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A Comparison of Deep Learning Techniques for Glaucoma Diagnosis on Retinal Fundus Images

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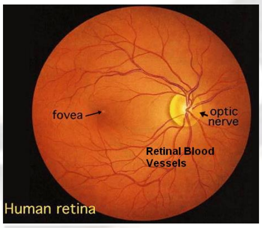
Abstract— Glaucoma is one of the serious disorders which cause permanent vision loss if it left undetected. The primary cause of the disease is elevated intraocular pressure, impacting the optic nerve head (ONH) that originates from the optic disc. The variation in optic disc to optic cup ratio helps in early detection of the disease. Manual calculation of Cup to Disc Ratio (CDR) consumes more time and the prediction is also not accurate. Utilizing deep learning for the automatic detection of glaucoma facilitates precise and early identification, significantly enhancing the accuracy of glaucoma detection. The deep learning technique initiates the process by initially pre-processing the image to achieve data augmentation, followed by the segmentation of the optic disc and optic cup from the retinal fundus image. From the segmented Optic Disc (OD)and Optic Cup (OC) feature are selected and CDR calculated. Based on the CDR value the Glaucoma classification is performed. Various deep learning techniques like CNN, transfer learning, algorithm was proposed in early detection of glaucoma. From the comparative analysis glaucoma diagnosis, the proposed deep learning artifact Convolutional Neural Network outperform in early diagnosis of glaucoma providing accuracy of 99.3 8%.

Keywords- Glaucoma, CNN, Deep Learning, CDR, Optic Disc, Optic Cup.

I. Introduction

Glaucoma is a disease that adversely impacts the optic nerve head, leading to permanent vision loss. The optic nerve originates from the optic disc (OD), the brightest portion of the retina illustrated in Figure 1. The optic cup, an inner segment of the optic disc, exhibits a circular shape, with the neuro retinal rim serving as the boundary between the Optic Disc and Optic Cup. Increased intraocular pressure in the retina can alter the size and shape of the Optic Cup as it extends toward the optic disc. The normal Cup to Disc ratio is typically 0.3. Notably, glaucoma stands as the second leading cause of blindness worldwide. Around 11.9 million people affected in India and about 79 million people around the world affected by Glaucoma. Glaucoma mainly affects the people of above 60 years of age. Why this of much of got affected by this disease because they are not aware of the disease yet, most of the cause is not diagnosed early and treated early.

Glaucoma causes peripheral vision loss initially; the progress is also slow. So, most of case the people do not came to know about disease till they got complete vision loss. Periodic diagnosis of patient helps in early detection and treating of the disease. Figure 2 shows the normal and vision of glaucoma patients. Manual diagnosis of the glaucoma involves of retinal fundus image. The technicians took the fundus image in which they manually mark the OD area and OC area. On finding Optic Cup and Optic Disc they manually calculate the Cup to Disc ratio. Manual detection CDR is tedious process in which consumes the enormous time and the result not that much accurate.



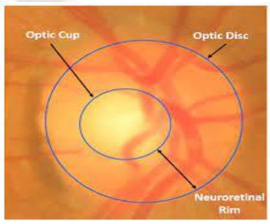


Figure 1a A Retina 1b OD and OC Segmented

In the proposed work, we employ a deep learning algorithm known as Artifact Convolutional Neural Network (ACNN) to classify retinal fundus images into either normal or glaucoma categories. Initially the preprocessing is done in order to get noise free image, then segmentation and feature extraction is performed which segment the Optic Disc and Optic Cup Area. From the OD and OC area value ACNN classify the image. The flow of the proposed work is shown in Figure 3. For this analysis Drion DB dataset is utilized to train and test the algorithm.

