OVER RETINAL FUNDUS IMAGES USING DEEP LEARNING ALGORITHM

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ABSTRACT

Glaucoma is characterized by a progressive retinal ganglion cell loss and alters the optic nerve head in neuro retinal rim tissue, as well as restriction of the visual field. Glaucoma is a type of eye disorder that is the leading cause of permanent vision loss globally. The main symptom of glaucoma is the changes in the optical nerve head (ONH) which assist in the early recognition of glaucoma This misalignment of ONH reflects on Optic Disc (OD) and Optic Cup (OC) size and shape, creating changes in Cup to Disc Ratio (CDR). By calculating CDR, glaucoma can be diagnosed at early stage. In order to calculate CDR correctly, proper segmentation of the OD and OC is essential. In this proposed work an Adaptive median filter with TOPHAT is utilized for improving quality of the retinal image, further segmentation of OD and OC is performed by utilizing Multilevel Statistical Region of Interest (MSROI) and classification of Glaucoma is done by using a novel Artefact Convolutional Neural Network (ACNN). The accuracy of 99.38% is obtained using ACNN architecture. Further, dice coefficient of 0.79, Intersection Over Union (IOU) of 0.67, Mean of 73, Standard Deviation of 55 and Mean Square Error of 410 is achieved using MSROI based segmentation. The proposed work can be utilized as desktop application in early diagnosis of Glaucoma. This Computer Aided Diagnosis (CAD) method highly helpful in improving accuracy, reduce time consumption and also provide ease of diagnosing the disease since glaucoma require periodic diagnosis. The proposed model is trained and validated using Drion-DB dataset, the system provides robust and accurate result compared with the existing method.

KEYWORDS: *Glaucoma, Segmentation, Optic Disc, Optic Cup, Artefact CNN, Deep Learning*.

I. INTRODUCTION

Glaucoma was first described by the ancient Greek in 400 BC. The name “Glaykoseis” is used by Hippocratic to describe the irreversible vision loss in elder people. Glaucoma is characterized by a progressive retinal ganglion cell loss and alters the optic nerve head in neuro retinal rim tissue, as well as restriction of the visual field. Glaucoma is a type of eye disorder that is the leading cause of permanent vision loss globally. It creates peripheral vision loss which progress at slow rate, because of this reason many people do not notice the disease at early stage. The other name of glaucoma is “Silent killer of vision”. It is one of the second major cause of visual field misalignment in elder person above 45 years throughout the world. As per the statistics 2020 in India about 11.9 million persons were affected by the disease, about 79.6 million people throughout the globe got affected by the disease [1] and this count rise exponentially in a year. Early diagnosis is essential in order to treat the disease before it creates permanent vision loss.

Glaucoma mainly affects the Optic Nerve Head (ONH) creating peripheral vision loss. The image captured by the retina is converted into light signal and is transmitted to the brain through the optic nerve fibre. The OD is where the optic nerve emerges, which is brightest region in the retina shown in figure 1. Due to Inter Ocular Pressure (IOP) change inside the retina, ONH get affected due

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to which the optic signal cannot reach the brain creating permanent vision loss. The recognition of the disease can be determined by five different ways [2] they are measurement of Interocular pressure (IOP), analysis of the optic nerve head, analysis of the visual field, and measurement of the thickness and angle of the cornea. First IOP measurement is performed by using Tonometry device which measure the pressure of the eyes. This initial step helps the ophthalmologist to screen out the disease. If the IOP is abnormal then remaining procedure need to be carried out. Secondly the ophthalmologist analyses the size, shape and other feature of eye manually. The manual analysis may create error or inaccurate result due to several reason. Automatic analysis of size and shape of OD, OC and retinal rim are widely adopted for glaucoma diagnosis in recent days. Once IOP and ONH is abnormal then Visual Field is analysed to find out how far the vision got lost. The visual field is analysed using Standard Automated Perimetry (SAP). Finally, the draining angle of cornea and thickness estimated using gonioscopy and pachymetry respectively.

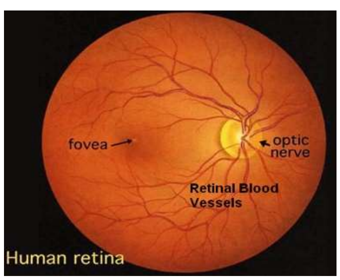

Figure 1 Human Retinal Image

In the above discussed methods size and Shape of Optic Nerve Head (ONH) plays a vital role in early recognition of glaucoma [3]. Examination of Optic Nerve Head include identification of CDR that can be obtained by segmenting OD and OC, then by calculating diameter of OD, OC. In manual measurement ophthalmologist dilate the eye using drops, then by passing light rays through the retina they measure the OD and OC diameter. This manual examination is time consuming and may produce inaccurate result while examining lot of people. Thus, automatic segmentation of OD and OC are widely used nowadays because of its ease computing, accurate result and produce result within a fraction of time. The Computer Aided Diagnosis (CAD) [4] is one the automatic diagnostic procedure adopted to segment OD an OC accurately.

First will find what is OD and OC, how it is helpful in vision. The visual image seen through the retina is changed into optical or light signal which is then passed to the brain using optic nerve fiber. Optic nerve fiber is bundle of fiber connected together to form the pathway between the eye and the brain. The OD is the retina's brightest region where all the optic nerve starts. The OD captures all features of the image like color, texture, brightness etc. from the visual image. The OD composed of two layers Optic Cup and neuro retinal rim shown in figure 2. The innermost region of OD composed of Optic Cup which covers about 30% in normal eye. The boundary between OD and OC is filled with the neuro retinal rim. If any change in percentage of OC occurs then Optic cupping occur. Optic cupping is early symptoms of Glaucoma. By identifying the Optic Disc to Cup ratio, glaucoma can be easily determined. Since OC and OD merge each other the exact determination of OD and OC diameter is difficult for manual analysis. Thus, an automatic segmentation OD and OC plays a vital role in glaucoma diagnosis. Several deep learning techniques has been proposed for accurate segmentation of OD and OC automatically.

