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AN ANALYTICAL SURVEY OF DETECTION, SEGMENTATION, AND CLASSIFICATION METHODS FOR GLAUCOMA

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ABSTRACT

Objectives: Deep Learning (DL), empowered by significant advances in computing and the surge of large-scale medical imaging datasets, has emerged as a central technology in modern Artificial Intelligence (AI). Among its most impactful uses, medical imaging has particularly benefited, with Convolutional Neural Networks (CNNs) excelling in image classification tasks—often matching or exceeding human expertise. Ophthalmology, a specialty heavily reliant on visual diagnostics, has naturally embraced DL advancements. Glaucoma, a leading cause of irreversible blindness globally, exemplifies a condition where DL can add substantial clinical value. Method: Diagnosis and monitoring of glaucoma rely on multiple imaging modalities, such as fundus photography, Optical Coherence Tomography (OCT), and visual field tests, which collectively provide a rich source of data for CNN-based analysis. These datasets support a wide range of tasks, from early disease screening to diagnosis and tracking progression. However, current literature reviews in this field often fall short. Many are outdated, failing to incorporate recent developments like transformer-based CNN architectures, self-supervised learning, or multimodal data integration. To fill this gap, the current review offers a comprehensive and up-to-date synthesis of CNN applications across all stages of glaucoma management. It integrates both conventional ophthalmic practices and cutting-edge DL techniques, critically evaluating research that spans fundus image analysis, OCT interpretation, and AI-assisted progression monitoring. Findings: In addition, this review examines statistical modeling and computer-assisted tomography to present a broader perspective on glaucoma diagnosis. It highlights unresolved issues like inconsistent performance metrics, limited transparency, and the need for standardized clinical validation. Significance: By identifying these challenges and synthesizing recent innovations, this work proposes clear research directions to guide future development. Ultimately, it aims to foster the creation of reliable, interpretable, and clinically implementable CNN-based solutions that can improve glaucoma diagnosis, enhance monitoring, and elevate patient care in ophthalmology.

KEYWORDS: Glaucoma, Segmentation, image processing, Open Angle Glaucoma, and Angle Closure Glaucoma.

I. INTRODUCTION

A class of eye ailments known as glaucoma cause injury to the optic nerve. Glaucoma is a fatal eye condition that causes the retina to gradually deteriorate over time [1]. The optic nerve is essential for clear vision because it carries visual information from the eye to the brain. Harm to the optic nerve is much of the time connected with high tension in your eye. Be that as it may, glaucoma can happen even with typical eye pressure. Glaucoma can happen at any age, but older people are more likely to get it. It is one of the most common reasons why people over 60 become blind. There are numerous forms of glaucoma without symptoms. Because the effect is so gradual, you may not notice a change in your vision until the disease is more advanced. Regular eye examinations that take your eye pressure are very important. Early detection of glaucoma can slow or stop the progression of vision loss. If you have glaucoma, you will need treatment or monitoring for the rest of your life.

1.1. Glaucoma Causes

A mesh-like channel [2] usually leads out of your eye to release the fluid known as aqueous humor. The liquid builds up if this channel becomes blocked or the eye is producing too much fluid. Experts sometimes have no idea what causes this blockage. However, it can be passed down through generations through hereditary. (Figure.1) A more uncommon cause of glaucoma is severe eye infections, blocked blood vessels in the eye, inflammatory conditions, and a blunt or chemical injury to the eye. Although it is uncommon, eye surgery to treat another condition may occasionally cause it. Although it may be more severe in one eye than the other, it typically affects both eyes.

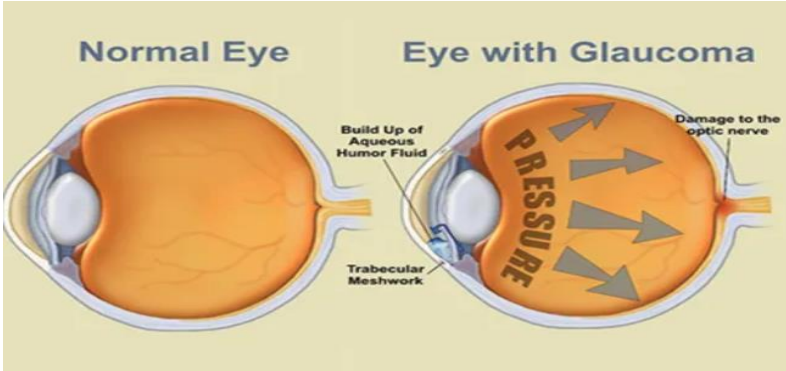

Figure.1 Difference between normal and affected eye.

