Glaucoma diagnosis utilising Le-Net and supervised machine learning techniques in retinal fundus images

Dr.R.Muthalagu,
Associate Professor, Department of ECE,Agni college of Technology,Chennai,rajamuthalagu1970@gmail.com
Dr.S.Vijayanand,
Assistant Professor, Department of ECE, Sri Venkateswara College of Engineering,Chennai, vijayanand.s@svce.ac.in
Dr.M.Ganesh Mani,
Professor , Shadan college of engineering and technology ,HimayatSagar Road, Peerancheru, Hyderabad, ganesh.mecse@gmail.com

Abstract

Several types of health care systems use content-based image analysis and computer vision to find diseases. Glaucoma is thought to be the second most common eye disease that can lead to a neurodegenerative illness. Glaucoma is an eye disease that starts when the pressure inside the eye is too high. When it gets worse, it can make it impossible to see. Whereas early treatment based on glaucoma screening can keep a person from losing all of their vision. Accurate screening methods depend on the availability of experts who can look at samples of the retina by hand to find the areas where glaucoma is present. But because glaucoma screening is hard and there aren't enough people to do it, we often have to wait, which can cause more people around the world to lose their sight. There is an immediate and pressing need to develop an efficient automated framework that is capable of reliably identifying Optic Disc (OD) and Optic Cup (OC) lesions in their early stages to reportthe issues that are caused by manual methods.Identifying and classifying glaucomatous areas is hard because lesions vary in size, colour, orientation, and shape. Also, there are a lot of similarities between the lesion and the colour of the eye, which makes it harder to classify. To solve these problems, we've come up with a Deep Learning (DL)-a based method called EfficientDet-D0, which uses EfficientNet-B0 as its backbone. Based on the CDR structure, a deep learning method is then used to figure out the CDR value. In this proposed method, the fundus images are cleaned up using wavelet-based denoising. In this proposed method, the optic disc and optic cup should be taken out using the best methods and two similar neural networks with deep convolutions architectures. One method gives perfect results. The OC and OD segmentation design was tested and trained using data from SCES and ACRIMA. With this data set, it was found that 96 per cent of glaucoma diagnoses were correct. Lastly, we talk about the different problems with research and how to fix them, which can help researchers do more work on glaucoma detection.

Keywords: Classification, cup-to-disc ratio, glaucoma, Convolutional Neural Network, Deep Convolution Neural Network, DIARETDB1 data set, MESSIDOR data set.
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1 Introduction

Glaucoma is a bad eye diseasetriggered by the normal intraocular pressure (IOP) in the eye, which hurts the optic nerve. IOP is caused by the difference between how much intraocular fluid (IOF) the eye makes and how much it drains. In turn, this has an effect on the nerve fibres (NF). Damage to the NF produces issues in the retinal nerve fibre layer (RNFL), which increases the cup-to-disc ratio (CDR), commonly known as "cupping," as well as the optic disc (OD) or optic nerve head (ONH) [2]. Glaucoma affects the optic nerve and the Retinal Nerve Fiber Layer (RNFL). It is possible to become blind if the condition is not addressed. When anything like this takes place, fluid accumulates in the anterior portion of the retina. This produces a rise in intraocular pressure, which eventually leads to optic nerve injury.Estimates say that by 2020, there will be 79.6 million cases around the world, and by 2040, there will be 111.8 million. Asians are also thought to make up 47 percent of glaucoma patients and 87 percent of Angle Closure Glaucoma (ACG) patients [3]. People over the age of 60 are more likely to be at risk [4]. Early detection is very important to avoid damage to the structure and loss of vision that can't be fixed [5]. The ISNT rule was used to figure out that the person had glaucoma [6]. CDR was then worked out by doing morphological operations. A lot of research has been done to try to figure out how many people have this long-term illness [7–9]. Glaucoma is said to be the second most common reason why people lose their sight [10]. According to the statistics, around 60 million individuals were affected by glaucoma in the year 2010, and it is anticipated that this figure would climb to approximately 80 million by the year 2020 [11]. Glaucoma damage the optic nerve, which is in charge of visual control.It lasts a long time, there is no treatment for it, and it has been connected to a broad variety of eye disorders [12]. WHO [13] says that about 65 million people around the world have glaucoma. Because the disease has no symptoms, it is important to find it and treat it early to prevent vision loss. Figure 1 shows how the retinal fundus was often used by doctors to track how glaucoma was getting worse.

