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Increasing the speed of diagnosis of glaucoma by using multitask deep neural network from retinal images

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Abstract

Glaucoma stands out as a prevalent ocular ailment in the elderly population, causing substantial harm to the optic nerves and eventual vision impairment. Fundus photography plays a pivotal role in the clinical assessment of glaucoma, facilitating the exploration of associated morphological alterations. Computational algorithms, capable of processing fundus images, have emerged as indispensable tools in this diagnostic domain. Hence, the imperative development of an automated diagnostic system leveraging image processing techniques is underscored. In this study, a novel approach to the segmentation and classification of retinal optic nerve head images is introduced. This method concurrently executes both tasks through a deep learning framework, thereby enhancing the learning speed within the network. The proposed network encompasses approximately 29 million parameters and demonstrates an efficiency of 2.5 seconds for segmenting and classifying retinal images. Central to this strategy is a multi-task deep learning network, harmonizing segmentation and classification processes, and leveraging information from both tasks to optimize learning efficacy. Validation of the proposed method is conducted using the publicly available ORIGA dataset. The attained performance metrics for accuracy, sensitivity, specificity, and F1-score are 99.461, 93.46, 100, and 98.7006, respectively. These results collectively affirm the substantial advancement achieved by the proposed method in comparison to existing methodologies.

Keywords: deep learning, convolutional neural network, classification, retinal images, disease diagnosis, multitasking network
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1 Introduction

Glaucoma is a group of diseases in which the optic nerve is damaged, eventually leading to irreversible visual field loss and possibly increased intraocular pressure. Glaucoma symptoms are only noticed in the advanced stages. Early diagnosis of glaucoma prevents blindness in people because this disease can only be diagnosed by the patient in its advanced stages. Fundus photography using a fundus camera from the optic nerve head is one of the diagnostic

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methods that physicians use to diagnose glaucoma. Changes in the shape of the cup region, which is the central part of the optic nerve, is a parameter to diagnose glaucoma [18]. Figure 1 shows the retinal fundus images.

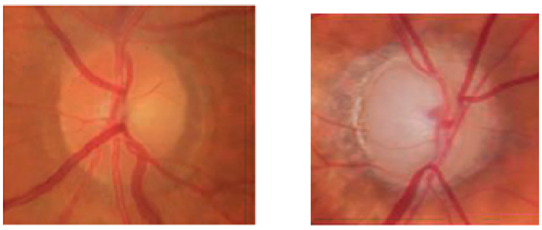

Figure 1: Retinal fundus images: (a) Normal eye, (b) Deep Glaucoma [36]

Recently, various image processing and deep learning algorithms have become important for glaucoma diagnosis. In this research, we propose a method for retinal optic nerve head image segmentation and classification that performs both operations simultaneously. Our proposed network is a multitasking network that performs segmentation and classification simultaneously using deep learning and increases the learning speed in the network. Figure 2 shows the structure of the Optic Nerve Head (ONH).

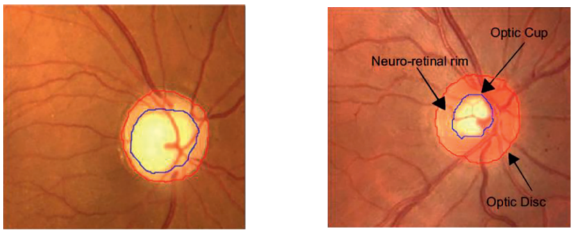

Figure 2: Structure of ONH: (a) Glaucoma and (b)non-Glaucoma [31]

Several schemes for detecting glaucoma in retinal images have recently been proposed by various researchers. The cup-to-disc ratio has been used to diagnose glaucoma by Khalil et al. [18]. Marques devised a method for calculating the cup-to-disc ratio from segmentation of the internal limiting membrane surface using a set of global intensity thresholds applied to each image, with corrections such as missing point interpolation, outlier removal, low-quality image removal, and feature analysis [22]. They proposed that the pigment epithelium layer is the retina. The proposed system's average sensitivity, accuracy, and specificity in the Armed Forces Ophthalmology Institute dataset are 81%, 75%, and 78%, respectively. Ramzan et al. [26] have used the cup-to-disc ratio to segment the retinal layers and automatically diagnose glaucoma. The proposed system's average sensitivity, accuracy, and specificity are 87%, 79%, and 72%, respectively.