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Figure 2 Normal and Glaucoma Patients

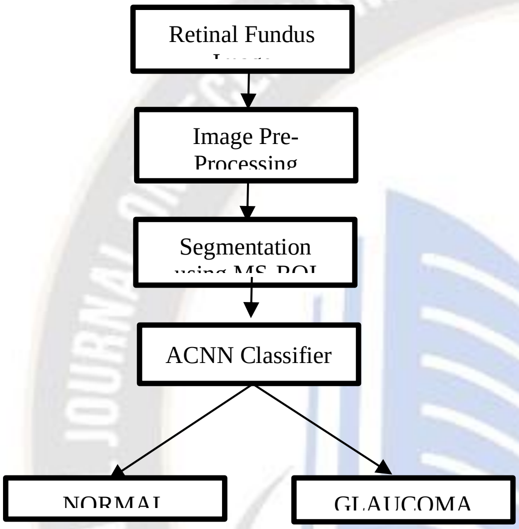

Figure 3 Overview of Proposed work

II. RELATED WORKS

A brief overview of various segmentation algorithm proposed on glaucoma diagnosis is discussed below

Glaucoma detection using the Cup to Disc Ratio (CDR) calculation was proposed by Kavitha et al. [1]. Here, segmentation of the optic disc is carried out utilising three distinct methods: manual thresholding, ROI-based segmentation and component analysis. Colour component analysis is utilised in place of manual thresholding, which uses morphological operations to detect the optic disc border but suffers from imprecise disc boundary identification. For disc extraction, this image's colour feature has been taken into consideration. When the provided image has higher contrast, it produces an accurate result; otherwise, segmentation is wrong. Here, pixel intensity is used to segment the disc using an analysis of region of interest-based segmentation. Comparing the final segmentation to manual thresholding and colour component analysis, it is precise. Component analysis method is used for optical cup segmentation.

For the purpose of segmenting OC and OD, Cheng et al. [2] suggested categorization using super pixels. In OD segmentation, the histogram and centre surround statistic were utilised to classify pixels as disc or non-disc, and OC segmentation is carried out using the histogram, centre surround statistics, and location data. For automatic glaucoma screening, the accuracy achieved by this technology is unacceptable. By giving a high contrast image, the limitation of this OD and OC segmentation by super pixel classification can be solved. Singh et al. [3] suggested the wavelet transform for extracting and segmenting the optic disc. An image's green channel is used to pre-process or prepare the retinal fundus. To calculate the centre of the optical disc and segment the OD, the extracted picture is transferred to the Kaiser window. From the segmented optic disc, the wavelet feature is taken out. Glaucoma is identified via supervised classification from the feature extracted. The method's accuracy of 94%, which is also the same as how ophthalmologists classify it, is a concern. This flaw was fixed by the deep learning model that was proposed.

In the study conducted by Raghavendra et al. [4], a deep convolutional neural network (CNN) is introduced. The research proposes an automated classification system for glaucoma in retinal fundus images, employing an 18-layer convolutional neural network. The input layer of the CNN receives the image, which is subsequently resized. The scaled image is then processed through the 18-layer convolutional module, utilizing the ReLU activation function to transform the image data into feature maps. Finally, a fully connected layer is implemented to classify the image as either indicating the presence of glaucoma or not, marking the conclusion of the 18-layer process. Utilising training data, the CNN aids in automating feature extraction and categorization. Typically, 70% of an image is used for training and 30% for testing. 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. introduced a multi-label deep network with polar transformation for the joint segmentation of optic disc (OD) and optic cup (OC) [5]. The proposed M-net employs a multiple labelling method and includes output, convolutional, and multiple scale input layers to simultaneously segment OD and OC. The incorporation of polar transformation enhances categorization accuracy. In this process, the input fundus image undergoes transformation into polar coordinates to facilitate the polar transformation. Using the ORIGA dataset, the suggested work is trained and tested.

In Zhao's work [6], a semi-supervised learning approach is proposed for calculating the Cup-to-Disc Ratio (CDR) from fundus images. The methodology involves a two-step process: initially, unsupervised features are extracted through deep learning. The MFPPNet model is employed for segmenting the optic disc (OD) and optic cup (OC), and random forest regression is utilized to determine the CDR. Additionally, a densely linked network is introduced as a supervised learning model, incorporating pyramid pooling and a fully connected layer to extract features from the input. Deep convolutional neural networks' primary flaw is insufficient feature extraction caused by poor image quality, which results in subpar classification performance.