Figure 1. Fundus image

The chief symptoms of this eye disease with no outward indications are optic nerve inflammation and/or high intraocular pressure. It has been shown that measuring intraocular pressure (IOP) is not a reliable method for determining whether or not a person has glaucoma. This is due to the fact that vision loss may occur even if IOP does not increase.The chief symptoms of this eye disease with no external indications are optic nerve inflammation and/or high pressure within the eye.It has been shown that measuring intraocular pressure (IOP) is not a reliable method for determining whether or not a person has glaucoma. This is due to the fact that vision loss may occur even if IOP does not increase. Convolutional neural networks, often known as CNNs, are a sort of architecture for deep learning that has lately seen widespread usage in the effective segmentation and classification of pictures [14, 15, 16]. The development of DL architectures is a natural progression from multilayer neural networks (NN).To make

them competitive, they need to be designed and trained in different ways. These strategies include not being affected by space, learning features in a hierarchical way, and being able to grow [17, 18]. Glaucoma is a condition that may be induced by a number of different factors all occurring at the same time [19]. ONH, the nerve fibre layer, structural changes, and functional stopping of the visual field are among these variables. The retina is what senses light and sends a message to the brain. The brain uses these signals to figure out what things are around [20]. Early DR and advanced DR are the two stages of DR. At the initial stages of DR, there is no growth of new blood vessels. This kind of diabetic retinopathy is known as non-proliferative diabetic retinopathy (NPDR). As a result of NPDR, the walls of the blood vessels become more fragile.Microaneurysms, which are tiny bulges, protrude out from the narrower artery walls and often leak fluid and blood into the eye. These types of aneurysms are more common in those who have high blood pressure. The form of the large blood vessels in the retina also begins to alter as they begin to enlarge. NPDR goes from being mild to being severe as more blood vessels get blocked. Depending on how bad it is, the nerve fibres in the retina may start to swell. Edoema of the macular pigment epithelium is a condition that produces swelling in the macula, which is the centre section of the retina. The National Particle Deposition Disorder (NPDR) may range from mild to moderate to severe [21]. Proliferative diabetic retinopathy is the term used to describe DR that has advanced to a more advanced stage (PDR). In this particular instance, the blood arteries have been injured, and as a result, they are leaking the clear.

2 Related works

Several applications of medical imaging have seen great success because to the usage of deep learning technologies [22–26] in recent years. These methods can do a good job of catching latent representations and, in the end, lead to better detection and classification. In addition, the techniques of deep learning eradicate diagnostic distinctions and enhance diagnosis by locating issues early, allowing for quicker treatment of such issues. Recent research [20–22] has focused on the segmentation and categorization of the patterns seen on the optic disc in an effort to diagnose eye illnesses. Diabetes-related retinopathy [23, 24], haemorrhage detection [25], optic disc abnormality detection [26], age-related macular degeneration (AMD) [27, 28], diabetic macular edoema (DME) [29], multiclassification [30, 31], and other conditions [32–34] have each been given different ways to be put into groups. [23, 24] [25, 26] [27, 28] [29, 30]

2.1 ROI extraction

The field of artificial intelligence has paid a lot of attention to machine learning. This lets the system learn from its mistakes and get better over time. This makes the output more efficient without having to tell the system what to do. ML approaches have been used to find glaucoma for the past 20 years [35]. [36] In 2016, SVM was used as a classifier in a machine learning (ML) approach to automatically find glaucoma. The developers of this approach [36] applied pre-processing to the picture, which resulted in the photos having a greater degree of clarity and the removal of noise. The authors discovered that pre-processing has a considerable influence on how well the whole technique performs. They used SVM as a classifier and took 100 pictures to tan. After the pre-processing was done, the image was normalised and the colours were changed. After that, the principal component analysis approach was used so that the characteristics could be extracted. In the end, SVM was applied to the data from both the training set and the test set in order to categorise the pictures as either glaucomatous or non glaucomatous. [37] was able to calculate ROI by locating the centre of the optic cup. The coordinates of the optic disc are first determined to be approximately correct, and then they are refined until they are accurate.While [38] used four types of image processing: changes to the brightness of individual pixels, changes to the shape of the image, and changes to a small part of the image. and go back to where it was before in

order to find the ROI. ROI is cut out by hand with a non-automated method [39].