Sahlsten et al. [30] proposed an artificial intelligence-based method for diabetic retinopathy using retinal images. They analyze the deep learning model using 41,122 retinal images. Their model has sensitivity values ranging from 0.968 (0.961-0.974) to 0.893 (0.883-0.902).

Chatterjee et al. [4] conducted a comprehensive review of edge detection algorithms for retinal image segmentation. They used various edge-based segmentation methods for detection, including the Kirsch filter, Canny, Prewitt, Sobel, and Fuzzy-C detector algorithm. The evaluation was carried out using DRIVE datasets. The results show that the Kirsch filter outperforms the other methods. The accuracy value ranges from 0.77 to 0.94, while the specificity value ranges from 0.76 to 1.00. The sensitivity ranges between 0.20 and 0.84. Pathan et al. [25] evaluated several machine learning algorithms, including SVM, AdaBoost, and NB on two additional datasets for glaucoma diagnosis in 2021. With the exception that a threshold method is used to segment the images in this work, and the accuracy of the work for the Drishti and KMC datasets using the SVM algorithm reaches 96.4%. Because the images in these data sets are limited for training the network, it should be tested with larger data sets to ensure that the results are accurate. Different deep learning models for diagnosing diabetic retinopathy from retinal image were investigated by Yip et al. [40]. They used models such as VGGNet model [32], ResNet model [15], DenseNet model [16] for analysis and Ensemble. Four deep learning models with AUCs ranging from 0.936 to 0.944 demonstrated comparable diagnostic performance in the diagnosis of diabetic retinopathy. Gupta et al. [14] A learning model for retinal image classification is presented. They used directed filtering and adaptive median filtering to preprocess the images before sending them to the neural network. Images are classified using Mayfly model [41] optimization with a kernel-based machine learning model. For retinal image classification, Abdel-Hamid [2] proposed the VGG16 transfer learning model. This method is employed to validate the retinal image before to be used in other applications. Goel et al. [13] proposed using retinal images to classify different stages of diabetic retinopathy using a deep learning model based on VGG. On the IDRID dataset, it achieved an accuracy of 95%. A classifier system based on k-nearest neighbors for retinal image classification was proposed by Kaur and his research team [17]. This system classifies retinal images using wavelet characteristics to diagnose diabetic retinopathy. The proposed scheme is evaluated using the DIARETDB1 dataset, which yields accuracy, sensitivity, and specificity values of 95%, 92.6%, and 87.56%, respectively. Saba et al. [29] proposed a triage system to classify retinal images using two deep learning models. The U-net model is used in this system to extract features, which is then sent as input to the dense network to determine whether the optical disk is normal or abnormal. This system has an accuracy of up to 96%. Sudhan et al. [36] proposed a model that used U-Net architecture for optic cup segmentation and a pre-trained transfer learning model. For feature extraction, the DenseNet-201 network is combined with a deep convolutional neural network. Glaucoma images are evaluated using the ORIGA dataset. The proposed model had a training accuracy of 98.82% and a testing accuracy of 96.90%.

According to the related articles, the existing glaucoma screening system uses different data sets to verify performance and a combination of traditional features and techniques as well as machine learning. Thanki also revealed that many of the proposed systems for retinal image classification are based on artificial intelligence [38] and deep learning approaches. However, these systems have a maximum accuracy of 98%. Many evaluations have used private data sets that are not publicly available to compare the performance of other methods under the same conditions.

