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PAPER

Convolutional Neural Network for Segmentation and Classification of Glaucoma

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ABSTRACT

Glaucoma is an eye disease that is caused by elevated intraocular pressure and commonly leads to optic nerve damage. Thanks to its vital role in transmitting visual signals from the eye to the brain, the optic nerve is essential for maintaining good and clear vision. Glaucoma is considered one of the leading causes of blindness. Accordingly, the earlier doctors can diagnose and detect the disease, the more feasible its treatment becomes. Aiming to facilitate this task, this study proposes a method for detecting diseases by analyzing images of the interior of the eye using a convolutional neural network. This method consists of segmentation based on a modified U-Net architecture and classification using the DenseNet-201 technique. The proposed model utilized the DRISHTI-GS and RIM-ONE datasets to evaluate glaucoma images. These datasets served as valuable sources of diverse and representative glaucoma-related images, enabling a thorough evaluation of the model's performance. Finally, the results were highly promising after subjecting the model to a thorough evaluation process. The segmentation accuracy reached 96.65%, while the classification accuracy reached 96.90%. This means that the model excelled in accurately delineating and isolating the relevant regions of interest within the eye images, such as the optical disc and optical cup, which are crucial for diagnosing glaucoma.

KEYWORDS

glaucoma, U-net model, convolutional neural network (CNN), deep learning, image segmentation, image classification

1 INTRODUCTION

Glaucoma is a term used to describe a group of eye diseases that affect the optic nerve, located at the back of the eye. The optic nerve is responsible for transmitting information from the eye to the brain [1]. When this nerve is damaged, the ability to see can be lost.

The World Health Organization (WHO) estimates that glaucoma affects approximately 60 million people worldwide. Approximately 4.5 million people are blinded

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due to the primary type of glaucoma. This accounts for approximately 12 percent of the total number of blind individuals globally [2]. It is the second-most common cause of blindness and vision loss worldwide and the leading cause of permanent vision loss. However, the disease can be cured, and blindness can be prevented through early diagnosis. While the disease can affect children and adults at an early age, the risk is higher for the elderly (with an increasing risk after age 40), uncontrolled diabetics, and individuals with a family history of glaucoma. By and large, cases of glaucoma fall into two major classes: open-angle glaucoma, which is more common than closed-angle glaucoma. In the case of open-angle glaucoma, the eye's drainage channels are gradually obstructed by minuscule micro-deposits over a period of months or even years. This type of glaucoma is referred to as open-angle glaucoma because the drainage channels appear clear when examined with a slit lamp at high magnification. However, the drainage that flows through these channels is not functioning properly [3]. The intraocular pressure slowly rises as fluid production remains normal while drainage is hindered. However, in angle closure glaucoma, the eye's drainage channels are blocked due to a significant narrowing of the angle between the iris and the cornea. This type of glaucoma is referred to as angle closure because the obstruction of the canals is easily observed during examination [4]. It can occur either suddenly or slowly. If clogging occurs suddenly, the pressure in the eye will increase rapidly. If the clog occurs slowly, the pressure inside the eye gradually returns. When a patient is suspected of having glaucoma, the doctor will conduct a comprehensive examination [5]. The comprehensive glaucoma examination consists of five steps: eye pressure measurement, optic nerve assessment, field of vision test, ophthalmoscopy, and keratometry. The intraocular pressure is measured using a painless instrument called a tonometer. Normal eye pressure ranges between 11 and 21 mmHg. In most cases, an eye pressure above 21 mmHg is considered higher than normal [6].

All of these methods involve manual processes, which can be time-consuming and may potentially lead to decisions that are influenced by the biases of multiple specialists. As a result, a computer-aided diagnostic (CAD) tool is required as a supplementary tool for doctors. This CAD system consists of three main steps: preprocessing, segmentation, and classification. These steps are used to classify fundus eye images as either "glaucoma" or "normal." The doctor focuses on aligning the fundus camera with the pupil. When he presses the shutter button, the flash goes off and creates an image of the inner surface of the eye. The image consists of the optic cup, optic disc, and retinal vessels, as illustrated in Figure 1.