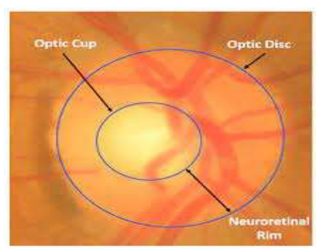

Figure 2 Retinal Fundus Image

For glaucoma diagnosis Magnetic Resonance Image, Optical Coherence Tomography, Retinal fundus image are used by ophthalmologist. Figure 2 shows fundus image which gives detailed information about OD, and OC. In our proposed work retinal fundus image has been utilized for OD and OC segmentation in early diagnosis of the disease. From segmentation of OD and OC, diameter of OD and OC can be determined. From the segmentation, CDR is calculated. If there is any change in size or shape of OC then CDR value changes which gives glaucoma prediction at early stage. The CDR value of healthy eye is 0.3 if the value greater than 0.3 then glaucoma can be determined. The normal and glaucoma Optic Cup and Disc boundaries are shown in figure 3, the disc

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boundary is shown has outer dotted line, while the cup boundary is shown has inner dotted line.

a. b.

Figure 3 Retinal Fundus Image a. Normal Image, b. Glaucoma Image

Existing techniques perform well on standard datasets but do not generalize well to real-world scenarios. The main reasons for performance degradation are the occurrence of blurring, noise, and light variations during the image capturing process, whereas standard datasets are acquired in controlled environments. In this work, our primary motivation is to propose techniques that can localize and segment fundus images despite these factors. We selected standard datasets like Drion-Db, which contain light variations and noise effects. Therefore, we proposed a novel technique, namely ACNN, to detect and segment the Optic Cup (OC) and Optic Disc (OD) from fundus images.

Proposed work can be done by following the steps,

1. At first Pre-processing is to performed to the retinal fundus image using adaptive median filter with TOPHAT. For each pixel of the image adaptive median filter with TOPHAT calculate median value of the neighbour pixel. By comparing the median value with the threshold, it decides to replace or keep the pixel. Filter only replaces the pixel having noise content. This will enhance the quality of the image by removing noisy information. The TOPHAT which perform morphological filtering on grayscale image. Here structural element has been used.
2. Next Multi level Statistical Region of Interest (MSROI) is utilized for segmenting OD and OC by extracting the region of interest from the image. The OD and OC is extracted from the fundus image by calculating pixel intensity.
3. Finally, classification of glaucoma and normal from retinal fundus image is performed using Artefact Convolutional Neural Network (ACNN) model. The deep learning technique where adopted to get more accurate result. In this work ACNN model is applied on retinal fundus image to improve the accuracy.

The proposed deep learning methodology helps in glaucoma diagnosis at early stage. The remaining content of the paper are as follows Section 2 gives an explanation of existing work going in this research. Section 3 explain the proposed architecture in glaucoma detection. Section 4 provides dataset description of the proposed model. Section 5 provides the result and discussion. Section 6 gives conclusion.

2. RELATED WORKS

The optic disc segmentation is not only required for glaucoma detection, it is also helpful in processing retinal image for various diagnosis. Now will see segmentation of optic disc proposed related to glaucoma diagnosis. Kavitha et al [7] proposed glaucoma detection by calculating Cup to Disc Ratio (CDR). Here optic disc segmentation is performed using three different procedure manual thresholding, component analysis and ROI based segmentation. Manual thresholding uses morphological operation to detect the optic disc boundary it has the drawback of inaccurate determination disc boundary thus colour component analysis is used. In this colour feature of the image has been taken into account for disc extraction. It provides accurate result when the image provided has higher contrast or else segmentation is inaccurate. Region of interest-based segmentation is analysed here pixel intensity is utilized to segment disc. The resulting segmentation is accurate compared with manual thresholding and colour component analysis. Optic cup segmentation is performed using component analysis method. In our proposed method multi statical region of interest (MSROI) is utilized to segment optic disc and optic cup which provide more accurate than ROI and component analysis-based segmentation.

Joshi et al [8] proposed an automatic OD and OC segmentation using contour localization model and r-bends respectively. Contour based segmentation selects the colour contour of the image, based on the active contour OD segmentation is performed. Blood vessels are segmented using r bends, From the segmented OD and OC vertical Cup to Disc Ratio (CDR) is calculated. The segmentation provides effective glaucoma screening. The accuracy of the method is calculated by comparing the obtained segmentation result with the three individual segmentations obtained from the three experts. Drion DB dataset is utilized for segmentation. cheng et al [9] proposed classification using super pixel for segmenting OD and OC. The histogram and centre surround statistic were used to categorise pixels as disc or non-disc in OD segmentation and OC segmentation is performed by using histogram, centre surround statistics along with location information. Accuracy achieved by this method is not acceptable in case of automatic screening of glaucoma. Limitation of this OD and OC segmentation by super pixel classification can be overcome by providing high contrast image.

Wavelet transform for extracting and segmenting optic disc is proposed by singh et al [10]. Retinal fundus is pre-processed or prepared by taking green channel from the image. Extracted image is sent kaiser window for calculating centre of Optic Disc to segment the OD. The wavelet feature is extracted from the segmented from the optic disc. From the feature extracted glaucoma is detected using supervised classification. The problem in this method is accuracy 94% which is moreover same as classified by ophthalmologist. The proposed deep learning model overcome this drawback. A texton based early recognition of Glaucoma is proposed by Acharya et al [11]. In this work pre-processing is performed by converting RGB image in grey image using adaptive histogram equalization to improve the contrast of the image. This grey image is sent to three filter bank LM, S, MR4 and MR8 to extract the texton. The texton basic feature constructed in the image. On extracting the texton is processed using Local Configuration Pattern to determine pattern matching normal or glaucoma. The accuracy obtained is 95.7% using KNN classifier. Deep learning model improves the accuracy.

Empirical Wavelet Transform based automatic glaucoma diagnosis is proposed by Maheshwari et al. Here colour retinal fundus mage is converted into grey image, the grey image is fed to empirical wavelet transform whish decompose the image into component of different frequency bands. Then the feature extraction from the decomposed component is done by using correntrophy. [12] Correntropy is one of the non-linear measurements of likeness which store both temporal and statistical data. This correntropy measured non-linear features helps to calculate the texture of the image decomposed. The feature selection done by using standard t-test which the select the feature. This feature is standardized using zero mean and unity standard deviation. The Least Square Support Vector Machine (LSSVM) is utilized to segregate the glaucoma and normal image. Classification accuracy obtained is 98.33%. [13] variational mode decomposition in an iterative mode is used to decompose the image into different frequency component, renyi entropy, Kapoor entropy, fractal dimensions and yager entropy are used to extract the feature from the decomposed image. LSSVM is used as classifier to discriminate the glaucomatous and non-glaucomatous image. The accuracy obtained 95.19%. Our proposed model improves this classification accuracy by learning large feature information.