1.2. Symptoms of Glaucoma

The main Symptoms that cause for Glaucoma are:

(i) Vision that is hazy or unclear: vision that is distorted or blurry, along with other symptoms

(ii) Eye pain: Head and eye pain that is severe

(iii) Redness: Eye pressure causes red eyes

(iv) Colored halos around lights: Around light sources, bright colored circles form.

(v) Nausea or vomiting: Queasiness or regurgitating close by eye torment

1.3. Glaucoma Types

The types of glaucoma are OAG and ACG.

(i) OAG – Open Angle Glaucoma

(ii) ACG – Angle Closure Glaucoma

1.3.1. Open Angle Glaucoma

OAG in its main form is the most common kind. Figure 2 shows both Alzheimer's disease (AD) and primary OAG (POAG) have a sizable prevalence and illness burden [2]. It affects more than three million Americans and gradually compromises their eyesight. This harm happens when the drainage ducts in your eyes silt up. Your IOP (Intraocular pressure) increases as a result of the inability of the fluid in your eye to drain correctly. Although the entrances to your drainage canals are open and clear, problems develop farther into the drainage system. Think of this problem as a blocked pipe that slowly accumulates liquids. Your eye pressure increases due to this fluid accumulation, which also harms your optic nerve. The condition might ultimately cause irreversible eyesight loss.

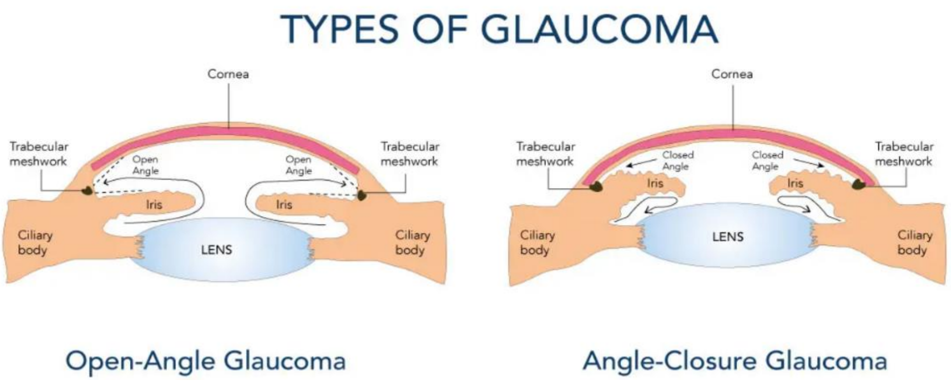

Figure.2 Types of glaucoma.

1.3.2.Angle Closure Glaucoma

It is less common, but it can cause major problems. Similar to a covered drain, it occurs when the drainage canals are completely or partially blocked. Primary ACG (PACG), has few treatment options at the moment [2]. Glaucoma with angle closure can progress quickly or slowly. Your iris is not as wide and open as it should be when you have angle-closure glaucoma. Instead, it pushes forward and changes the drainage angle in your eye. The narrowing or complete blockage of this angle can slow or prevent fluid from moving, resulting in increased eye pressure. The type of angle-closure glaucoma you have is determined by the condition of this angle. Narrow angle-closure glaucoma is the condition in which fluid can still move through the drainage angle. Acute angle-closure glaucoma is characterized by a drainage angle that is completely blocked off. If left untreated, this form of the disease, which is a medical emergency, can result in rapid vision loss.

This paper deals with the overall survey of the Glaucoma detection, segmentation, classification and 3D Visualization of Glaucoma. Section 2 deals with literature survey of the techniques. Section 3 deals with the various methodologies used for this techniques. Finally section 4 deals with conclusion.