2.2 OD and OC segmentation

A-zone and b-zone are the names for these groups. The authors say that the b-zone category is linked to the progression of glaucoma. They went on to say that the retinal nerves of glaucomatous eyes with PPA thin out faster than those of normal eyes. In this study, images from an OCT B scan were used to find out the sizes of the optic discs. In the study, 115 people were checked out. Peripapillary atrophy was used to figure out if someone had glaucoma. Authors say that peripapillary atrophy is a very progressive sign of open-angle glaucoma from a morphological point of view [40]. Glaucoma can sometimes be found with the help of a variable called peripapillary atrophy. When you have glaucoma, your eyes have a lot of peripapillary atrophy. In order to measure peripapillary atrophy, confocal scanning laser tomography is used [41]. The test was done on 102 pairs of eyes. Here, the entropy was split into two different areas. The first zone, in the centre, had visible and large blood vessels, and the second zone, on the edges, had a lot of pigmentation. The authors came to the conclusion that peripapillary atrophy is linked to damage to the optic nerve, which is glaucoma's main cause [41]. Authors [42] say that future work should use a bigger set of fundus images to make sure a good evaluation. [43] suggested a way to find out if someone has glaucoma by looking for haemorrhages in a certain area near the optic disc in an image with fundus features. This method is thought to be efficient in terms of computing and gives good and accurate results when glaucoma is suspected. [44] A proposed method uses an algorithm that combines CDR and hybrid textual and different intensities features to find glaucoma. This has to do with mechanical squeezing or cutting off blood flow to the optic nerve, which can sometimes lead to glaucoma [45]. When the pressure in the eye goes up, the CDR and RDR change. The CDR and RDR are the most important measurements for diagnosing glaucoma [46]. The optic cup is what makes the circle, and the area in the middle is called the neuro-retinal rim (NRR). CDR and RDR are differences in how they are built that are used to find glaucoma [47], as shown in fig.2. When IOP goes up in an eye with glaucoma, an optic cup gets bigger. This causes NRR to go down, which makes the CDR big and the RDR small. Figure 3 shows an image of a fundus that has been labelled [48].

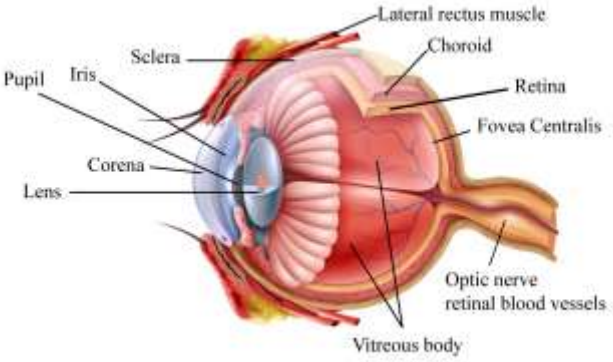

Figure 2. The anatomy of human eye

In the early stages, people with glaucoma don't have any symptoms or signs that they are sick. However, when the disease gets worse, people lose their vision. High pressure in the eye, which is caused by too much aqueous humour or a blockage in the way the liquid gets rid of gas, makes it hard for the optic nerve to work.

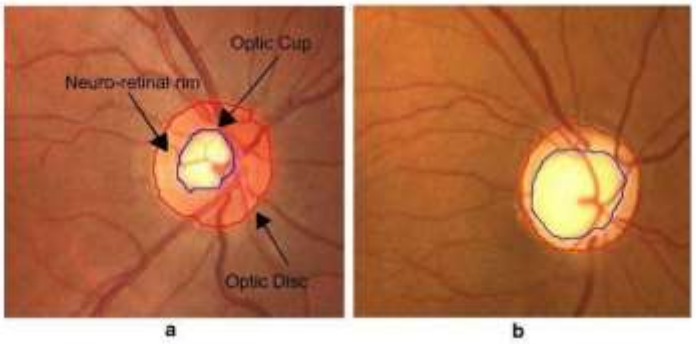

Figure 3. A labelled fundus image

2.3 Feature Extraction

This work does better than the heuristic approaches to localization, but it doesn't work well when the input images have a lot of different colours. In addition, a system known as weakly supervised multi-task learning (WSMTL) was shown in [49] for automatically diagnosing and categorising glaucoma. The method [49] is good in terms of how well it works with computers, but it needs more work to make it good at classifying. A similar strategy, described in [50], was utilised to map between global semantic information and exact localisation using the ResNet framework with multi-layer average pooling. The approach is more effective in detecting glaucoma, although the model may not perform well with fuzzy pictures. In Table 1, an analysis of the current methods used to spot glaucoma is given. From Table 1, it is clear that there is still a need for a more solid framework that can classify glaucomatous regions in a way that is both effective and quick.