However, segmenting retinal images with high sensitivity and accuracy remains a significant challenge. Deep convolutional neural network architectures are effective in diagnosing eye diseases and have predicted levels comparable to ophthalmologists. In this paper, we propose a new framework for retinal optic nerve head image segmentation and disease classification from medical images based on deep convolutional neural networks. Our proposed network investigates the benefits of multi-task learning by combining segmentation and classification tasks. This strategy is based on the U-Net network. Our proposed network takes retinal images as input and evaluates the classification and segmentation results for glaucoma based on the image's normality and abnormality. The proposed framework was evaluated using the ORIGA dataset in the paper by Zhang et al. [42], which is available to the public. According to our findings, the U-Net network is the first to attempt to segment and classify retinal images at the same time.

2 The proposed method

We are going to perform segmentation and classification of the retinal optic nerve head image for the diagnosis of glaucoma at the same time. We use a deep convolutional neural network with a specific structure as multitask Learning. Our proposed network technique transfers retinal images to a deep neural network based on the U-Net backbone. Two tasks are completed in this step. One task is segmentation, and the other is classification. This end-to-end network wishes to carry out both actions at the same time.

U-Net architecture is a convolutional neural network originally designed for image segmentation in the medical field. The architecture of this network consists of two parts; The left part is the encoding path and the right part is the decoding path. The purpose of the encoding path is to understand the content of the image and the role of the decoding path is to help in the process of accurately locating objects [28]. In our proposed method, retinal image classification and segmentation is performed simultaneously using the u-net network. These operations are structurally dependent and the network learns concurrently with separate loss functions. Figure 3 shows the overall network architecture.

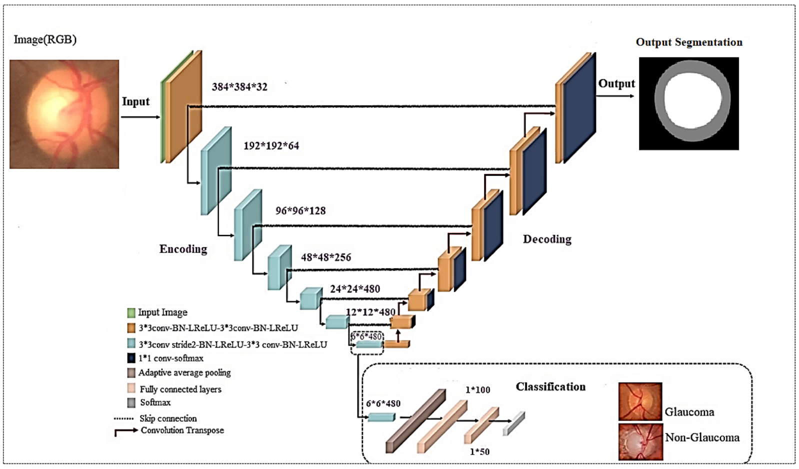

Figure 3: Proposed architecture for retinal image Segmentation and Classification

a) **Network Details:**

The network operations are carried out in accordance with the image guide. Three types of convolution operations are done in this design.

3*3 conv [27]: modifies the input image with a sequence of kernels, allowing the network to learn the data changes. This convolution occurs at the surface and reduces data size. On the other hand, stride 2 has been utilized to reduce network calculations, prevent network overfitting, and boost network accuracy and speed.

1*1 Convolutional [9]: The input depth or number of filters employed in the convolution layers frequently increases with network depth, resulting in a greater number of feature maps. Because the convolution operation must be done through the input depth, a large number of feature mappings in a convolutional neural network might cause issues. If the convolution operation done is quite large, resulting in more computations to perform the convolution operation, leading to spatial and temporal complexity. Deep convolutional neural networks necessitate the use of a hybrid layer capable of reducing the depth or number of feature maps. The goal of this sort of convolution is to manage data depth, which minimizes depth and the number of feature maps.

convolution transpose [23]: The purpose is to increase the size of the data and transform it from vector to matrix format. A transposed convolution layer functions similarly to a conventional convolution layer, except that the convolution operation is performed in the opposite direction. A transposed convolution layer, rather than sliding the kernel over the input and performing element-wise multiplication and addition, slides the input over the kernel and performs element-wise multiplication and addition. As a result, the output exceeds the input.