II. REVIEW METHODOLOGY

Paper [3] discusses an AI-based glaucoma diagnosis on Keras-based systems. CNN was able to differentiate between different types of myopia. Deep learning algorithms can find associations and predict outcomes in glaucoma given a significant quantity of data [4].

CNN, a deep learning algorithm, has proven useful in image identification, including glaucoma detection [5].If there aren't enough samples, data supplementation can help reduce overfitting. Numerous information enhancement methods, such as objective interpretation, pivot, reflecting, or scaling, as well as commotion reduction, have been defined for various picture order problems. In this research, it was possible to see if a Keras-based CNN model could differentiate various phases of glaucoma without using augmented fundus pictures [6,7].

The work [8] discusses an innovative DL decision support system for detecting glaucoma.The suggested framework is divided into two stages. In the first step, the normalization and MAD technique are used to preprocess glaucoma illness data, and in the second stage, the artificial algae optimization algorithm is used to teach deep learning models. Precision, recall, false positive rate, accuracy, and F1-score are performance measures for categorization methods, and the suggested method outperformed other algorithms by 0.9815, 0.9795, 0.9835, 0.0165, and 0.9815, respectively.

The goal of this article [9] is to increase the accuracy of the prediction method used to identify whether a patient has glaucoma or not. The suggested technique is divided into three stages. To begin, the incoming picture is preprocessed, which includes cutting and enhancing the image to determine the Region of Interest (ROI), as well as resizing all image examples to a consistent size of 256 by 256. In the second step, pictures of the optic disc and optic cup in the retinal fundus are used to retrieve features. Finally, the SoftMax algorithm is used in the third step to identify glaucoma and distinguish between image samples of normal eyes and those with glaucoma. The proposed system's outcomes were thoroughly discussed, and they demonstrated high classification accuracy and reached (99%).

To enhance classification accuracy, an Alexnet model and SVM classifier are used in this automatic glaucoma screening system.The three datasets used in this study were (Drishti_GS1, Origa, and HRF) [10]. The precision of the outcome is 91.21 percent.

Six layers of the proposed Deep Learning model are described by Utkarsh Sharma, Ravi Kumar Gupta, and others [11]: two fully functional levels, and four convolution layers. More accurate glaucoma diagnoses are achieved by the use of methods like cessation and augmentation. SCES and ORIGA's specifics have been thoroughly investigated. Using deep learning, Mary, J., and others [12] construct a CNN-based system for automatic glaucoma identification. The suggested architecture contains six learning techniques, including two fully interconnected and four convolutional strata. The results show that the recipient's area under the curve, or AUC, is higher than that of the most modern approaches for identifying glaucoma, with 0.831 for the ORIGA database and 0.887 for the SCES database, respectively. Their segmentation approach uses a U-shape architecture with tightly connected convolutional blocks that is based on U-Net [13].

They beat outcomes from the newest segmentation approaches on a variety of fundus datasets, including ORIGA. But even after combining frequently used vertical and horizontal CDR for glaucoma diagnosis, they could only get an AUC of 0.778. Additionally, Fu et al. [14] proposed and named a U-Net-like architecture for combined OD and optic cup segmentation. A multi-scale input layer was used, which generates receptive fields of varying sizes at different scales from the input picture. Hierarchical representation is acquired using the fundamental U-shaped convolutional network. The side-output layers' are what create the prediction maps for the first layers. Not only do these side-output layers help improve output by keeping track of the output maps for each scale, but they also solve the vanishing gradient problem by directly back propagating side-output loss to the earlier layers.

They evaluated their model on the remaining 325 pictures for glaucoma screening after training it on the 325 images from the ORIGA data set. They achieved an AUC of 0.851 using their sectioned plates' vertical CDR and cups. In this study [15], we describe a brand-new fuzzy broad learning system-based technique for OD and OC segmentation with glaucoma screening. Data augmentation, picture extraction from the red and green channels, input to two different fuzzy wide learning system-based neural networks for OD and OC segmentation, and CDR calculation were all combined into a single method. The results of our experiments show that our fuzzy wide learning system-based technique beats a variety of state-of-the-art approaches.