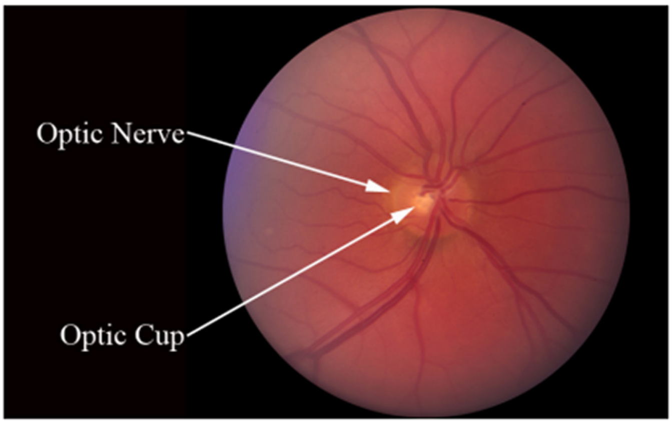

Fig. 1. Retinal fundus image

The optic disc is the beginning of the optic nerve and the point of the main blood vessels that supply the retina. The optic cup is the variable-diameter depression located on the optic disc [3].

In this CAD system, pre-processing is used to remove outliers from input fundus images. In the segmentation section, a modified U-Net model is employed. For the final stage, a pre-trained transfer learning model, DenseNet-201, is used for feature extraction in conjunction with a deep convolutional neural network (CNN). The classification task utilizes a CNN approach, with the ultimate outcome indicating whether or not glaucoma is present in the diagnosis [7].

The remaining sections of this paper are structured as follows: Section 2 provides extensive details about previous works related to object segmentation and classification for glaucoma. Section 3 outlines the details of the materials and methods used in this study. Section 4 presents an analysis of the comparative results obtained in this work. Finally, Section 5 presents the conclusion.

2 RELATED WORKS

Several research models have been reported by various authors for glaucoma detection, segmentation, and classification. Each model employs a different algorithm from the others. Most of these models are based on deep learning, exhibiting varying degrees of performance evaluation. In many research studies, the primary approach for diagnosing glaucoma involves capturing fundus images using digital imaging equipment, which has emerged as the most widely adopted method. The captured images were subsequently preprocessed to normalize any irregularities.

Signh et al. [8] developed a novel pre-processing model using Gaussian filtering. The authors utilized an optimized CNN framework to classify various features, including morphological features such as disc area, cup area, and blood vessels, as well as non-morphological features like color, shape, and modified LBP. Their proposed method demonstrated successful validation in detecting glaucoma, while also assisting in removal of noise from the images.

Veena et al. [9] implemented a framework using the CNN model to segment the optic cup and optic disc in order to determine the cup-to-disc ratio (CDR). The model is designed to provide a diagnosis of glaucoma, achieving a high accuracy rate of 98% for optic disc segmentation and 97% for optic cup segmentation.

Rutuja Shinde [10] presented a model that utilized the U-Net architecture for segmenting the optic disc and optic cup. Furthermore, classifiers such as support vector machines (SVM), neural networks, and Adaboost were utilized. This model demonstrated exceptional performance, surpassing other approaches in terms of accuracy and effectiveness.

Pal and Chatterjee [11] applied morphology-based operations and a histogram equalizer to enhance the edges of the optic disc in an RGB (red, green, blue) image. The edge of the optic disc was identified using Canny's edge detector and then segmented using the fill algorithm.

Jun et al. [12] introduced a method for glaucoma detection based on the transferable ranking CNN (TRk-CNN) using DenseNet. The fundus images are classified as normal, glaucoma suspect, and glaucomatous eyes. TRk-CNN achieved high values in terms of accuracy, sensitivity, and specificity.

Soltani et al. [13] attempted to segment the optic disk using the Laplace, Sobel, and Canny edge detection methods. They used the Canny detector because it provided the best performance in detection and localizing of the disk, while the Laplacian operator had lower accuracy.