Deep convolutional neural network (CNN) is proposed by Raghavendra et al [14]. 18 layer convolutional neural is proposed for automatic classification glaucoma for retinal fundus image. Image is fed to the input layer of CNN where the image dimension is resized. The resized image is fed to the 18m layer convolutional module which convert the image data into feature maps in this layer Relu activation function is used. After these 18 layers finally a fully connected layer which classify the image into glaucoma or not. The CNN helps in automation of feature extraction and classification based on training data. Usually, for training 70% of image is taken and for testing 30% is utilized. The accuracy obtained by this method be 98.13%. The limitation of this work be they did this work on 1426 image. On reducing the number of images, the accuracy gets reduced. Fu et al proposed multi label deep network and polar transformation for joint OD and OC segmentation [15]. For joint segmentation of OD and OC M-net is proposed which utilize multiple labelling system. The M net consist of multiple scale input layer, convolutional layer and output layer which segment OD and OC simultaneously. In order to improve the classification accuracy, the polar transformation is used. For polar transformation input fundus image is converted into polar co-ordinate. The proposed work is trained and tested using ORIGA dataset.

Gao et al proposed a LSACM-AS and Modified LSACM-AS [16] for segmenting OD and OC for calculating CDR in glaucoma screening. Wang et al proposed two-layer level set method for automatic OD and OC segmentation [17]. The two different layers inside and outside contour of the image were extracted using two-layer level set algorithm it may be either circular or elliptical shape feature in the image. some two-level set function segment both the Optic disc and optic cup to finalize the segmentation result. By using this method, the computational efficiency achieved is better compared to existing approaches. Limitation of the method, calculating contour is time consuming and tedious process in automatic glaucoma screening. Zhao [18] To compute the CDR from the fundus image, a semi-

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supervised learning approach was proposed. The implementation proposes a two-step process: first, deep learning is used to represent unsupervised features. The OD and OC are segmented using the MFPPNet model, and the CDR is calculated using random forest regression. To extract features from the input, a supervised learning model called densely linked network is proposed, which contain pyramid pooling, and a fully connected layer. The main drawback of deep convolutional neural network be inadequate feature extraction due to low quality image leading to poor accuracy in classification.

Jiang et al [19] proposed generative adversarial networks to segment of OD and OC. The limitation of deep convolutional neural network is overcome by using GL-net which is multi label deep convolutional neural network which has two network parts one generator and another is discriminator. Here generator combines the feature information of bot low and high level providing detailed information about feature. Transfer learning and data augmentation is utilized to increase the accuracy training and testing. They utilized Drishti-GS1 dataset to train the model. Zhou et al proposed segmentation of OD and OC using locally statistical active contour model (LSACM) with structure prior [20]. Initially the retinal fundus image is pre-processed to increase the contrast and quality. The image contour is initiated. From the contour LSACM is applied to extract the feature information then the structural prior is applied for OD and OC segmentation from the retinal image.

Parashar et al proposed automatic glaucoma classification using 2D tensor empirical wavelet transform. [21] The empirical wavelet transform decompose the image into different frequency band. Here tensor product is used for wavelet transform which rows and column of the input image. Initially they find the mean spectrum of rows or column which detects the Fourier spectrum of the image. They utilised LV-SVM classifier for automatic classification of glaucoma. This proposed work provides less computational complexity but the accuracy not acceptable. Martins et al [22] proposed a mobile app for glaucoma screening reducing the bulky equipment utilised for glaucoma diagnosis in current situation. The flow of this work be first all the dataset ORIGA, DRISHTI GS1, RIMONE, iChallenge, RIGA dataset was merged together to form around 2618 images, to increase the size of the dataset data augumentation is performed, then joint segmentation of the optic disc and optic cup are performed using GFI-ASPP-Depth algorithm. From the segmented result the parameter like CDR, ISNT are calculated. With the calculated value the glaucoma classification is performed. This entire work is implemented in mobile app for ease of computation. This implemented mobile application perform glaucoma screening within two seconds of image input. Our proposed work also needs to be implemented in mobile.

Ali et al [23] proposed OD and OC segmentation using fuzzy board learning system. Here retinal fundus pre-processed to determine the region of interest. The extracted ROI is augmented to improve the size of samples. Fuzzy board learning system (FBLS) is proposed here for segmenting OD and OC from red and green channel. From segmented result the vertical cup and vertical disc diameter is measured. By utilizing this CDR is calculated. Then classification is performed using CDR value to segregate glaucoma and normal image. This proposed method is tested on the RIMONE dataset. FBLS is time consuming compared with our work. Veena et al [24] proposed segmentation of OD and OC using deep CNN. To reduce noise and increase image quality, the input fundus image is first pre-processed with a gaussian filter. Then morphological operation dilation, erosion, Contrast Limited Adaptive Histogram Equalization (CLAHE) and shape detection were utilized for obtaining Region of Interest of the image. Then the segmentation and feature extraction is done by using deep Convolutional Neural Network (CNN). Two-individual 39-layer CNN model are used for OC and OD segregation separately. Finally, prediction of disease is obtained by calculating the Cup to Disc Ratio (CDR) from OD and OC segment. This model has a segmentation accuracy of 98% for the Optic Disc and 97% for the Optic Cup. Two individual model of convolutional Neural Network (CNN) consume more time for computation and also results in increased energy utilization. Our proposed model modifies the CNN model to obtained both OD and OC segmentation simultaneously and accurately.

Shanmugam et al [25] proposed Glaucoma detection using Adaptive network for segmentation and feature extraction, random forest classifier to classify the normal and glaucomatous image. Initially the red, green, and blue channels are extracted from the input image. For ROI extraction, a green channel retinal image is used. The extracted image is fed to adaptive network to segment OD and OC. This AU-net or Adaptive network is similar to the u-net having adaptive convolution layer instead

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of Convolutional layer. This AU-net provide increased accuracy and reduces computational time. After OD and OC segmentation the CDR is calculated. The resulting CDR is provided to the random forest classifier to classify normal and glaucomatous image. Xu et al [26] proposed an automation glaucoma detection using Transfer Induced Attention network (TIA-Net). The proposed work has two main stage first general feature are extracted from the fundus image using CNN model, second the general feature extracted is provided to TIA-net to extract specific feature. Seven-layer CNN model is used to extract the general feature, specialized deep layer is required to extract the specific feature. In order to efficiently extract specific feature, they used soft attention CNN model. This attention layer in deep learning model provides most specific feature which is then transferred to the transfer learning model to predict the glaucoma. This model achieves an accuracy of 85.7%.