Pooling operations [8]: In deep learning architecture, there are two types of pooling operations. Max Pooling and Average Pooling. This stage shrinks the image so that the network can recognize the change in data size. If the distance between the patient and the camera varies while taking an image of the retina, the pooling layer corrects the scale shift. We employed a unique pooling approach. The adaptive average pooling method is utilized. In fact, the kernel's size is determined automatically based on the size of the input and output images. And the fixed value is not, for example, 2×2, and it is affected by data size and network efficiency.

The batch normalization operation [1]: normalizes the inputs at each level of the network and reduces the disparity between inputs and outputs such that the data distribution remains constant. This ensures that no data is lost during the transmission from the first to the last layers. This layer's advantages include faster network training, improved gradient diffusion, removal of correlation between samples, less susceptibility to weight initialization, and reduced Vanishing Gradient.

Leaky ReLU activation function [39]: We utilized LReLU instead of the ReLU activation function. The distinction between these two functions is that, as shown in Figure 4, the ReLU function returns zero for negative values, but the LReLU function returns a tiny value for negative numbers. That is, it does not saturate for little and big inputs, respectively. In fact, the learning time is lowered, the mean is not zero, and the computing cost is reduced.

b) **Network Training**

- **Loss Function for Classification**

  In classification issues, our objective is to predict the probabilities of all the classes involved. To learn labels,

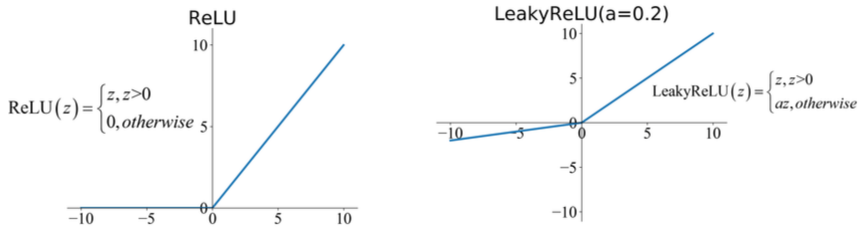

Figure 4: ReLU and LeakyReLu activation function [39]

we employed multi-class cross-entropy [11] for classification loss function, like in previous classification tasks. The disparity between the actual labels and the predicted labels should be lowered for all classes, according to equation 1. To reduce the loss quantity, this relationship should be minimized. According to the relationship, executing the multiplication operation increases the value of $y_c * \log(\hat{y}_c)$. A negative is added to it to make it a minimization problem, and this value is minimized for all classes. It makes use of Z space information, and using this function, the classification part is trained, and the classification loss is minimized. For each class c, y and $\hat{y}$ indicate the Ground Truth Label and Predicted label.

$$L_{class}(y, \hat{y}) = -\sum_{c=1}^{c} y_c * \log(\hat{y}_c) \tag{2.1}$$

- **Loss Function for Segmentation**
Cross-Entropy loss function and DICE function are combined for retinal image segmentation [23], [11]. The DICE loss function is widely used to calculate the similarity among images, which is in fact, the relationship between p and g. It reduces the amount of loss for all classes and i's. In addition to this loss function, we applied another loss function called Cross-Entropy, which minimizes p and g loss. Then, according to equation (2.2), these two functions are merged to yield L_{seg}, which is the segmentation loss function. p represents the projected segmentation output, while g represents the pixel values associated to Ground Truth. i represents the number of pixels in the image, and ε is a constant value used to avoid division by zero.

$$L_{seg} = \left(-\frac{1}{c} * \sum_{c=1}^{c} \frac{2 * \sum_{I=1}^{I} g_c^i * P_c^i}{\sum_{i=1}^{I} g_c^i + \sum_{i=1}^{i} P_c^i + \varepsilon}\right) + \left(-\sum_{c=1}^{C} g_c^i * \log(p_c^i)\right) \tag{2.2}$$