Hatanaka et al. [14] attempted to identify the optic disc by analyzing the shape and color of the fundus image. The P-tile threshold algorithm was implemented on the three channels of an RGB image. An optical disk estimate was obtained by merging the three images, and the Canny edge detector was applied. The vertical CDR was used to diagnose glaucoma.

The following section describes the utilization of various state-of-the-art methods for comparison with the proposed approach.

3 MATERIAL AND METHODS

3.1 Database

A collection of two datasets has been used for the purpose of this paper.

Diabetic retinopathy image dataset for segmentation, grading, and screening **(DRISHTI-GS)**: This dataset contains 101 retinal fundus images acquired using a retinal fundus camera. Out of these images, 30 are classified as normal, and 71 are classified as glaucomatous. The reference standard for evaluating the implemented methods consists of labeling the images as “normal” or “abnormal” and using the optic disc/cup maps created by researchers from IIIT Hyderabad in collaboration with Aravind Eye Hospital in Madurai, India [15].

Retinal image for optic nerve evaluation **(RIM-ONE)**: This dataset includes 169 retinal fundus images that have been labeled as either “glaucoma” or “non-glaucoma.” There are a total of 118 images classified as normal: 12 images representing early-stage glaucoma, 14 images for moderate-stage glaucoma, 14 images for advanced-stage glaucoma, and 11 images for ocular hypertension. These retinal images were captured at three different hospitals located in various regions of Spain [16].

3.2 Preprocessing

Cropping. The initial dimensions of the fundus image were too large to be directly inserted into the neural network. Therefore, to reduce the dimensionality of the original image, the significant section containing the disc was cropped to 512×512 pixels. The cropping causes a data loss, but since the approach in this study is based on CDR, the cropped area, which does not include part of the cup or disc, does not have a significant impact on the detection results. In addition, it reduces computational time, increases segmentation accuracy, and standardizes the input image for further processing, as shown in Figure 2.

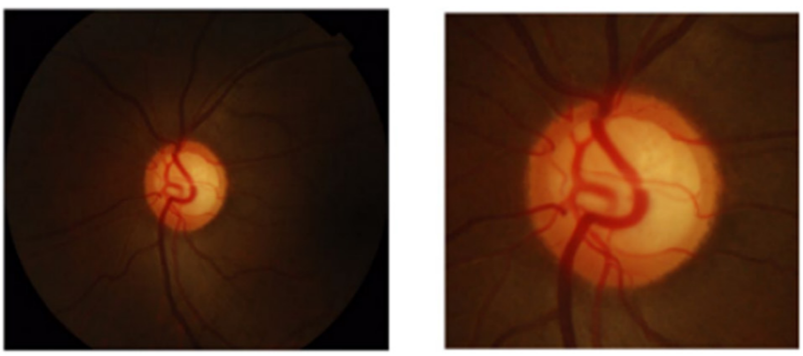

Fig. 2. Cropped fundus image

Data augmentation. Image augmentation is a technique that involves applying various transformations to the original images in order to generate multiple transformed copies of the same image [17]. Every copy, however, is quite different from the other in some aspect, depending on the augmentation techniques you apply, such as shifting, rotating, flipping, etc. These techniques not only enable the use of a larger dataset but also incorporate a level of variation into the data. This helps the model generate unseen data more effectively. In addition, the model becomes more robust when trained on new, slightly modified images. In the final output, we obtained 2,000 eye fundus images.

Channel separation. The images were divided into separate red, green, and blue channels, as shown in Figure 3. The red channel was selected for optic disc segmentation due to its superior visibility in capturing the optic disc compared to the green and blue channels. On the other hand, the blue channel was used for optic cup segmentation because it offered better contrast in delineating the boundaries of the optic cup compared to the other channels [18].