Shinde et al [27] proposed glaucoma detection using supervised model named U-net. The model proposed utilized retinal fundus image which is pre-processed and validated using LeNet architecture to remove unwanted information. From the pre-processed image Brightest spot algorithm is utilized to extract the region of interest, segmentation of Optic Disc and Cup is obtained by applying U-net model, feature extracted from segmented OD and OC by calculating CDR, ISNT and blood vessel ratio. Finally, the classification of glaucoma is performed by utilizing SVM neural network classifier. Limitation of this model using two separate networks for segmentation and classification leads to create more computational time. Nazir et al [28] proposed glaucoma detection by segmenting OD and OC from blur fundus image by using improved mask RCNN. The proposed a Densenet-77 in mask RCNN helps in glaucoma detection from blur image. Initially pre-processing is performed by data augmentation and adding blurriness to the image. After that ground truth image is labelled, applied to the Densenet-77 architecture to extract feature using mask RCNN. Then by using extracted feature OD and OC segmentation is performed by employing mask-RCNN. The performance of this model is good, but some deep learning technique can be utilized to improve the computational efficiency.

Nelson et al [34] proposed CDR evaluation using Deeplabv3+ algorithm. The validation intersection over union (IOU) of 94.6% and 85% was obtained for optic disc and cup segmentation respectively. The model achieved an IOU of 96.2% and 88.31% on the test data kept separately from the training data and an IOU of 90% and 74% on a new clinical anonymised patient data collected from the hospital. In comparison with our proposed algorithm the accuracy and time consumption is acceptable. Peng et al [35] proposed OD and OC segmentation using swin Unet model. They proposed the combination of the Swin Transformer and U-Net++ network, along with the introduction of the acmix module. The entire network structure retains the advantages of convolutional neural networks while incorporating the currently mainstream self-attention mechanism. The working of proposed model is satisfactory to only for those considered dataset. If we apply for our dataset it does not work good. Accuracy obtained is very low for our dataset.

3. PROPOSED METHODOLOGY

The methodology proposed here is classification of retinal fundus image into normal and glaucomatous image. Flow of the proposed methodology has been shown in figure 4. The method proposed comprises of Image pre-processing, segmentation of OD and OC and finally classification of normal and glaucomatous image. First the input retinal fundus image is pre-processed using adaptive median filter with TOPHAT algorithm to remove noise and unwanted information in the input image, MS-ROI algorithm is used for extracting the region of interest in order to segment Optic Disc and Optic Cup, then Cup to Disc Ratio (CDR) has been calculated. From the CDR, the classification of normal and glaucoma is obtained by using Artefact Convolution Neural Network (ACNN). The following subsection provides the detailed description of the proposed model.

a. Pre-Processing

Pre-processing is the process of improving an image quality by removing noise and unnecessary information. Here the retinal fundus image is pre-processed using adaptive median filter with TOPHAT. For each pixel of the image, adaptive median filter calculates median value of the neighbour pixel. By comparing the median value with the threshold, it decides to replace or keep the pixel. Filter only replaces the pixel having noise content. This will enhance the quality of the image by removing noisy information. The TOPHAT which perform morphological filtering on grayscale image. Here structural element has been used.

b. Segmentation

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The process of extracting image region of interest is said to be image segmentation. Region of Interest hold some unique attributes. Here Multilevel Statistical Region of Interest (MS-ROI) is utilized for extracting Region of Interest. Initially grey level of the input image is calculated, then histogram of the grayscale image is computed, finally foreground and background of the image is segregated using maximum entropy. From the survey, Statistical Region of Interest (SROI) provide better result in extracting the region of interest in fundus image. From SROI, a new algorithm is proposed here, that is Multilevel Statistical Region of Interest (MS-ROI).

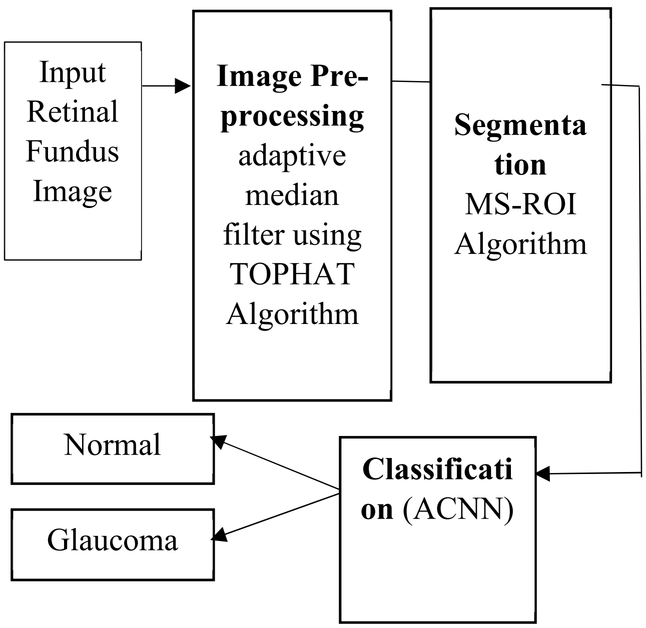

Figure 4 Proposed Methodology

3.1 S-ROI

Region of Interest is the area of the retinal fundus image that contains diagnostically important information. This region of interest is then segmented into fixed size region which provide predominant information. This region is said to be SROI that provide important feature for further process.

Selection of Segmented Regions-of-Interest Size

The section of the image with the greatest diagnostic information is segmented regions-of-interest, which makes it the perfect representative of the image. In addition, SROIs shorten the time it takes to extract features. As a result, determining the optimum size of SROIs is critical. The image with 75X75 pixels and 100X100 pixels were found to be unsuitable because they included blood arteries. Furthermore, SROIs of 10x10 pixels and 25X25 pixels were not recommended since they lacked adequate data for a reliable statistical analysis. This narrowed the options down to 64X64 pixels and 32X32 pixels. However, it was discovered that both 32-pixel and 64-pixel SROIs carried the same information. In addition, 227X 227-pixel SROIs were employed as the input for deep learning.