Table 1. Comparative analysis of existing approaches

Reference	Technique	Accuracy	Limitation
	ML-based		
[19]	CED, FEM along with the SVM classifier.	93.22%	The model is tested on a small dataset.
[20]	Glowworm Swarm Optimization algorithm	94.86%	The work is unable to compute the cup-to-disc ratio.
[21]	SS-QB-VMD along with the LS-SVM classifier.	92.67%	The classification accuracy requires further improvements.
[22]	Pixel-based threshold along with the watershed transformation	96.1%	The approach is not robust to scale and rotation alterations in the input image.
[23]	The disk selective COSFIRE filters along with the GMLVQ classifier.	97.78%	The work is not robust to noisy samples.
	DL-based		
[24]	MobileNetV2 with CNN classifier.	88%	The work requires extensive data for model training.
[25]	ECNet along with the KNN, SVM, BPNN, and ELM classifiers.	96.37%	The technique is economically expensive.
[27]	CNN	98%	The approach needs evaluation on a standard dataset.
[28]	ResNet-50	NA	The work is not robust to noise and blurring in the suspected images.
[29]	DenseNet-201	97%	This approach requires further performance improvements.
[30]	AlexNet, ResNet-50, and ResNet-152	88%	The work requires extensive processing power.
[31]	Mask-RCNN	96.5%	The work needs further performance improvements.
[32]	FRCNN along with the FKM	95%	The work is computationally inefficient.
[33]	UNET	96.44%	Detection accuracy is dependent on the quality of fundus samples.
[34]	VGG-16	83.03%	The model needs extensive training data.
[35]	Faster-RCNN	96.14%	The work is not robust to color variations of the input images.
[36]	WSMTL	NA	The classification performance requires improvements.
[37]	ResNet	88%	The method is not robust to blurry images.

2.4 Classification

There is just a handful of publicly available datasets containing glaucoma-labeled pictures that may be used to test glaucoma classification algorithms. The Spanish Ministry of Economy started the AMRICA project to create automated algorithms for evaluating retinal diseases. The Topcon TRC retina lens and the IMAGE visualising collection system are both used. We had two people with glaucoma for at least eight years look through the ACRIMA database and comment on every photo we could find there. Figure 4 shows that there was no thought given to any other clinical data while the labels were being added to the photos.

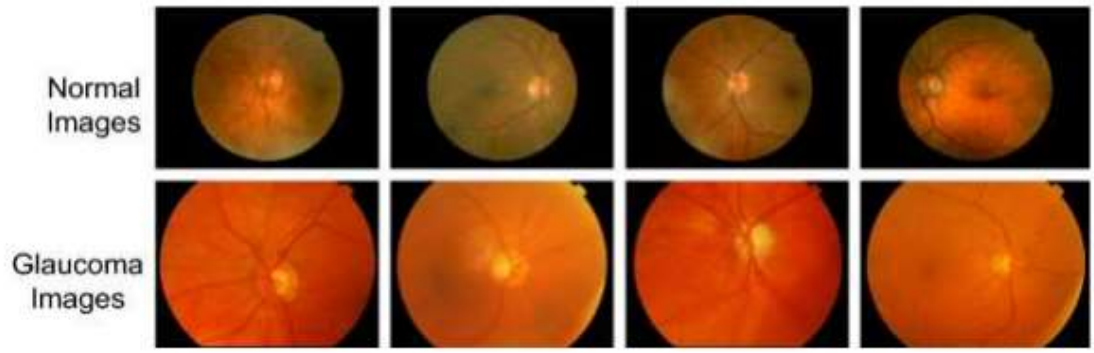

Figure 4. Normal Vs Glaucoma Images

The first version of the ACRIMA database could only do categorization tasks. Segmentation is not possible with an optical disc or an optical cup. Figure 3 is a collection of photos from the ACRIMA database. In this assessed task, the cup-to-disc ratio needs to be calculated and split correctly for glaucoma identification to go well. Figure 5, which you can see below, shows how the whole system works.