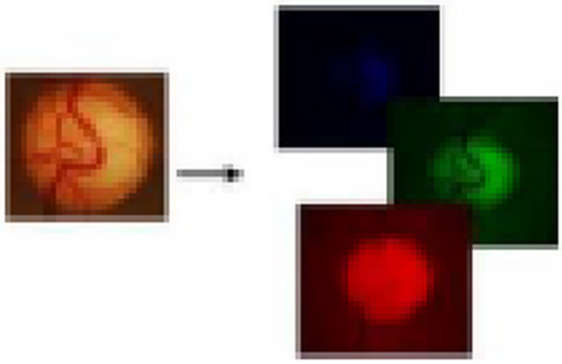

Fig. 3. Channel separation

3.3 Method

The proposed approach consists of five steps: data resizing, data augmentation, channel separation, segmentation of the optical disc and optical cup using a modified U-Net architecture, and classification using the DenseNet-201 technique. Figure 4 illustrates an overview of the proposed method.

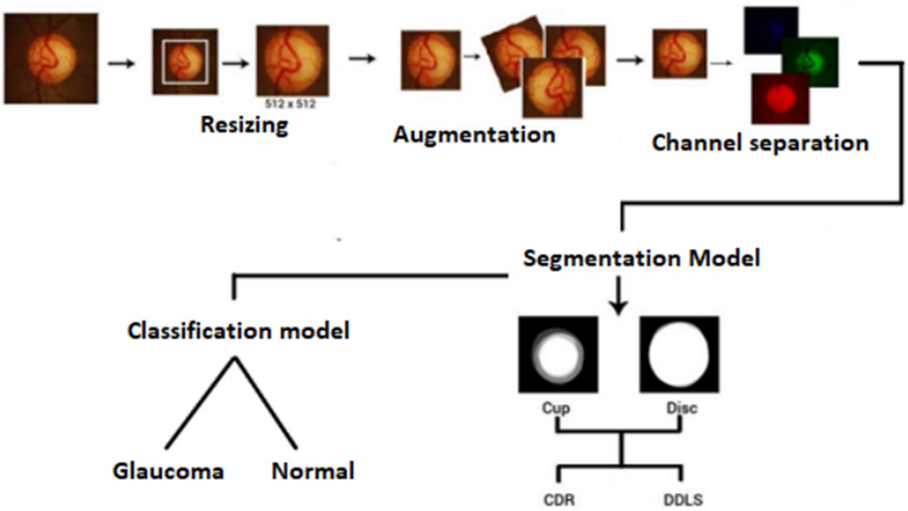

Fig. 4. Proposed method

Segmentation approach. U-net is an image segmentation technique primarily focused on image segmentation tasks. These features make U-net highly versatile in medical imaging and have resulted in its widespread adoption as a key tool for medical imaging segmentation tasks [19]. The success of U-net is evident in its extensive utilization across various imaging modalities, ranging from MRI (magnetic resonance imaging) to microscopy. It has a “U” shape visually. The structure is symmetrical and is composed of three main sections: the contraction, the bottleneck, and the expansion section. The first section, known as the encoder, is responsible for extracting contextual information from an image. This element consists of a combination of convolution layers and max pooling layers, which help to capture the unique features of the image while also reducing its dimensions. This reduction in size helps to decrease the overall parameters of the network. It involves the iterative application of two sets of 3×3 convolution layers, each followed by a ReLU activation function and batch normalization. Subsequently, a 2×2 max pooling operation is conducted to reduce the spatial dimensions. The bottleneck, which connects the encoder and decoder networks, facilitates the flow of information. It consists of two layers of 3×3 convolutions, with each layer being followed by a ReLU activation function. The second block is the decoder block. It provides accurate localization through transposed convolution and also allows for the recovery of the initial size of the image. The decoder block initiates by upsampling the feature map using a 2×2 transposed convolution layer. Subsequently, two sets of 3×3 convolution layers are applied, with each convolution operation being followed by a ReLU activation function. The final output of the decoder is passed through a 1×1 convolution layer with a sigmoid activation function. We will change the filter size to (4×4) in the conv2d layers, the upsampling layer, and the pooling layer. A larger filter size enables us to extract more features from the image. Since each layer adds a significant number of parameters, a larger maxpool size means more efficient subsampling [20]. The middle exclusion layer was removed in the modified U-net because it resulted in information loss. In the model output, we will have the image on the right, which is called a mask and represents the label of the optical disk truth. This is what our model should predict [21] (see Figures 5 and 6).