3.2 MS-ROI

The SROI provides superior results, but it takes too long to produce them. MS-ROI is proposed as a solution to this problem. Maximum entropy is achieved by using a colour image.

Steps involved in MS-ROI

- Each row of the image is evaluated separately. Each pixel in that image row is analysed separately whether, the row crosses the ROI at any point.
- Each pixel is intersected by the ROI.
- The sum of all crossed form regions equals the overall ROI area. For Text, Marker, and Line ROIs, the area is 0. Let I_i stand for the intensity of pixel I with a non-zero intersected area, $I\partial_i$ for pixel I's intersected area, and A for the total area of all crossed forms $(i.e., \Sigma(\partial_i))$
- The mean intensity of pixel is

$$\frac{\Sigma(\partial_i \times I_i)}{A} \qquad (1)$$

- The intensity of the pixel in the centre of the text or under the marker represents the ROI's mean pixel intensity. Assume the average pixel intensity is..
- The pixel intensity standard deviation is:

$$\sqrt{(((\Sigma(\partial_i \times I_i \times I_i) - \mu \times \mu \times A) / A).)} \qquad (2)$$

3.3 Classification

[14,19,24,29,30,31] proposes a remarkable neural network model called the Convolutional Neural Network, which perform image categorization, recovery, and target recognition. Artefact Convolutional Neural Network (ACNN) includes fewer neurons and variables due to weight sharing, making it easier to train. The Alex-Net model is ACNN's most powerful delegate model, with superior performance, fewer training parameters, and high robustness. Figure 5 depicts the ACNN architecture. Two input and output layers, seven rectified linear unit (ReLU) layers, two normalisation levels, three pooling layers, two dropout layers, one softmax layer, and eight trainable weight layers includes three fully connected (FC) layers and five convolutional layers make up the architecture. Images with a dimension of 227X227X3 pixels are accepted by the input layer. The ReLU layer cuts down on the number of epochs, resulting in a lower learning error rate. The normalisation layer enhances generalisation while lowering mistake rates. In order to minimize parameters count and computations in the network, pooling layer dynamically reduces the spatial size of the representation. Both the dropout layer and the Softmax layer successfully reduce overfitting, while the output layer categorises images into numerous groups. The model is fine-tuned by tweaking the last two layers of the 25 layers that make up the model. We use the Fully Connected layers to extract features for classification because the layers at the start of the model can only detect picture edges.

By precisely tweaking the pre-trained ACNN on the Drion-DB data set, a deep transfer learning technique is used in this study for classification tasks. First, we divided the images into two categories: glaucomatous and normal, and then labelled them accordingly. The photos in the dataset were collected under a range of imaging settings, and they were all preprocessed before being scaled, normalised, and cropped to segment the optical disc component from each image. According to ACNN's computational requirements, all cropped images must have a consistent size of 227X227X3, and ACNN's output is a 4096X1X1 feature map. The dataset is divided into train and test image, train images were utilized to highlight and learn features, while test images were used to determine the correctness. Finally, the remaining two convolutional layers are tweaked using a pretrained ACNN that was trained using dataset images. The performance of ACNN is evaluated using the result obtained from fully connected layer data.

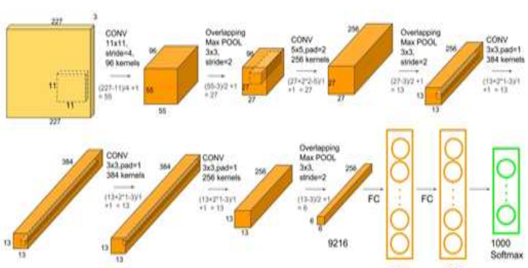

Figure 5 Architecture of ACNN

4. DATASET DESCRIPTION

DRION-DB is a publicly available dataset utilized to segment optic nerve head for various retinal disorder diagnosis. This dataset contains 110 digital retinal fundus images, obtained from 124 retinal fundus images, selected randomly from a fundus image got from Ophthalmology Service at Miguel Servet Hospital, Saragossa (Spain). This dataset contains about 124 images where some of them contain cataract which were eliminated and we got about 110 images were taken into account. In these 110 images selected, the average age of the patient were 53 years, male of 46.2% and female about 53.8%. Here about 23.1% patients were affected by chronic glaucoma about 76.9% got eye hypertension. These photographs were captured with a colour analogical fundus camera that was centred on ONH and saved as a slide.

5. EXPERIMENTAL RESULT

The model proposed is trained and tested on DRION-DB dataset, contain 110 images from which 70% is taken to train the model and 30% to test the model. All the images were pre-processed, OD and OC segmented, finally classified into glaucoma or normal. Figure 6 shows the pre-processed, OD and OC segmented result. Various metrics were analysed for the obtained result and compared with the existing model.

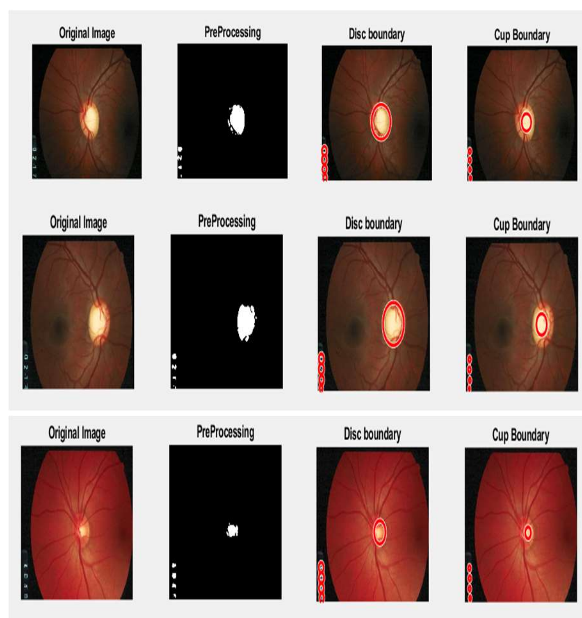

Figure 6 PROPOSED RESULT

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5.1 Segmentation Performance Metric

The segmentation accuracy of Optic Disc and Optic Cup were analyzed by the calculating following performance metric:

Mean

Mean is one of the important parameters in analyzing image. It always measures the geometric feature of the image. The mean of the segmented image is calculated as the sum of the pixels present in the segmented image to number of pixels in total in input retinal fundus image.

$$Mean = \frac{\sum pixel\ in\ segmented\ image}{Total\ number\ of\ pixel\ in\ input\ image} \quad (1)$$

Standard Deviation

Standard deviation measures how much the pixel deviate from the measured value or mean. In segmentation the standard deviation measures the how the pixel disperses in gray scale level from the mean value.

$$Standard\ Deviation = \sqrt{\left(\frac{1}{n-1}\sum_{i=1}^{n}(g_i - \bar{g})^2\right)} \quad (2)$$

Where $g_i$represent the gray value of pixel i and $\bar{g}$ represent the mean value of the gray image.