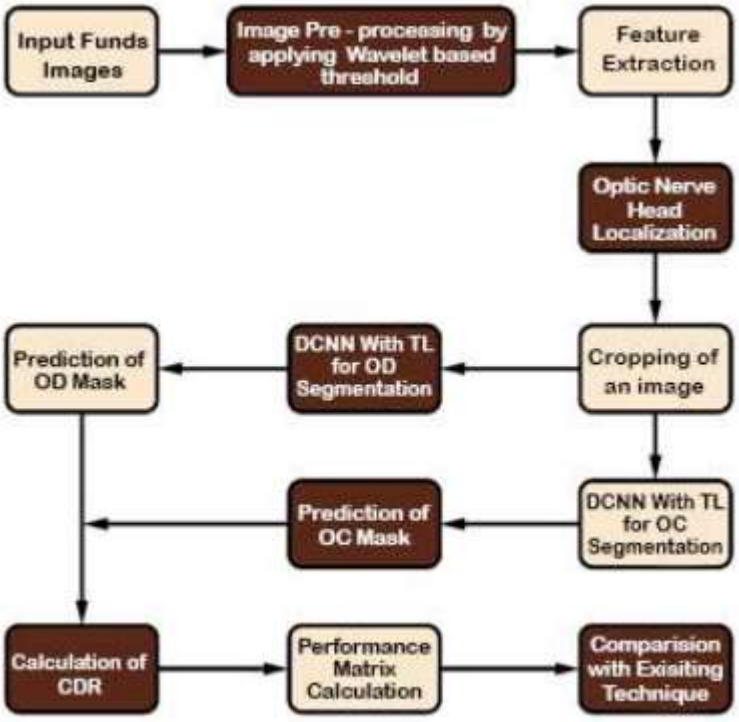

Figure. 5. System Work Flow

3 Data

Figure 5 illustrates an overview of the suggested automated technique for identifying glaucoma using feature learning. Five multilayer perceptron convolutional layers [50] and one fully connected layer comprise the CNN network's six layers. As illustrated in [51], our proposed learning architecture also incorporates response-normalization layers and overlapping levels. In traditional CNN, the convolution filter is a generalised linear model (GLM) for the underlying data patch.It has been seen that GLM has a low level of abstraction.

In this part, we replace the GLM with a more powerful nonlinear function approximator, which improves the local model's abstracting capabilities.If you don't know anything about how the latent concepts are spread out, it's best to use a universal function approximator to extract features from the local patches. This is due to the fact that it can mimic more

abstract methods of describing latent notions. Both the radial basis network and the multilayer perceptron are well-known approximators of universal functions [52].

3.1. Segmentation

In addition, [53] developed a method for testing for glaucoma utilising optic disc and optic cup segmentation from digital fundus pictures. They have looked at glaucoma disorder by looking at the structure and grey level of the optic cup. In this study, they looked at 59 pictures of the retina to find signs of glaucoma. With an F-score of 89 per cent, glaucoma was diagnosed using the SVM classifier and the particular findings of both the optic cup and the optic disc parameters. [54] developed an automated technique for detecting glaucoma. This method has been extensively employed in digital colour fundus imaging. They developed a two-stage probabilistic classification approach for calculating the competitive, reliable, and probabilistic glaucoma risk index (GRI) using low-cost digital colour fundus camera pictures. Finally, the SVM classifier was utilised to relate GRI performance to medically important glaucoma metrics. This was done with an accuracy of 88 percent.

3.2. Feature extraction and classification

Glaucoma Using TL to automatically find Gl has been the subject of a number of research projects. Phan et al. [55] used the Deep Convolutional Neural Network on 3,312 images. There were 369 images of eyes with glaucoma, 256 images of eyes that might have glaucoma, and 2687 images of eyes without glaucoma. 3 The score the AUC got was 90%. Ghamdi et al. [56] demonstrated a semi-supervised TL CNN model for identifying Gl. They obtained an accuracy of 92.4 percent, a specificity of 93.3 percent, and a sensitivity of 91.7 percent using the RIM-ONE (1989) database. Asaoka et al. [57] used ResNet architecture to examine two datasets from separate institutions. They employed data augmentation to get additional data and the area under the receiver operating characteristic curve to determine their accuracy (AROC).

