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A Critical Review on Ophthalmic Diagnosis of Glaucoma in Fundus Images of Eye using Deep Learning Models

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***Abstract*— A condition known as glaucoma, which affects the optic nerve, can cause vision loss that is either partial or total. It happens as a result of abnormal intraocular pressure within the eye, which damages the optic nerve. Since glaucoma does not have any symptoms when it is first diagnosed, it is crucial to stop blindness from occurring. Therefore, there is a critical need for glaucoma screening at an early age. Ophthalmologists prefer fundus photography, which is both convenient and affordable, to aid in the diagnosis of glaucoma. The use of CAD (computer Aided Detection) is particularly helpful in the diagnosis of glaucoma and can greatly lessen the clinicians' effort. We've also talked about the benefits of employing state-of-art techniques, including deep learning (DL), when developing the automated system. The DL methods are effective in glaucoma diagnosis. This survey examines different cutting-edge CAD tools and techniques for the precise identification of glaucoma utilizing deep learning methodology.**

***Index Terms*— Fundus Images, Glaucoma, CAD, Deep learning technique.**

I. INTRODUCTION

The majority of the current algorithms for automatically assessing glaucoma using fundus pictures rely on manually created characteristics based on segmentation, which are hampered by how well the features were extracted and the segmentation technique were performing. Convolutional neural networks (CNNs)[1] are renowned for a variety of qualities, including their capacity to extract highly discriminative features from unprocessed pixel intensities. Glaucoma, an irreversible neuro-degenerative eye disease, is one of the leading causes of blindness worldwide [2]. Over 65 million people worldwide suffer from glaucoma, according to the World Health Organization (WHO). Early detection and treatment are essential to prevent vision loss because it may be asymptomatic [3]. The primary feature of this silent eye disease is optic nerve fibre loss, which is caused by either decreased blood supply to the optic nerve or elevated intraocular pressure (IOP). However, it is discovered that IOP measurement is neither precise nor sensitive. Traditionally, the optic cup to disc ratio has been used to diagnose glaucoma. Ophthalmologists also employ visual fields, abnormalities in the retinal nerve fibre layer, and neuroretinal rim loss as diagnostic indicators. Another typical reason why people lose their vision is diabetic retinopathy (DR). The percentage of people with diabetes is predicted to rise from 2.8% in 2000 to 4.4% in 2030. People over 30 are extremely likely to have diabetes, and uncontrolled diabetes can cause DR [4]. Early phases of DR are clinically controlled and less severe. It is characterised by a number of abnormalities in the retina, including microaneurysms and other minor lesions brought on by the rupture of fragile retinal capillaries; these are early signs for DR.comparision image of normal versus Glaucoma fundus image is depicted in fig 1.1

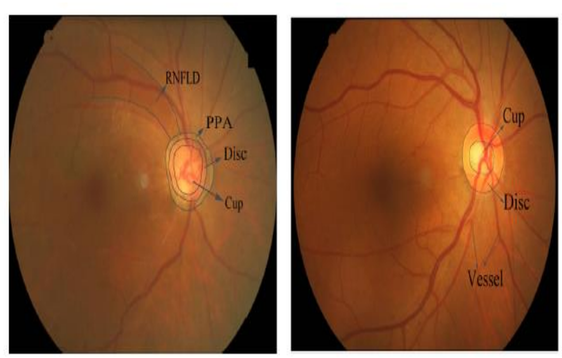

Fig.1.1 Comparison between Glaucoma Fundus Image and Normal Image [5]

II. CRITICAL REVIEW OF LITERATURE

Due to the exponential growth of the computing infrastructure, there has been an unheard-of increase in the deployment of computer vision and deep learning in recent years. The same was observed in the analysis of retinal images, and effective artificial intelligence models were created for the diagnosis of numerous retinal diseases using a wide range of visual markers extracted from images of the eye fundus. The diagnosis of five important eye diseases namely diabetic retinopathy, glaucoma, age-related macular degeneration, cataract, and retinopathy of prematurity as well as cataract surgery are covered in major articles in this paper we urge mainly on glaucoma.

A. Background

Clinically, the utilisation of fundus pictures for early eye disease detection is crucial. Deep learning is becoming more and more common in related applications, such as lesion segmentation[6], biomarkers segmentation, disease diagnosis, and picture synthesis, due to its potent performance. As a result, it is imperative to provide a review paper that summarises the most current advancements in deep learning for fundus pictures. We introduce a few application papers with properly thought-out hierarchies in this review. The suggested review's primary goal is to provide a thorough analysis of the many DL techniques that have lately been used to diagnose retinal diseases utilising fundus pictures. For new researchers interested in AI-based retinal disease diagnosis, this work also aims to describe potential future possibilities.

B. Comprehensive Analysis

Wong et al. [7] presented a method to calculate the CDR after obtaining the optic cup and optic disc masks using level-set techniques. They tested their method on 104 images and found that their method produced results with a variation of up to 0.2 CDR units from the ground truth.

Yuki Hagiwara et al. [8] presented a method a computer-aided detection (CAD) system is proposed to make an accurate, reliable and fast diagnosis of glaucoma based on the optic nerve features of fundus imaging. it is observed that nonlinear features, especially cumulant features, could be useful to discriminate the subtle pix- ular difference between normal and glaucomatous fundus images relatively well. It is also been noted that DL has advantages over the conventional machine learning techniques, JoseIgnacio Orlando et a l[9] In this paper he proposes a novel method for red lesion detection based on combining both deep learned and domain knowledge. Features learned by a convolutional neural network (CNN) are augmented by incorporating hand crafted features. Such ensemble vector of descriptors is used afterwards to identify true lesion candidates using a Random Forest classifier. A similar behavior is observed when evaluating our screening system both for DR and need-for- referral detection, reporting higher AUC values than those obtained by other existing approaches based not only on red lesion detec- tion but also on analyzing other pathologies such as bright lesions or neovascularizations, or even learning classifiers using additional clinical information. Considering the high cost of manually label- ing fundus photographs at a lesion level, our method represents a robust alternative to improve performance of other deep learn- ing based approaches.