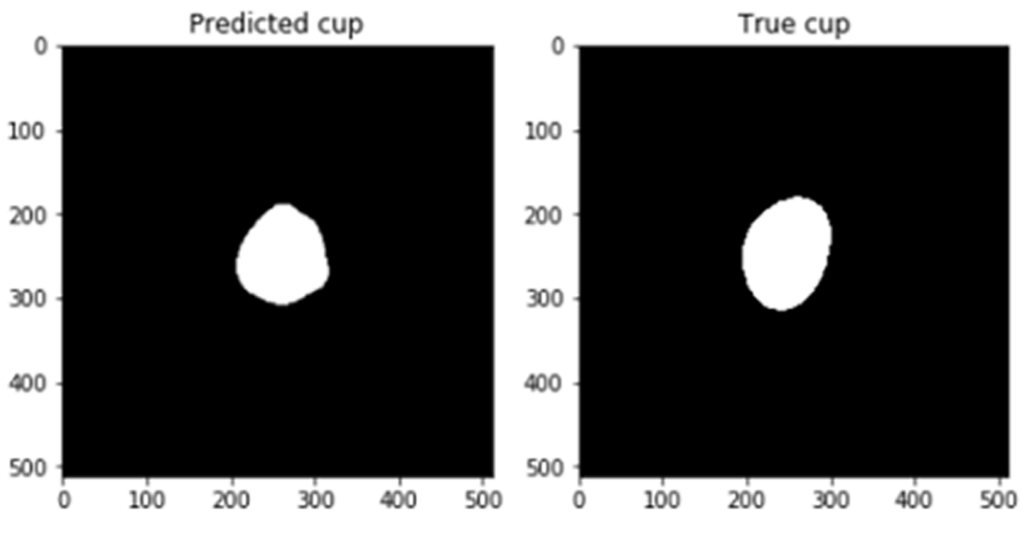

Fig. 5. Optical cup segmentation

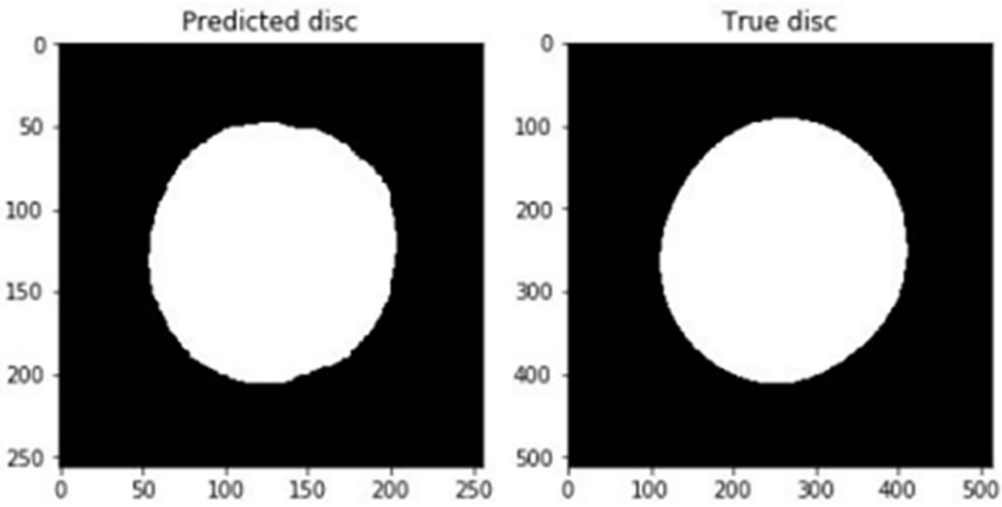

Fig. 6. Optical disc segmentation

Classification approach. The research [16] suggested using the CNN model with pre-trained DenseNet-201. DenseNet was specifically designed to address the declining accuracy caused by gradient leakage in high-level neural networks. Due to the significant gap between the input layer and the output layer, there is a risk of data loss before reaching the final destination. The objective is to classify glaucoma images using a dataset of retinal fundus images. To extract features from the dataset, we utilize a pre-trained DenseNet-201 model, and the classification task is executed using a CNN model. The dataset is divided into 70% for training and 30% for performance analysis validation. For classification, two dense layers with 128 and 64 neurons are being used. The feature extraction network is followed by sigmoid activation for binary classification. Calculation of CDR and DDLS (disc damage likelihood scale). The CDR is an important indicator for detecting glaucoma. A healthy eye is typically considered to have an average CDR value below 0.3. In contrast, a CDR exceeding 0.5 indicates glaucomatous eyes, and values ranging from 0.3 to 0.5 suggest suspected cases [17]. On the other hand, the DDLS value for a normal eye is typically higher than 0.3, while a glaucomatous eye tends to have a DDLS value below 0.3. They are calculated as follows:

$$\text{Horizontal CDR} = \frac{\textbf{Horizontal Cup}}{\textbf{Horizontal Disc}} \tag{1}$$