Finally, we have a segmentation loss function and a classification loss function. We multiplied them by a λ before adding them. We want to reduce the overall amount of loss. λ is a number between zero and one. It informs the network that the segmentation loss should be minimized or that the classification loss should be minimized. If $\lambda_{seg} < \lambda_{class}$, it indicates that we want the classification to be given more weight. A tiny λ signifies that class will receive more attention. Equation (2.3) is used to calculate the loss function of the proposed network [33].

$$L = \lambda_{class} * L_{class} + \lambda_{seg} * L_{seg} \tag{2.3}$$

c) **Data Augmentation**
Deep convolutional neural network approaches necessitate a vast quantity of data to train the network. Access to generic medical data sets, on the other hand, is difficult. As a result, data augmentation was employed to address issues caused by a lack of data, such as overfitting.

All images have been scaled to [384*384] pixels. Normalization was then performed for the [0,1] range. With a chance of 0.3, Input images were randomly flipped horizontally, vertically, or both. Rotation with a probability of 0.2 and an angle in the range $[-180°, 180°]$ randomly selected from a Gaussian distribution was used [24]. As an image scale was selected with a probability of 0.2 and with the same distribution in the range [-0.3, 0.3].

d) **Dataset**
The Singapore Eye Research Institute experts generated the ORIGA dataset. This dataset contains 650 images, 168 of which are glaucoma images and 482 of which are healthy images. To evaluate the suggested system's performance, we divided the complete dataset into two parts: training (80%) and testing (20%). Figure 5 shows some retinal images from this collection. The ORIGA database shares real retinal clinical images and is open to the public to test their segmentation and classification algorithms.

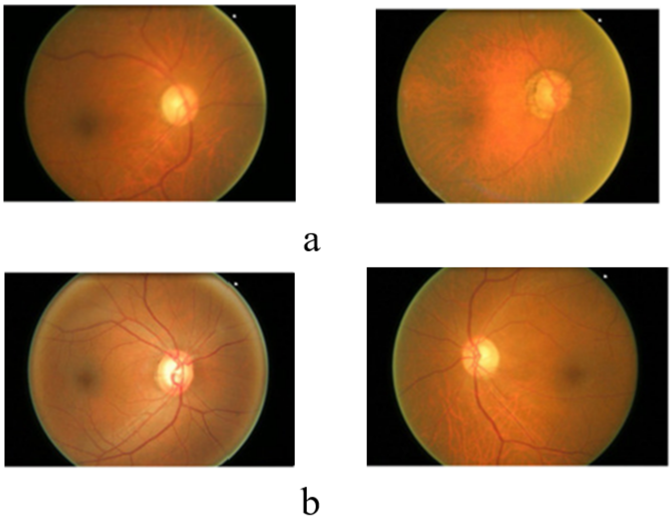

Figure 5: Example of ORIGA dataset images:(a) Glaucomatous retinal images,(b) Normal retinal images [42]

3 Results

a) **Evaluation Metrics of the Machine Learning Algorithms**

The results were acquired using typical error evaluation methods, as demonstrated in relationships 4 to 10. [12].

$$\text{Precision} = \frac{TP}{(TP + FP)} \tag{3.1}$$

$$\text{Recall} = \frac{(TP + TN)}{(TP + FP)} \tag{3.2}$$

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{3.3}$$

$$BF - \text{Score} = \frac{(2 * \text{precision} * \text{recall})}{(\text{recall} + \text{precision})} \tag{3.4}$$

$$\text{IOU} = \frac{TP}{(TP + FP + FN)} \tag{3.5}$$

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \tag{3.6}$$

$$\text{Specificity} = \frac{TN}{(TN + FP)} \tag{3.7}$$

b) **Evaluation of the Proposed Method**

The proposed network was trained for classification and segmentation tasks at the same time. For training, a learning rate of 0.001 and the ADAM optimizer were utilized. Python code was used to generate the results, which were ran on a 12th generation Intel(R) Core (TM) i7-12650H 2.30 GHz processor with 16 GB of RAM and an NVIDIA GTX 3070 GPU with 8 GB of graphics memory. In this part, the proposed network's performance is evaluated using the ORIGA dataset. Accuracy, Precision, Recall, Specificity, and F-Score are used to evaluate the model.