Mean Square Error

The Mean Square Error is a measurement that is used to assess the image compression quality. It measures the cumulative square error between compressed and the original image. MSE is used in measuring PSNR.

$$MSE = \frac{\sum_{M,N}[I_1(M,N) - I_2(M,N)]}{M*N} \quad (3)$$

Peak Signal to Noise Ratio (PSNR)

The Peak Signal to Noise Ratio is the ratio of an image's maximum power to the noise power that degrades the image's quality. The PSNR is calculated by comparing the ideal clear image with the corrupted image to estimate the maximum power.

$$PSNR = 10\log\left(\frac{(J-1)}{MSE}\right)^2 \quad (4)$$

Where J Number of maximum intensity possible in an image.
MSE Mean Square Error

Dice Co-efficient

Dice Co-efficient (DC) is measures the spatial overlap between the segmented image and ground truth image. The measured value of DC is between 0 and 1. If two images overlap each other then, the value of dice co efficient will be 1, If there is no overlap between two images then DC will be 0. DC value won't be greater than 1.

$$Dice\ coefficient = 2\left(\frac{|A\cap B|}{(|A|*|B|)}\right) \quad (5)$$

Where A Segmented image,
B Ground truth image.

Intersection Over Union

Intersection Over Union (IOU) defines the similarity index within the segmented and the ground truth boundary. IOU value usually range from 0 to 1. The value will be 0 if there is no similarity index between two images, and 1 if two images has similar boundaries.

$$Intersection\ Over\ Union = \frac{|A\cap B|}{|A\cup B|} \quad (6)$$

Where A Segmented image,
B Ground truth image.

5.2 Classification Performance Metric

The retinal fundus image is classified into glaucomatous and non-glaucomatous using ACNN is analyzed by following parameter,

CDR

The vertical cup to disc ratio is a significant element in identifying glaucoma. Here, the optic disc and optic cup have been segmented, and the segmentation result is utilised to calculate the CDR. CDR is calculated using the vertical diameter of the cup and disc.

$$CDR = \frac{Cup\ Diameter}{Disc\ Diameter} \quad (7)$$

Accuracy

Accuracy parameter measures how much accurate the model classifies the image as glaucoma and normal image. The expression for accuracy be

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + f_p + f_n} \quad (8)$$

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Sensitivity

Sensitivity measures the ability of the model to correctly identifies the glaucomatous image from the input image. The expression for sensitivity be

$$Sensitivity = \frac{T_p}{(T_p+f_n)} \tag{9}$$

Specificity

Specificity measures the ability of the model to correctly identifies the normal image from the input image. The expression for specificity be

$$Sensitivity = \frac{T_n}{(T_n+f_p)} \tag{10}$$

The performance validation of the proposed model is shown in figure 7. Model execute at 27 epoch having best validation performance. The confusion matrix of the model proposed is shown in figure 8. The maximum specificity, accuracy and sensitivity of the model be 89%, 99.38% and 100% respectively.

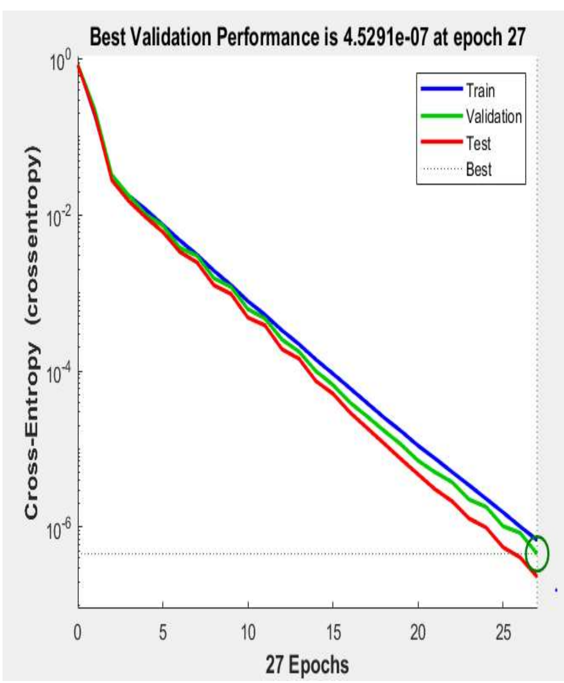

Figure 7 Performance validation of the model proposed

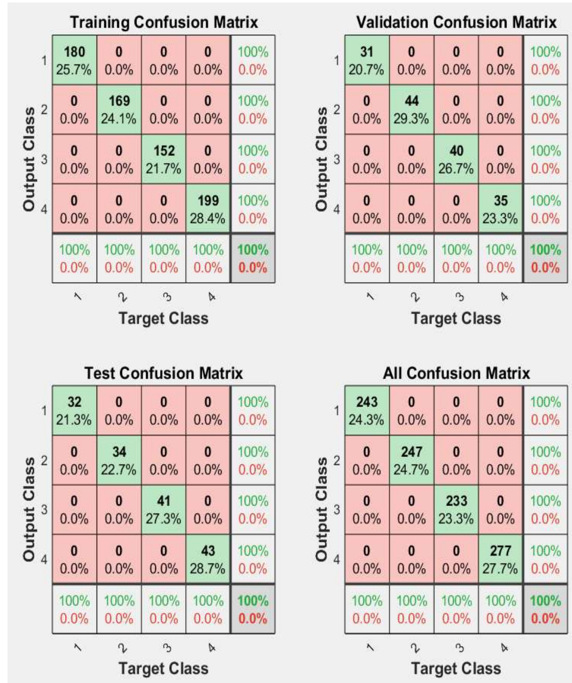

Figure 8 Confusion matrix of the model proposed

6. CONCLUSION

In this paper, we propose an early diagnosis method for glaucoma from retinal fundus images using an Artefact Convolutional Neural Network (ACNN). Glaucoma is a leading cause of blindness in patients over 45 years old, and early diagnosis is essential for timely treatment. Our approach begins with the pre-processing of retinal fundus images using an adaptive median filter combined with the TOPHAT algorithm to remove noise and improve image quality. Subsequently, the Optic Disc (OD) and Optic Cup (OC) are extracted using a Multi-level Statistical Region of Interest algorithm. The segmented OD and OC are then classified as either glaucoma or normal images using the novel ACNN algorithm. We validated our model using the publicly available Drion DB dataset, and our results show that the proposed ACNN outperforms state-of-the-art models, achieving an accuracy of 99.38%, sensitivity of 100%, and specificity of 89%. While our model utilizes a limited dataset, further validation with other publicly available datasets or real-time images could enhance its performance.