This work [16] presents a fundus image analysis technique for automatically assessing fundus-related glaucoma markers. The input fundus was categorized as having glaucoma or not using CDR, ISNT rule verification, DDLS, and a random forest model. The findings for the different performance metrics were 1, 0.93, and 0.97, respectively. This approach has the best classification accuracy when compared to works that have been investigated in the present state of the art; as a consequence, ophthalmologists can utilize it as a computer-aided glaucoma diagnostic system to enhance their screening methods. This paper[17] introduces the two-stage deep learning framework UNet-SNet for glaucoma detection. In the second step, a SqueezeNet is fine-tuned using deep OD characteristics to differentiate between normal and glaucomatous fundus pictures. The UNet is trained and tested on the RIGA and RIM-ONEv2 datasets, with 97.84 percent and 99.85% accuracy, respectively. The Edge ONEv2 dataset's ODs were used to create the classifier, which was then tested on the ACRIMA, Drishti-GS1, and Edge ONEv1 datasets and achieved accuracy rates of 99.86%, 97.05%, and 100%, respectively.

For accessing glaucoma and finding the cupping, many measures (such as CDR, cup vertical diameter to disc vertical diameter, cup horizontal diameter to disc horizontal diameter, etc.) were used. RONHA (Rodenstock Optic Nerve Head Analyzer) provides a three-dimensional topography of OD [18]. Out of the total number of subjects, eight groups were created. For each eye's OD, the cup-disc ratio, disc area, cup volume, elevation, and disc parameter were all calculated. Using linear regression analysis, it is possible to identify the relationship between age and the neural retinal rim regions.

Three phases make up the structure that is being described [19]. The EfficientNet-B0 feature extractor is used to initially compute the extracted characteristics from the probable samples. The BiFPN module of EfficientDet-D0 then employs the chosen features from EfficientNet-B0 to complete several top-down and bottom-up key point fusions. The last stage is the projected localized region containing the glaucoma lesion and associated class. Due to the glaucoma lesions' complex nature and wide range in size, color, and shape, diagnosing them at an early stage has proven difficult. In order to overcome the issues mentioned above, Efficient-B0 acts as the backbone architecture and a DL-based approach called EfficientDet [20] is used.

Three phases make up the structure that is being described [21]. The retrieved characteristics from the likely samples are initially computed using the EfficientNet-B0 feature extractor. The BiFPN module of EfficientDet-D0 then employs the chosen features from EfficientNet-B0 to complete several top-down and bottom-up key point fusions. The last stage is the projected localized region containing the glaucoma lesion and associated class. Due to the glaucoma lesions' complex nature and wide range in size, color, and shape, diagnosing them at an early stage has proven difficult.

A technique for recognizing the glaucomatous lesions was presented by Qureshi and colleagues. After picture preprocessing, the OD and OC were segmented using a variety of methods. Finally, the CDR was determined by dividing the disc pixels by the cup pixels. While the technique is effective in identifying glaucomatous areas, it may not be as effective at identifying scale and rotational differences in the suspected samples. In order to detect glaucomatous areas in fundus pictures, the VCDR was computed using an automated system built on machine learning in [22]. The vascular and disk-selective COSFIRE filters were initially used for OD localisation. The GMLVQ classifier was then used to categorize the OD and OC areas. The research demonstrates improved glaucoma detection accuracy, but it is not resistant to noisy samples.

A approach for glaucoma detection was provided by Martins and colleagues [23] along with the introduction of a simple CNN structure. The input photos were classified as normal or glaucoma-affected utilizing the deep features calculated using the MobileNetV2 technique after the preprocessing step. Model training requires a lot of data even though the operation is more computationally efficient.

In [24], a new DL-based method for automatically distinguishing samples with glaucoma from unaffected images was presented. A framework for an adaptive convolution network (ECNet) was developed to precisely extract significant features from photos. Then, a variety of ML-based classifiers, including an extreme learning machine (ELM), a back propagation neural network (BPNN), a K-nearest neighbor (KNN), and a support vector machine, were trained using a subset of key points. (SVM). Despite the increased processing load, the SVM classifier yields the best results for the work.

Similar techniques were proposed in [25], which transferred global semantic data to precise localisation using the ResNet architecture and multi-layer average pooling. The technique demonstrates an improved glaucoma identification rate, however fuzzy pictures may impair the model's performance.