Automatic glaucoma classification utilising a 2D tensor empirical wavelet transform was proposed by Parashar et al. [7]

The image is divided into various frequency bands by the empirical wavelet transform. In this case, the wavelet transform uses the tensor product with the input image's rows and columns. They begin by determining the average spectrum of the rows or columns, which identifies the image's Fourier spectrum. For the automatic classification of glaucoma, they used the LV-SVM classifier. Less computational complexity is offered by the proposed work, but the accuracy is unacceptable. Martins et al.'s [8] proposal for a mobile app for glaucoma screening would replace the existing situation's bulky equipment used for glaucoma diagnosis. First, all the datasets from ORIGA, DRISHTI GS1, RIMONE, iChallenge, and RIGA were combined to create approximately 2618 images. Subsequently, data augmentation was applied to expand the dataset size, and the joint segmentation of the optic disc and optic cup was performed using the GFI-ASPP-Depth algorithm. The segmented outcomes were then utilized for calculating parameters such as Cup-to-Disc Ratio (CDR) and ISNT. It is possible to classify glaucoma using the calculated value. For convenience of computation, the entire task has been implemented in a mobile application. Within two seconds of receiving an image, this smartphone application does glaucoma screening.

In their work, Ali et al. [9] introduced a fuzzy board learning system for the segmentation of the optic disc (OD) and optic cup (OC). The initial step involves preprocessing the region of interest extracted from the retinal fundus. To augment the sample size, the extracted region of interest is enhanced. The segmentation process utilizes a fuzzy board learning system (FBLS) to segment the red and green channels into the OD and OC. The segmented results are then used to measure the vertical cup and vertical disc diameters. This CDR is determined using. After that, classification is done using the CDR value to separate the glaucoma image from the normal image. The RIMONE dataset is used to test the proposed methodology. FBLS takes more time than our work does.

Deep CNN segmentation of OD and OC was suggested by Veena et al. [10]. The input fundus image is initially pre-processed with a gaussian filter in order to lessen noise and improve image quality. The image's Region of Interest was then determined using the morphological operations of dilation, erosion, Contrast Limited Adaptive Histogram Equalisation (CLAHE), and form detection. Next, a deep convolutional neural network (CNN) is used for segmentation and feature extraction. For OC and OD segregation independently, a two-individual 39-layer CNN model is used. Finally, by computing the Cup to Disc Ratio (CDR) from the OD and OC section, disease prediction is obtained. For the optic disc and cup, this model's segmentation accuracy is 98% and 97%, respectively.

Shanmugam et al. [11] proposed a glaucoma detection approach employing an adaptive network for segmentation and feature extraction. Additionally, a random forest classifier is utilized to distinguish between normal and glaucomatous images. The input image's red, green, and blue channels are initially extracted. A green channel retinal picture is employed for ROI extraction. To segment OD and OC, an adaptive network is given the retrieved image. This adaptive network, also known as an AU-net, is similar to a u-net but uses an adaptable convolutional layer in place of a convolutional layer. This AU-net offers improved accuracy while speeding up computation. The CDR is calculated following the OD and OC segmentation. The random forest classifier is given the generated CDR in order to categorise the normal and glaucomatous picture.

Xu et al. [12] introduced an automated glaucoma detection method based on the Transfer Induced Attention network (TIA-Net). The proposed approach involves two main stages: initially, general features are obtained using a CNN model from the fundus image, followed by the extraction of specific features using a TIA-Net that employs the previously acquired general features. In order to extract the relevant feature, a specialised deep layer is needed. A seven-layer CNN model is employed to extract the general feature. They employed a soft attention CNN model to effectively extract a certain characteristic. The most particular features from the deep learning model's attention layer are then transferred to the transfer learning model to predict glaucoma. The accuracy of this model is 85.7%.