The results are compared to several existing deep learning models for segmentation and classification [10], including VGG-19, Inception ResNet, Xception, and Resnet50. The proposed model outperformed models such as VGG-19 [35], Inception ResNet [37], Xception [7], and ResNet50 [15]. The primary goal of this procedure is to diagnose glaucoma utilizing retinal fundus pictures, which can be used to identify whether or not a person has glaucoma. The outcome of this model can be favorable or negative depending on whether or not the patient has glaucoma.

As shown in Table 1, the proposed model achieved better classification accuracy for classification of glaucoma images. The accuracy of the proposed method is improved by 8.77 % to 9.691%, F1-score by 7.45 % to 8.19 %,

Table 1: Performance analysis

Models	F1-Score	Precision	Specificity	Accuracy
VGG-19	91.25	94.70	88.46	90.69
Inception ResNet	90.56	91.52	88.52	90.00
Xception	90.51	95.37	85.80	89.77
ResNet50	90.76	93.02	89.43	90.29
Proposed	98.7006	100	100	99.461

Precision by 4.63 % to 8.48 %, and specificity by 10.57% to 14.2 % compared to other techniques. A graphical comparison chart is shown in Figure 6.

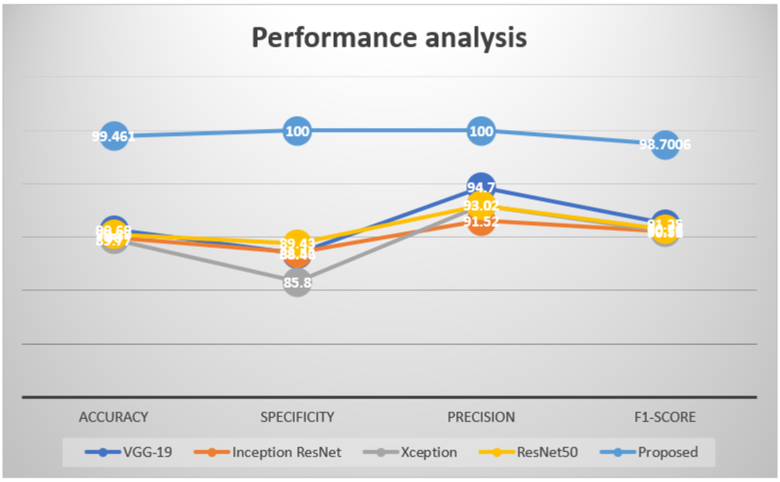

Figure 6: A graphical comparison of results

Table 2: Performance comparison of the proposed method for diagnosing glaucoma from retinal images

Model	Dataset	Accuracy	Sensitivity	Specificity
Maheshwari et al. [21]	RIM-ONE	98.90	100	97.50
Pathan et al.[25]	Drishti	96.4	100	98
Chaudhary and Pachori [5]	ORIGA	91.1	91.1	94.3
Sudhan et al. [36]	ORIGA	98.82	98.95	98.15
Akter et al. [3]	Private dataset	97	100	96
Shoukat et al. [34]	ORIGA	92.59	98.39	79.26
Proposed method	ORIGA	99.461	93.46	100

The proposed method, as previously stated, is a multitask learning and simultaneous recognition method with retinal image segmentation. Overall, it was demonstrated that joint training of both tasks improves the network's Ability to generalize and allows for the extraction of more meaningful information from retinal images. As a result, the benefits of joint classification and segmentation have been demonstrated. Improvement of work in segmentation has been better than classification. According to Table 3, it was acquired by improving the recall and precision parameters for classification of retinal images by completing an analysis of the results, demonstrating the benefit of the stated technique for regular clinical practice.