4 Proposed Methodology

The dataset has 188 pictures of people with glaucoma and 882 pictures of healthy people. In the two sets of data we've already talked about, data from both the left and right eyes of 106 glaucoma patients and 76 healthy people were collected. In our experiment, each person chose only one eye so that everyone would be the same. So, we chose 1,521 images with different levels of glaucoma and 1,366 normal images from the two sets for the experiment.

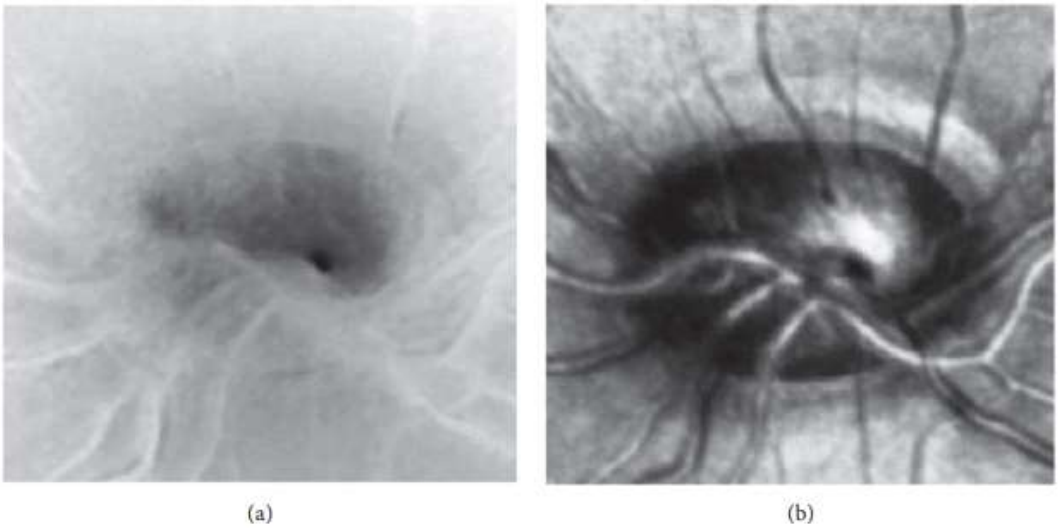

Figure 6: HRT data for a glaucoma patient: (a) topographic data and (b) reflection data.

Also, to check the proposed model's ability to generalise, we picked 60 percent, 10 percent, and 30 percent of the images at random and put them into training, validation, and test sets, respectively. Despite the fact that the data produced contains measurements of

light reflection intensity and topographic values, the data originates from many centres of varying quality, and certain measurement sections were not captured due to machine restrictions.As we've already said, the HRT data has two types of features [58]: the intensity of light reflection and what's shown in figure 6 below.

Heidelberg retina tomography (HRT) has been widely utilised to determine glaucoma by scanning optic disc topography and deriving parameter topographic values. The topography values provide the fundus ONH's height as well as other vital information about the terrain around it, such as the position, height, and slope of lights.Figure 1(a) shows where the optic nerve fibres and blood vessels are and how they look, while Figure 6(b) shows how much light is reflected, which shows how much light is absorbed by the fundus retinal reflex.

4.1. Input image validation

Most of the time, DCNNs are black-box classifiers, which means that we don't know which factors are most important in determining the final outcome of the network. However, in medical diagnosis, it is critical to understand which elements of the picture are significant since various sections of the body that are ill need different therapies.To make sure that our method can be used in clinical settings, we look at how to visualise our predictions that come from how a deep neural network responds to a certain input. When determining how to classify an image, our visualisation approach highlights sections of the picture that indicate evidence for or against a certain class. This point of view is based on [60]. Then, the decision weights in the prediction model are figured out using the instant-specific theory given in [61]. As a result, the region that contributes the most to the likelihood is shown, and we can see where the most relevant components have been collected. As a result, we may make educated guesses about where diseased tissues are most likely to be discovered.

4.2. ROI extraction

In this paper, the author [62] made a two-step plan for finding the ROI and classifying glaucoma. So, there were two steps to the first stage. Initially, a semi-automated ground truth (GT) using an RCNN-based architecture that detected the OD automatically was constructed. The categorization procedure was then carried out. The OD was obtained, and the deep network was employed. After that, the architecture was divided into four convolutional layers: a Max pool with overlapping steps and three layers that were all connected. The data used for training, testing, and validating came from the ORIGA [63], HRF [64], and OCT [65] databases. Cross-validation was the method that led to the best results.