Table I Performance Of Deep Learning Models

Technique	Dice Coefficient	Intersection Over Union	Accuracy
U-NET [27]	0.88	0.83	97.2
Modified U-NET [33]	0.94	0.88	98
Artefact CNN (Proposed)	0.98	0.94	99.38

REFERENCES

[1] Ahmad, Andes, Syed Zulfequar Ahmad, Najam Khalique, Mohammad Ashraf, and Yasir Alvi. "Prevalence and Associated Risk Factors of Glaucoma in Aligarh, India–A population-based study." *The Official Scientific Journal of Delhi Ophthalmological Society* 31, no. 1 (2020): 36-40. https://www.djo.org.in/articles/31/1/Prevalence-and-Associated-Risk-Factors-of-Glaucoma-in-Aligarh-India-A-population-based-study.html

[2] Jamous, Khalid F., Michael Kalloniatis, Andrew Hayen, Paul Mitchell, Fiona J. Stapleton, and Barbara Zangerl. "Application of clinical techniques relevant for glaucoma assessment by optometrists: concordance with guidelines." *Ophthalmic and Physiological Optics* 34, no. 5 (2014): 580-591. https://pubmed.ncbi.nlm.nih.gov/25103462/

[3] Lowell, James, Andrew Hunter, David Steel, Ansu Basu, Robert Ryder, Eric Fletcher, and Lee Kennedy. "Optic nerve head segmentation." *IEEE Transactions on medical Imaging* 23, no. 2 (2004): 256-264. https://ieeexplore.ieee.org/document/1263614

[4] Song, Xiaoyang, Keou Song, and Yazhu Chen. "A computer-based diagnosis system for early glaucoma screening." In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*, pp. 6608-6611. IEEE, 2006. https://pubmed.ncbi.nlm.nih.gov/17281786/

[5] Kavitha, S., S. Karthikeyan, and K. Duraiswamy. "Early detection of glaucoma in retinal images using cup to disc ratio." In *2010 Second International conference on Computing, Communication and Networking Technologies*, pp. 1-5. IEEE, 2010. https://ieeexplore.ieee.org/document/5591859

[6] Geethalakshmi, R., and R. Vani. "Overview of Automatic Segmentation of Retinal Fundus Image for Medical Diagnosis." *Ilkogretim Online* 20, no. 1 (2021). https://www.ilkogretim-online.org/fulltext/218-1618599890.pdf

[7] Kavitha, S., S. Karthikeyan, and K. Duraiswamy. "Early detection of glaucoma in retinal images using cup to disc ratio." In *2010 Second International conference on Computing, Communication and Networking Technologies*, pp. 1-5. IEEE, 2010. https://ieeexplore.ieee.org/document/5591859

[8] Joshi, Gopal Datt, Jayanthi Sivaswamy, and S. R. Krishnadas. "Optic disk and cup segmentation from monocular color retinal images for glaucoma assessment." *IEEE transactions on medical imaging* 30, no. 6 (2011): 1192-1205. https://ieeexplore.ieee.org/document/5762351

[9] Cheng, Jun, Jiang Liu, Yanwu Xu, Fengshou Yin, Damon Wing Kee Wong, Ngan-Meng Tan, Dacheng Tao, Ching-Yu Cheng, Tin Aung, and Tien Yin Wong. "Superpixel classification based optic disc and optic cup segmentation for glaucoma screening." *IEEE transactions on medical imaging* 32, no. 6 (2013): 1019-1032. https://pubmed.ncbi.nlm.nih.gov/23434609/

[10] Singh, Anushikha, Malay Kishore Dutta, M. ParthaSarathi, Vaclav Uher, and Radim Burget. "Image processing based automatic diagnosis of glaucoma using wavelet features of segmented optic disc from fundus image." *Computer methods and programs in biomedicine* 124 (2016): 108-120. https://www.sciencedirect.com/science/article/abs/pii/S0169260715002709

[11] Acharya, U. Rajendra, Shreya Bhat, Joel EW Koh, Sulatha V. Bhandary, and Hojjat Adeli. "A novel algorithm to detect glaucoma risk using texton and local configuration pattern features extracted from fundus images." *Computers in biology and medicine* 88 (2017): 72-83. https://www.sciencedirect.com/science/article/abs/pii/S0010482517302226

[12] Maheshwari, Shishir, Ram Bilas Pachori, and U. Rajendra Acharya. "Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images." *IEEE journal of biomedical and health informatics* 21, no. 3 (2016): 803-813. https://ieeexplore.ieee.org/document/7438741

[13] Maheshwari, Shishir, Ram Bilas Pachori, Vivek Kanhangad, Sulatha V. Bhandary, and U. Rajendra Acharya. "Iterative variational mode decomposition based automated detection of glaucoma using fundus images." *Computers in biology and medicine* 88 (2017): 142-149.