Shinde et al. [13] proposed a glaucoma detection method employing the supervised U-net model. The suggested model utilized a pre-processed and validated retinal fundus image through the LeNet architecture. In the modified image, the region of interest is extracted using the brightest spot algorithm. Subsequently, the U-net model is employed for the segmentation of the optic disc (OD) and optic cup (OC), from which features are derived, including the Cup-to-Disc Ratio (CDR), ISNT parameters, and blood vessel ratio. The classification of glaucoma is completed by using an SVM neural network classifier, as a last step. This model's limitation of using two different networks for segmentation and classification results in longer calculation times.

By employing an enhanced Mask R-CNN, the optic disc (OD) and optic cup (OC) can be effectively separated from a blurry fundus picture. Nazir et al. [14] presented glaucoma detection. The suggested Densenet-77 in mask RCNN aids in the identification of glaucoma from blurred images. Pre-processing is first carried out through data augmentation and image blurring. Following labelling of the ground truth image, the Densenet-77 architecture is used to extract features using mask RCNN. Subsequently, the extracted features are utilized, and mask-RCNN is applied to segment the optic disc (OD) and optic cup (OC). Although this model performs well, the computational efficiency could be increased by using some deep learning techniques.

III. METHODOLOGY

In this proposed methodology, a classification system for distinguishing normal and glaucomatous retinal fundus images is introduced. The approach encompasses pre-processing, optic disc (OD) and optic cup (OC) segmentation, and the subsequent classification of normal and glaucomatous images. The initial step involves the pre-processing of the input retinal fundus image, utilizing an adaptive median filter and the TOPHAT algorithm to distinguish the optical disc from the optical cup. Following this, the MS-ROI algorithm is applied to extract the region of interest, and the Cup to Disc Ratio (CDR) is computed. Leveraging the CDR, the Artefact Convolution Neural Network (ACNN) is employed to classify normal and glaucoma conditions in the fundus image.

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A. U-NET Architecture

U-net architecture [15]. Fig 4 displays the U-net model's block diagram. Architectural design symmetrical in a U shape on both sides. The U net's right side is said to be expanding, where transposed convolutional layers do upsampling, while the left side is thought to be shrinking, when convolutional layers perform down sampling. The main issue with U-net is that while upsampling, vague spatial information is obtained. To address this issue, the U-net employs skip connections, allowing for the integration of spatial information from both the upsampling and downsampling processes. By doing this, the network becomes overloaded with redundant features, which causes the system to crash during training.

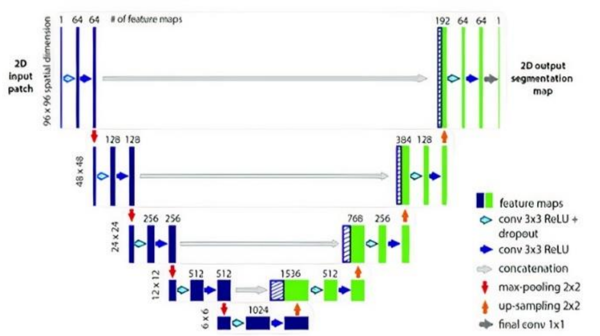

Figure 4 U-NET Architecture

B. Modified U-net Architecture

The modified U-net architecture is a modification of the original U-net architecture [16], as illustrated in Fig 5. The proposed model incorporates a reduced filter size in each convolutional layer, halving the filters with an input image size of 256 x 256. This reduction aims to minimize the number of trainable parameters, subsequently decreasing the training duration of the network. The total parameters required to train the proposed model amount to 6,56,257. Further details about the characteristics of various layers and functions are elaborated in the subsequent sections.