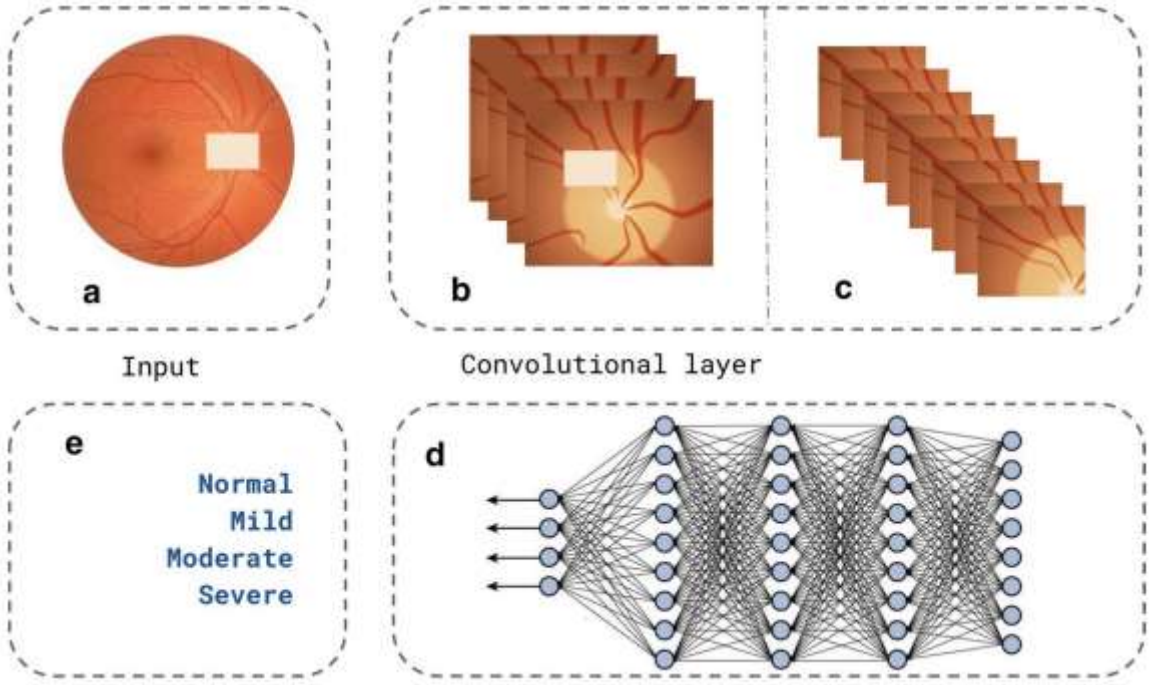

Fig. 7 Generic architecture using deep convolutional network

In 2019, [66] also created the FIGD, a massive collection of fundus pictures used to diagnose glaucoma, and created convoluted neural networks (GD-CNN) that can locate GON automatically. The ResNet [67] was used as a model for the network's design. The database was made up of 274,413 images of the fundus that came from the Chinese Glaucoma Study Alliance.

4.3. Optic disc and optic cup segmentation

The optic disc must be split to give a framework for recognising optic nerve head diseases such as glaucoma (OD). For automated screening of optic nerve head defects, therefore, a dependable OD segmentation method is necessary. The dazzling region at the centre of the optic disc is referred to as the optic cup. It is one of the most significant techniques to determine whether or not someone has glaucoma. The optic cup is smaller in size than the optic disc. One-third of the optic disc in a healthy individual is the form of the optic cup. This means that when you look through the pupil at the head of the optic nerve, also called the optic disc, it looks like a cup with raised edges and a hole in the middle. The nerve cells in a healthy optic nerve are closer together, so the edges are thicker and the centre cup is smaller. The optic cup is the white cup-shaped region at the centre of the optic disc. A healthy eye's optic cup can be seen in a wiggle stereogram. Since the optic cup started out as a single layer on the surface of the forebrain, the choroid and the sclera are very similar to the brain's pia mater and dura mater. These grow from the mesenchyme right next to the back part of the eye as it grows.

5. Results and discussion

In this post. Compare our proposed C-CNN in a systematic way with the different CNN architectures and testing strategies shown in Figure 8. When it says "among them CNN," it means that the final prediction comes from just one CNN. – 3.