https://www.sciencedirect.com/science/article/abs/pii/S0010482517301816
[14] Raghavendra, U., Hamido Fujita, Sulatha V. Bhandary, Anjan Gudigar, Jen Hong Tan, and U. Rajendra Acharya. "Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images." *Information Sciences* 441 (2018): 41-49. https://www.sciencedirect.com/science/article/abs/pii/S0020025518300744
[15] Fu, Huazhu, Jun Cheng, Yanwu Xu, Damon Wing Kee Wong, Jiang Liu, and Xiaochun Cao. "Joint optic disc and cup segmentation based on multi-label deep network and polar transformation." *IEEE transactions on medical imaging* 37, no. 7 (2018): 1597-1605. https://ieeexplore.ieee.org/document/8252743
[16] Gao, Yuan, Xiaosheng Yu, Chengdong Wu, Wei Zhou, Xiaonan Wang, and Hao Chu. "Accurate and efficient segmentation of optic disc and optic cup in retinal images integrating multi-view information." *IEEE Access* 7 (2019): 148183-148197. https://ieeexplore.ieee.org/document/8863488
[17] Wang, Ying, Xiaosheng Yu, Jianning Chi, and Chengdong Wu. "Automatic segmentation of optic disc and cup in retinal fundus images using improved two-layer level set method." *Mathematical Problems in Engineering* 2019 (2019). https://www.hindawi.com/journals/mpe/2019/4836296/
[18] Zhao, Rongchang, Xuanlin Chen, Xiyao Liu, Zailiang Chen, Fan Guo, and Shuo Li. "Direct cup-to-disc ratio estimation for glaucoma screening via semi-supervised learning." *IEEE journal of biomedical and health informatics* 24, no. 4 (2019): 1104-1113. https://ieeexplore.ieee.org/document/8794624
[19] Jiang, Yun, Ning Tan, and Tingting Peng. "Optic disc and cup segmentation based on deep convolutional generative adversarial networks." *IEEE Access* 7 (2019): 64483-64493. https://ieeexplore.ieee.org/document/8717627
[20] Zhou, Wei, Yugen Yi, Yuan Gao, and Jiangyan Dai. "Optic disc and cup segmentation in retinal images for glaucoma diagnosis by locally statistical active contour model with structure prior." *Computational and mathematical methods in medicine* 2019 (2019). https://www.hindawi.com/journals/cmmm/2019/8973287/
[21] Parashar, Deepak, and Dheeraj Kumar Agrawal. "Automatic classification of glaucoma stages using two-dimensional tensor empirical wavelet transform." *IEEE Signal Processing Letters* 28 (2020): 66-70. https://ieeexplore.ieee.org/document/9296796
[22] Martins, José, Jaime S. Cardoso, and Filipe Soares. "Offline computer-aided diagnosis for Glaucoma detection using fundus images targeted at mobile devices." *Computer Methods and Programs in Biomedicine* 192 (2020): 105341. https://pubmed.ncbi.nlm.nih.gov/32155534/
[23] Ali, Riaz, Bin Sheng, Ping Li, Yan Chen, Huating Li, Po Yang, Younhyun Jung, Jinman Kim, and CL Philip Chen. "Optic disk and cup segmentation through fuzzy broad learning system for glaucoma screening." *IEEE Transactions on Industrial Informatics* 17, no. 4 (2020): 2476-2487. https://ieeexplore.ieee.org/document/9109664
[24] Veena, H. N., A. Muruganandham, and T. Senthil Kumaran. "A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images." *Journal of King Saud University-Computer and Information Sciences* (2021). https://www.sciencedirect.com/science/article/pii/S1319157821000422
[25] Shanmugam, P., J. Raja, and R. Pitchai. "An automatic recognition of glaucoma in fundus images using deep learning and random forest classifier." *Applied Soft Computing* 109 (2021): 107512. https://www.sciencedirect.com/science/article/abs/pii/S156849462100435X
[26] Xu, Xi, Yu Guan, Jianqiang Li, Zerui Ma, Li Zhang, and Li Li. "Automatic glaucoma detection based on transfer induced attention network." *BioMedical Engineering OnLine* 20, no. 1 (2021): 1-19. https://pubmed.ncbi.nlm.nih.gov/33892734/
[27] Shinde, Rutuja. "Glaucoma detection in retinal fundus images using U-Net and supervised machine learning algorithms." *Intelligence-Based Medicine* 5 (2021): 100038. https://www.sciencedirect.com/science/article/pii/S2666521221000144
[28] Nazir, Tahira, Aun Irtaza, and Valery Starovoitov. "Optic Disc and Optic Cup Segmentation for Glaucoma Detection from Blur Retinal Images Using Improved Mask-RCNN." *International Journal of Optics* 2021 (2021).

https://www.hindawi.com/journals/ijo/2021/6641980/

[29] Elangovan, Poonguzhali, and Malaya Kumar Nath. "Glaucoma assessment from color fundus images using convolutional neural network." *International Journal of Imaging Systems and Technology* 31, no. 2 (2021): 955-971. https://onlinelibrary.wiley.com/doi/abs/10.1002/ima.22494

[30] Vanakovarayan, S., R. Sarath Kumar, S. Chinnapparaj, and S. Satheesh Kumar. "Classification using fundus image of eye by CNN method and self-sufficient glaucoma detection using IoT." *Materials Today: Proceedings* 37 (2021): 2812-2817. https://www.sciencedirect.com/science/article/pii/S2214785320365366

[31] Jun, Tae Joon, Youngsub Eom, Dohyeun Kim, Cherry Kim, Ji-Hye Park, Hoang Minh Nguyen, Young-Hak Kim, and Daeyoung Kim. "TRk-CNN: transferable ranking-CNN for image classification of glaucoma, glaucoma suspect, and normal eyes." *Expert Systems with Applications* 182 (2021): 115211. https://www.sciencedirect.com/science/article/abs/pii/S0957417421006448

[32] Carmona, Enrique J., Mariano Rincón, Julián García-Feijoó, and José M. Martínez-de-la-Casa. "Identification of the optic nerve head with genetic algorithms." Artificial Intelligence in Medicine 43, no. 3 (2008): 243-259. From: http://www.ia.uned.es/~ejcarmona/DRIONS-DB.html

[33] Rakesh Geethalakshmi, and Vani Rajamanickam. "A Novel Deep Learning Algorithm for Optical Disc Segmentation for Glaucoma Diagnosis." *Traitement du Signal* 39, no. 1 (2022). https://www.iieta.org/journals/ts/paper/10.18280/ts.390132

[34] Nelson, Alice Divya, J. Raghul, A. Devika Gireesh, Kalpana George, and S. S. Anup. "Automated cup-to-disc ratio evaluation for generalised glaucoma diagnosis using deeplabv3+." In 2024 IEEE 12th International Symposium on Signal, Image, Video and Communications (ISIVC), pp. 1-6. IEEE, 2024. https://ieeexplore.ieee.org/document/10577822

[35] Peng, Hao, and Ge Wang. "Cup and Disc Segmentation Algorithm Based on Improved Swin-UNet Model." In 2024 IEEE 7th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), vol. 7, pp. 485-488. IEEE,2024. https://ieeexplore.ieee.org/document/10503847