$$\text{Vertical CDR} = \frac{\textbf{Vertical Cup}}{\textbf{Vertical Disc}} \tag{2}$$

$$\text{Air CDR} = \frac{\textbf{Air Cup}}{\textbf{Air Disc}} \tag{3}$$

DDLS represents the ratio of the minimum rim width to the disc diameter, as shown in Figure 7. It is calculated using the following equation:

$$\text{DDLS} = \frac{\textbf{min Rim}}{\textbf{diameter Disc}} \tag{4}$$

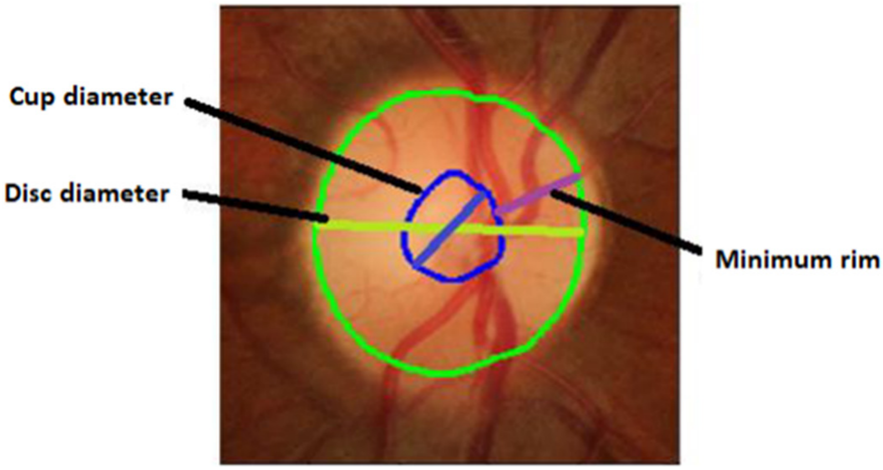

Fig. 7. Retinal fundus image

4 RESULTS AND DISCUSSION

Accuracy is a performance metric that reflects the model's evaluation of its performance on a specific subset of data. It serves as a fundamental measure for evaluating the success of the classification process. Accuracy is commonly used when both positive and negative classes are equally important. The calculation of accuracy is determined by using the following equation.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Precision is a measurement that signifies the ratio of accurately predicted positive instances to all instances predicted as positive. It reflects the cumulative positive predictive value of the model. A lower precision value indicates the presence of a significant number and quantity of false positives, highlighting the impact of these inaccuracies on the performance of the classification model. The precision metric can be calculated using the following equation:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

Lists should be used sparingly, and when necessary, they should be kept concise and brief.

$$\text{TN} = \frac{TP}{TP + FP} \tag{7}$$

TP stands for true positive, which refers to the total number of correctly predicted positive cases.