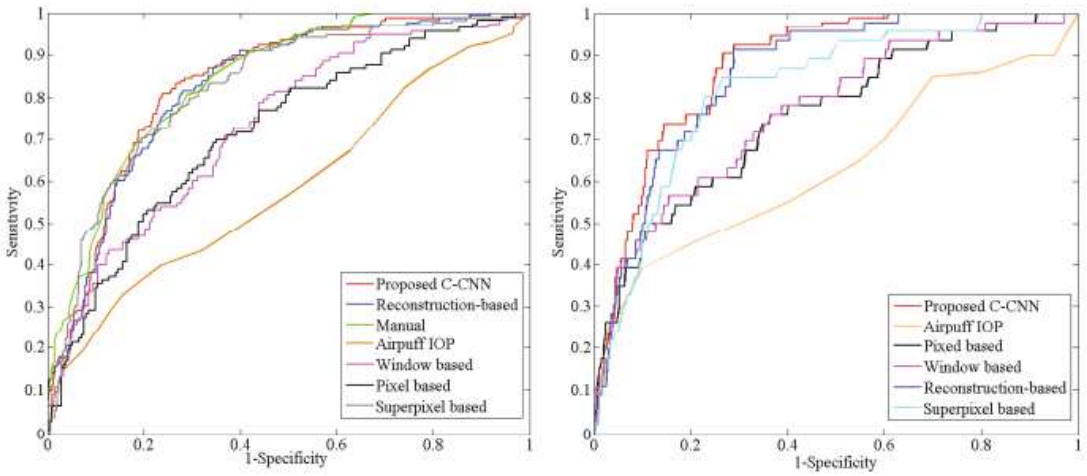

Fig. 8. Glaucoma diagnosis performance on dataset (left) and SCES dataset (right).

CNN denotes that glaucoma is predicted by averaging three comparable CNNs. – C-CNN denotes that the network contains two CNNs (Figure 8 indicates that CNN1 has five multilayer perceptron convolution layers and CNN2 contains an entire network). CNN2 is the source of the prediction. For example, better results have been seen when statistical features are used to find glaucoma from fundus images. Furthermore, fundus images may not be the greatest approach to photograph thin structures. So, based on previous research, new imaging technologies such as HRF, OCT, and US pictures are a promising method to improve automated glaucoma identification. Because there is still a lot of interest in glaucoma detection, image processing-based solutions are unlikely to go away very soon.It has already worked well in a lot of situations, and it can be changed and expanded to help with a lot more problems.

6. Conclusions

Medical imaging systems make pictures of the human body so that different kinds of diseases can be tracked. These technologies are used by public health care systems. Several types of health care systems use digital image processing and computer vision to find diseases. Glaucoma is a long-term eye condition that gradually destroys the optic nerve and may result in permanent blindness. The main cause of this disease is said to be that the eye's intraocular pressure is too high or too low. Glaucoma is said to be the second leading cause of vision loss. But because the glaucomatous areas are hard to reach and have complicated structures, a fully automated system is required. We introduced a DL-based method called EfficientDet-D0 that uses EfficientNet-B0 as its base network to automatically find and classify glaucoma lesions in images of the retinal fundus. We tried out our method on the database, which is hard because the glaucoma lesions vary in size, colour, position, and shape.For instance, a considerable quantity of data may be retrieved from an input image to differentiate between glaucoma and normal eyes. Previously, division was performed by the use of super pixels, forms, and graph cut models, all of which depended on hand-crafted details and a thorough understanding of customer preferences.Methods that concentrate on low-level criteria such as local quality sometimes overlook minor changes in how things seem. Similarly, the methodological technique is dependent on accurately converting a higher number of factors, which restricts how often the method may be employed.We also make a training strategy called "contextualising training," which is used to learn more about glaucoma. In the proposed deep CNN, the context is responsible for dynamically changing CNN model learning. Utilizing the outputs of one CNN as the background for the second CNN helps to enhance glaucoma identification.Lastly, we talk about the different problems with research and how to fix them, which can help researchers do more work on glaucoma detection. Nevertheless, the empirical test demonstrated that this was

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the most effective method for completing the task. Even though the distinctions between the two general designs were evident, study indicates that an automated system for glaucoma screening is feasible.

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