Table 3: Comparison with other Multitask Learning methods

Model	Segmentation			Classification			
	Recall	Precition	IOU	Accuracy	Recall	Precition	F1-score
Chen et al. [6]	70.08	73.4	75.5	97.1	96.7	97.5	97.1
Le et al.[20]	61.7	62.4	66.1	96.4	95.9	97.1	96.3
Kong et al. [19]	60.8	62.5	64.6	95.6	95.4	95.9	95.6
Proposed method	76.92	77.97	76.92	96.92	96.9	100	96.95

The proposed model can be used to segment and classify medical images to diagnose diseases such as diabetes, Alzheimer's, breast cancer, etc.

4 Discussion

We introduced a fully automated method for retinal image classification and optic disc segmentation in this paper. This strategy investigates the benefits of multitask learning by learning both tasks at the same time. The proposed method improves performance when compared to existing standard deep neural networks for classification and segmentation applications. This resulted in improved training robustness and stability for classifiers. The primary goal of this procedure is to diagnose glaucoma utilizing retinal fundus images, which can be used to identify whether or not a person has glaucoma. The outcome of this model can be favorable or negative depending on whether or not the patient has glaucoma. The suggested network was trained for classification and segmentation tasks at the same time. For training, a learning rate of 0.001 was used. In the training phase, the ADAM optimizer was also deployed. Training the network for classification and segmentation tasks at the same time is defined as 1000 sessions with a batch size of four. The cross-entropy loss function is utilized for classification, while a mixture of two cross-entropy loss functions and DICE is used for segmentation. Several experiments have been carried out in order to evaluate the accuracy of the proposed method. A comparison with other typical deep convolutional neural network approaches for retinal disease classification, as well as various retinal image segmentation methods and multitasking methods has been carried out. The results were obtained by running Python code on a system with the hardware specifications given.

Comparing the network with the classification methods presented in Table 2 shows the Precision parameter with a value of 100%, which indicates that all people suspected of glaucoma have been correctly diagnosed. In Table 3, classification results have generally performed better than image segmentation in multitasking mode. But compared to other tasks, the accuracy can be improved. But from the segmentation results, it can be concluded that the proposed method is completely improved compared to other methods. The existence of more parameters due to the voluminous nature of the data in medical image processing is the reason for the high image processing time and memory consumption in all deep learning algorithms. Therefore, reducing the two important parameters of time and memory consumption can be a big challenge in medical image processing. With multitasking neural networks, due to joint training in segmentation and classification, these two parameters can be saved. Currently, the proposed network has about 29 million parameters, which takes 2.5 seconds to infer a retinal image using the previously described computational settings.

5 Conclusion

We proposed an automatic retinal optic nerve head image segmentation and classification method that performs both operations simultaneously for glaucoma detection from ORIGA dataset images. Our proposed network is a multitasking network that performs segmentation and classification simultaneously using deep learning and increases the learning speed of the network. This method examines the benefits of multitasking learning by learning both tasks at the same time. In general, the automatic deep neural network technique can make glaucoma diagnosis simple and quick, it is a useful tool for doctors as well as a self-care module for patients, and it potentially minimizes the risk of misdiagnosis and improves glaucoma treatment in its early stages. Due to computational costs, the number of feature maps is limited to 480 during training. In the future, a learning technique to reduce this constraint can be investigated. Also, we could not examine the significance of disease severity. As we know, if the diagnosis error increases for those who have a severe disease, it is much worse than if the disease is at a low level. For low levels of the disease, diagnosis error is less important. In the next work, we plan to consider the levels of glaucoma, which are mild, moderate, and deep, and grade their importance by weighting these levels so that the network understands which data needs more accuracy.

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