FP indicates the total number of incorrectly predicted positive cases.

TN refers to the total number of correctly obtained predictions in the negative cases.

FN refers to the total number of incorrect predictions in the negative cases.

Intersection-over-union (IoU), also known as Jaccard's Index (JI), is one of the most commonly used metrics in semantic segmentation. The IoU is a simple and extremely efficient metric, as shown in Figure 8.

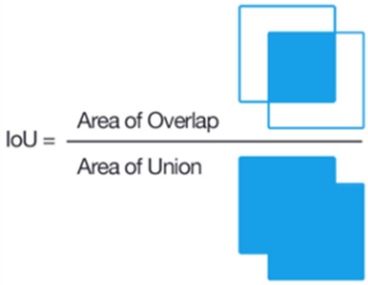

Fig. 8. Training and testing loss analysis

A modified U-Net architecture was introduced in this research to perform optic disc and optic cup segmentation and detect glaucoma by developing a model. The evaluation of glaucoma images involved using the DRISHTI-GS and RIM-ONE datasets. The dataset was divided into two subsets: a training set, which included 70% of the samples, and a testing set, which comprised the remaining 30%. The proposed method has achieved promising results in the segmentation of optical discs. The precision and accuracy metrics for the RIM-ONE dataset are 0.99 and 0.996, respectively. For the DRISHTI-GS dataset, and the values are 0.937 (Table 1).

Table 1. Performance of the optical disc segmentation

Dataset	TP	FP	TN	FN	JI	Accuracy
DRISHTI-GS	.87	0	1	.12	.12	.937
RIM-ONE	1.0	.007	.99	0	.36	.996

The classification of glaucoma employed a pre-trained model. Four neural network architectures were tested and evaluated: VGG16, Inception Resnet, Resnet 152v2, and DenseNet-201 [22], [23]. The evaluation criteria were used to assess the accuracy and precision of each model, as shown in Tables 2 and 3. The results have shown that DenseNet-201 achieves the highest values: 98.82% accuracy and 98.63% precision. Figures 9 and 10 illustrate the results.

Therefore, the adoption of the modified U-Net architecture and the application of the DenseNet-201 technique can be considered a practical approach that helps doctors prevent glaucoma and avoid missed diagnoses.

Table 2. Comparison of accuracy for different classification techniques

Model	Training	Test
VGG19	97.73	95.54
Inception Resnet	94.86	91.64
Resnet 152v2	97.56	93.21
DenseNet-201	98.82	96.90

Table 3. Comparison of precision for different classification techniques

Model	Training	Test
VGG19	97.30	94.70
Inception Resnet	93.81	91.52
Resnet 152v2	97.28	93.02
DenseNet-201	98.63	96.45