A method proposed by Joshi et al. [10] is based on anatomical evidence such as vessel bends at the cup boundary to segment the optic cup. They localised the optic cup using the vessel geometry and circular Hough transform obtaining a CDR error of 0.12 ± 0.10 In the study made by Yin et al. [11], they also used the knowledge-based Circular Hough Transform for segmentation of the optic disc and the optic cup. Their method was tested on 325 images obtaining an average Dice coefficient of 0.92 and 0.81, respectively.

Another approach for optic disc and optic cup segmentation is presented by Cheng et al. [12], who developed a technique to measure the CDR based on superpixel classification. They evaluated their method on 650 images achieving areas under the curve of 0.800 and 0.822 in two databases.

In the work made by Diaz-Pinto et al. [13], the authors presented an automatic algorithm to segment the optic cup and then obtain handcrafted features such as the CDR, area Cup/Disc ratio (ACDR) and the inferior–superior-nasal–temporal (ISNT) rule that checks the disc rim thickness from the fundus images. They evaluated their method on 53 images obtaining a specificity and sensitivity of 0.81 and 0.87 using the Luv colour space for optic disc and optic cup segmentation.

C. Dataset Forecast

As said, a wide range of datasets are readily available online and with collaboration with medical bodies fundus datasets can be accomplished easily table 2.1 shows few listings of datasets[14]

Dataset name	Number of images	Resolution	Camera
ONHSD	100	640 × 480	a Canon CR6 45MNf fundus camera, FOV 45°
Drishti-GS	101	2896 × 1944	a fundus camera with FOV 30°
Drions-DB	110	600 × 400	a colour analogical fundus camera
ORIGA	650 (168 glaucomatous, 482 normal)	3072 × 2048	-
RIGA	750	ranging from 2240 × 1488 to 2743 × 1936	multiple fundus cameras with different FOV
RIM-ONE	169 ONH	-	a fundus camera Nidek AFC-210 with a body of a Canon EOS 5D Mark II of 21.1 megapixels
ACHIKO-K	258 (144 glaucomatic)	640 × 480; 2144 × 1424; 3216 × 2136, etc	NIKON D80, NIKON D90
SEED	235 (43 glaucoma)	-	-
REFUGE	1200	2124 × 2056, 1634 × 1634	a Zeiss Visucam 500 fundus camera and a Canon CR-2 device
SCES	1676	3072 × 2048	-
SINDI	5783	3072 × 2048	-
LAG	11,760 (6882 glaucoma)	ranging from 582 × 597 to 3456 × 5184	3 types of devices: Topcon, Canon and Carl Zeiss

Table 2.1 Widely used Datasets for Glaucoma Diagnosis

III. PRE-PROCESSING TECHNIQUE

To improve the training process and build robust prediction models, fundus images are generally pre-processed before the training phase. This is done to compensate for the noise induced due to the variety of image capturing hardware used in varied illumination settings during the imaging. Considering the complexity of the retinal structure[15], many important biomarkers and lesions may not be identified due to the poor quality of the images, as A part from removing unwanted noise, pre-processing techniques are also used to enhance the fundus image features before DL model implementation. Some of the widely used preprocessing techniques on color fundus images for retinal disease diagnosis are covered to find efficiency

IV. DEEP LEARNING CONCEPT

A subclass of artificial intelligence techniques called deep learning (DL) is based on artificial neural networks, which are learning techniques influenced by the biological makeup of the human brain. Through mathematical representations, the latent and intrinsic relationship of the input data is automatically learned in the DL process. In contrast to conventional machine learning (ML) techniques, deep learning (DL) can operate with a great deal less human supervision because it directly extracts valuable characteristics from the data without relying on manually created features. This qualifies DL for medical image analysis, as the features can be automatically learned from intricate visual data.

In the section that follows, we go through some of the topologies of backbone models that are often employed, particularly for classification and segmentation tasks in the diagnosis of retinal diseases. Backbone models for classification task are CNN[16], VGGNet, ResNet[17], Backbone models for segmentation in fundus images are FCNs[18] and U-Net same is depicted in figure 4.1

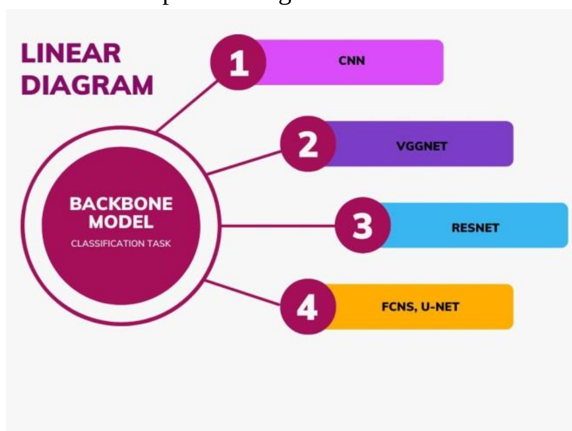

Fig 4.1 Backbone Models for Classification and Segmentation

V. CONCLUSION

Given the shortage of doctors compared to the number of patients, automated technologies for diagnosing illnesses of the eyes are urgently needed. In terms of medical image analysis, a colour fundus picture, which presents a wide range of eye-related disorders in image format, has greatly expanded the field of study. For automatic illness diagnosis, a wide variety of DL models are being applied and tested. Salient features from a given fundus image can now be extracted using sophisticated image processing techniques.

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