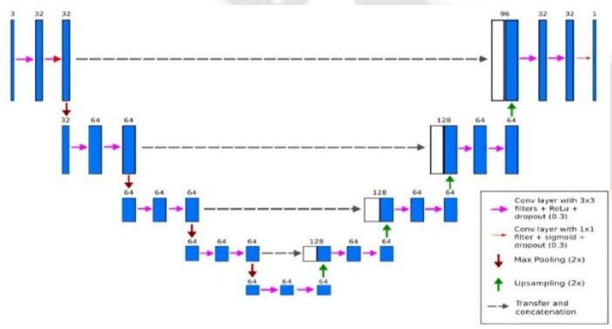

Figure 5 Modified U-NET Architecture

C. Artefact Convolutional Neural Network

The architecture of the Artefact Convolutional Neural Network (ACNN) is depicted in Fig 6, comprising three fully connected (FC) layers, five convolutional layers, and 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. The input layer will accept images up to 227X227X3 pixels in size. Reduced epochs due to the ReLU layer lead to a decreased rate of learning errors. The normalisation layer reduces error rates while improving generality. The pooling layer dynamically reduces the spatial size of the representation, effectively minimizing the number of parameters and computations within the network. While the output layer classifies images, the dropout layer and the Softmax layer successfully reduce overfitting.

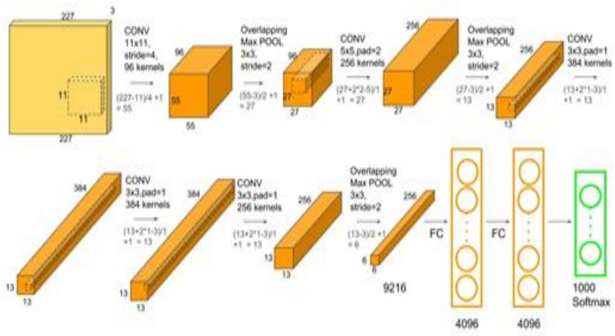

Figure 6 Architecture of ACNN

IV. DATASET DESCRIPTION

A publicly accessible dataset called DRION-DB is used to diagnose various retinal disorders by segmenting the optic nerve head. This dataset includes 110 digital retinal fundus photos that were compiled from 124 fundus images of the retina that were randomly chosen from a fundus image received from the ophthalmology department at Miguel Servet Hospital in Saragossa, Spain. This dataset includes roughly 124 photos, some of which have cataracts and were removed, leaving us with about 110 images. The average patient age in the 110 photographs that were chosen was 53 years old, with 46.2% men and around 53.8% women. About 23.1% of the patients at this location had chronic glaucoma, while 76.9% had ocular hypertension. On was the focal point of a colour analogue fundus camera that took these pictures, which were then preserved

V. EVALUATION METRICS

A. Accuracy

Accuracy [17.18] parameter measures how much accurate the model classifies the image as glaucoma and normal image. The expression for accuracy be

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + f_p + f_n} \text{ --------------------------- (1)}$$

B. Dice Co-efficient

Dice Co-efficient (DC) [19,20] 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.

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

Where A Segmented image,
B Ground truth image.

C. Intersection Over Union

Intersection Over Union (IOU) [21] 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.

$$Intersection\ Over\ Union = \frac{|A \cap B|}{|A \cup B|} \text{----------------------- (3)}$$

Where A Segmented image,
B Ground truth image.

TABLE I PERFORMANCE OF DEEP LEARNING MODELS

Technique	Dice Coefficient	Intersection Over Union	Accuracy
U-NET	0.88	0.83	97.2
Modified U-NET	0.94	0.88	98
Artefact CNN	0.98	0.94	99.38

VI. CONCLUSION

This comparative analysis provides the best deep learning algorithm for early glaucoma diagnosis in order to save vision. Glaucoma and Normal fundus image were classified from retinal fundus image. We analysed the effectiveness of deep learning models like U-Net, Modified U-Net and Artefact CNN model. From the analysis Artefact CNN model is then determined to be more accurate based on the performance criteria, with an accuracy of 99.38%. In the future, the model can be implemented into a real-time online service to provide patients in remote places with an efficient diagnosis.

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CONFLICT OF INTEREST

The authors declare that there are no actual or potential conflicts of interest, financial or otherwise, associated with this paper

DATA AVAILABILITY

E.J. Carmona, M. Rincón, J. García-Feijoo and J. M. Martínez-de-la-Casa (2008). Identification of the optic nerve head with genetic algorithms. Artificial Intelligence in Medicine, Vol. 43(3), pp. 243-259.

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