The goal of [26]is to compare the pros and cons of various computer-aided techniques, point out their shortcomings and potential improvements to the current model. This work suggests a computer-aided diagnostic (CAD) technique for detecting glaucoma in fundus images.

Deep learning (DL), which can analyze a lot of data, has revolutionized computing. Through the analysis and processing of retinal images and difficulties associated with the prediction of daily pressure changes in the eye, DL algorithms offer enormous potential for diagnosing diseases such diabetic retinopathy and glaucoma in ophthalmology [27].

30 pictures were tested for glaucoma using the HRF database in [28]. The results showed a responsiveness of 1.0 and an accuracy of 100%. The system is reliable when it comes to helping doctors diagnose glaucoma.

III. OVERVIEW

3.1. Segmentation Methods

Techniques such as optic disc and cup segmentation are used to identify and evaluate the papilla. Traditionally, ophthalmologists estimate this visually through manual inspection during clinical examinations. However, accurately segmenting the optic disc excavation is more complex due to interference from the nerve fiber layer. The presence of blood vessels and pathological conditions such as atrophy, drusen, edema, or hemorrhage can distort the boundaries of the papilla and its excavation, making it difficult to define the true extent of the excavation. These challenges fall into several categories:

3.1.1.Clustering Algorithms

The most popular clustering algorithms are:

a) K-Means

An unsupervised algorithm that uses an averaged model to break up images into their component parts.

b) Fuzzy K-Means

In order to group data values with comparable values, medical images usually employ an unsupervised method based on the mean of each group, which calculates this similarity using fuzzy logic.

3.1.2. Super Pixel

By dividing the image into multiple pixel clusters and analyzing it region by region, this approach reduces interference from image noise. However, it requires a preprocessing step, which carries the risk of data loss near the image boundaries. In their study, analyzing 101 DRISHT images using CDR and ISNT evaluation metrics, achieving 97.23% accuracy in optic disc detection and 98.42% accuracy in cup segmentation.

3.1.3. Active contour

Curved evolution-based imaging and detection methods are capable of representing curves as they support topological changes. However, these techniques are highly sensitive to the initial conditions, meaning that any variation in the object being detected or the initial curve can significantly influence the final result. The most successful results, achieving an accuracy of 99.22% and demonstrating the advantage of effective image segmentation.

3.1.4. Morphological mathematics

Dilation, erosion, opening, and closing are examples of morphological processes. are used to enhance the image. It has the advantage of being easy to put into practice. With 96% correct answers in the CDR and ISNT ratios.

3.1.5. Convolutional neural network

Neural networks require minimal preprocessing to standardize optic disc images in terms of brightness, contrast, and quality when used for detecting and classifying images and videos. Unlike traditional methods, a single neural network can effectively recognize patterns across a diverse set of images featuring various objects. From DRIONS-DB, DRISHTI-GS, and RIM-ONEv3 using F-score metrics and overlay comparisons. They reported F-scores of

83.5% for cup segmentation and 94.5% for optic disc segmentation, with overlay accuracies of 72% and 89% respectively.

The authors of [29] deal with automated glaucoma diagnosis as well as the segmentation of the optic disc and optic cup using a number of datasets, including G1020 and ORIGA. The three approaches that were put into practice were Restnet50, Inception-V3, and R-CNN, and they all received an F1 score of 88.6%. For segmenting the optic cup and the optic disc, the authors of [30] used modified region growth and threshold-based algorithms, respectively.

3.2.Classification Method

A deep learning model based on the Inception-V3 architecture was effectively applied to identify signs of glaucomatous optic nerve damage. Before implementing the algorithm, image datasets were analyzed by experts in ophthalmology, and preprocessing methods were used to normalize lighting inconsistencies across images. The resulting diagnostic system demonstrated both high accuracy and precision in detecting glaucomatous changes in the optic disc. Its effectiveness was confirmed by clinical professionals, with a notable performance gap observed between specialized glaucoma experts and general eye care providers.