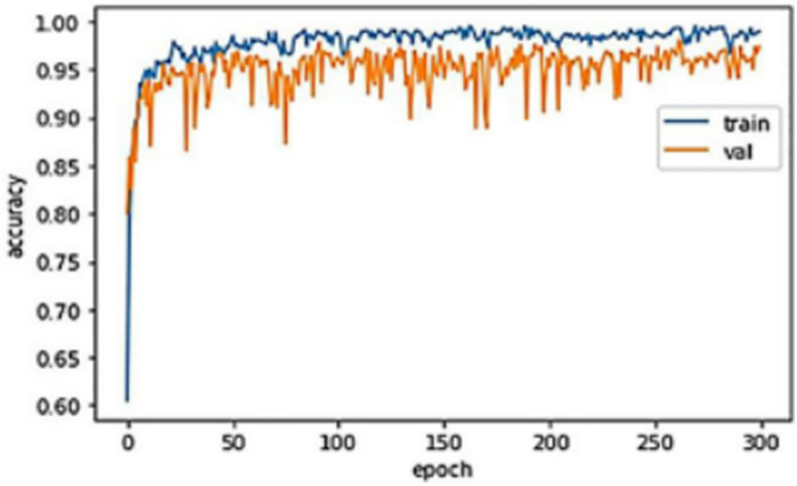

Fig. 9. Training and testing accuracy analysis

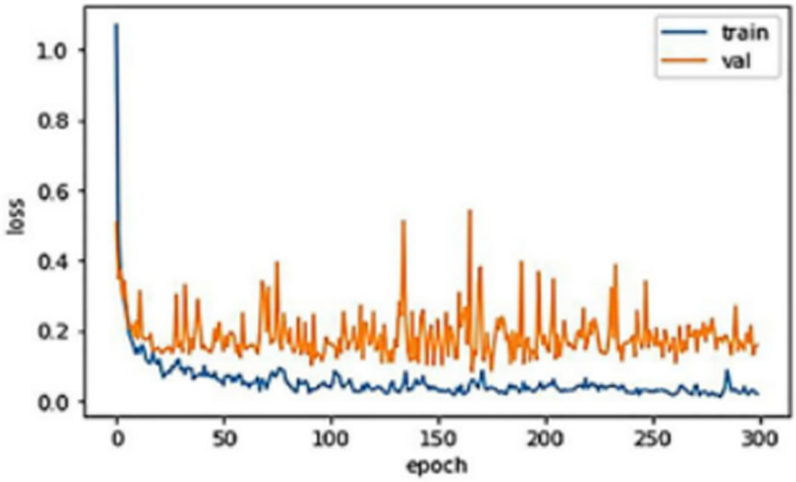

Fig. 10. Training and testing loss analysis

Numerous studies have been conducted using fundus images from various datasets to detect glaucoma. Table 4 presents a comparison of the accuracy achieved by our method with the results obtained in several recent studies.

Table 4. Comparison with previous studies using the same DRISHTI-GS and RIM-ONE datasets

Study	Dataset	Method	Accuracy
Shinde et al. [10]	DRISHTI-GS	Segmentation with U-Net	98.00
Pathan et al. [24]	DRISHTI-GS	Classification with SVM	96.70
Esengönül et al. [25]	RIM-ONE	MobileNet with CNN	72.80
Haider et al. [26]	RIM-ONE	Classification with Resnet-18	85.00
Haider et al. [26]	RIM-ONE	Classification with Resnet-50	78.30
Haider et al. [26]	RIM-ONE	Semantic segmentation	95.00
Haider et al. [27]	RIM-ONE	Separable linked segmentation residual network	90.00

5 CONCLUSION

Glaucoma is a leading cause of vision loss worldwide. Because symptoms of glaucoma do not appear until later in the disease, it is challenging to accurately detect it at an early stage. Regular testing for glaucoma is essential and recommended. However, the testing is time-consuming and challenging, and there is currently a shortage of eye specialists available. CNN has emerged as the primary approach for addressing challenges related to extracting information from digital images. This study presents a deep learning-based model for detecting glaucoma. The proposed model utilized the DRISHTI-GS and RIM-ONE datasets to evaluate glaucoma images. 70% of the data has been used for training, while the remaining 30% has been allocated for testing. The segmentation of the optic disc and optic cup is performed using a modified U-Net architecture. U-Net proves to be a highly efficient algorithm for medical image segmentation. Secondly, the features of CDR and DDLS CDR were considered as decision-making criteria for glaucoma detection. Finally, a DenseNet-201 classification model was used to classify between normal and glaucoma-affected eyes. The proposed model achieved a training accuracy of 98.82% and a testing accuracy of 96.90%. We believe that our trained approach can be utilized and further developed for clinical applications in hospitals. Therefore, although the reported results are promising, our ongoing efforts and the future direction outlined in this paper are focused on enhancing the performance of the proposed model. Our objective is to achieve improved results by exploring an alternative approach during the preprocessing stage, specifically the incorporation of transfer learning techniques. Additionally, there is potential to develop a system that combines clinical factors with images, further enhancing the accuracy of glaucoma detection.

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