Another approach focused on analyzing retinal fundus images using a deep learning technique capable of detecting various eye conditions, including glaucoma, diabetic retinopathy, and age-related macular degeneration. This method showed promising results and could serve as a potential tool for glaucoma screening. Among the different models tested, GoogleNet performed better in detecting advanced stages of the disease compared to early-stage detection.

Advanced deep learning architectures such as Inception ResNet V2 and VGG19 were also utilized. These models were initially trained on large-scale image datasets and later fine-tuned for medical imaging tasks. When tested on a specific eye imaging dataset, one model achieved over 90% sensitivity and specificity, even during repeated evaluations.

An innovative technique involving a recurrent neural network (RNN) was used to detect defects in the retinal nerve fiber layer. The method, trained on thousands of localized regions from a small number of images, demonstrated high efficiency—successfully identifying most of the abnormalities with minimal errors. Similarly, another model employed a backpropagation neural network to classify the condition of the retinal nerve fiber layer using a test set of segmented images. The system achieved high accuracy in distinguishing between healthy and compromised RNFLs, with the majority of misclassifications linked to conditions like severe myopia, diabetic retinopathy, and physiological variations in optic disc structure.

Another model incorporated a technique based on gradient-based visual explanations to improve classification accuracy. This involved training the model using a dissimilarity loss function and implementing attention mechanisms to enhance focus on critical regions. With data collected from multiple institutions and advanced convolutional neural networks, this method achieved a high success rate in identifying glaucoma, further validating its potential in clinical diagnostics.

3.3.3D Visualization Techniques

A novel method has been introduced for classifying background images of the eye into either healthy or unhealthy categories. This technique involves transforming two-dimensional retinal images into volumetric data and then analyzing them using a three-dimensional convolutional neural network (3D-CNN). The network, called MicroNets, is designed with multi-scale 3D convolutional branches to extract diverse spatial features. These MicroNets then contribute to forming a deep, asymmetric 3D-CNN architecture tailored for recognizing patterns related to specific actions in eye imagery.

Additionally, another method has been proposed that improves on traditional 3D convolution by introducing an efficient, one-directional asymmetric convolutional process. This approach optimizes the way features are extracted from volumetric data while reducing computational complexity.

This figure.3 outlines the key stages in the image analysis pipeline. It begins with acquiring the input image, followed by preprocessing to enhance quality. Segmentation isolates important regions, classification identifies disease presence or type, and 3D visualization aids in detailed clinical interpretation.

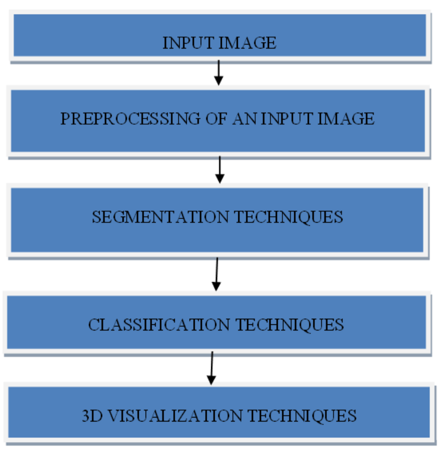

Figure.3 Overall Architecture for the Glaucoma Review.

IV. CONCLUSION

Glaucoma is an evasive and dangerous eye disease. Because glaucoma cannot be cured, early diagnosis can assist doctors in providing appropriate treatment and preventing blindness. We have provided a systematic review of the different types of glaucoma, the current clinical methods for diagnosing it, and the automatic detection, segmentation, classification, and 3D visualization of retinal features-based methods. Methods for glaucoma screening that rely on public image banks require an ongoing expansion of the data pool of information that might include the morphological diversity of the fundus. The classification of papillary pictures using deep learning approaches has been demonstrated in the literature to increase diagnostic precision and aid in glaucoma screening. The sampling of photos from multiple cameras and the linkage of data from various designs still show flaws, especially in light of the limited data from public sources. With the technological advancement of the Internet, smartphones, and programmes that can assist professionals in tracking glaucoma, particularly in more remote locations, we anticipate obtaining photographs of higher quality in the future. We might simplify, lower the cost, and increase the precision of papilla glaucoma diagnosis, particularly in its early stages. The secret to encouraging adoption techniques among patients and physicians and fostering patient empowerment is developing a trustworthy solution.

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