A Review on Recent Development for Diagnosis of Glaucoma

M.Ponni Bala¹, P.Rajalakshmi², A.Maria Sindhuja³, S.Naganandhini⁴

 ¹Associate Professor, Department of Electronics and Instrumentation Engineering, Kongu Engineering College. Perundurai, Erode.<u>ponnibala@kongu.ac.in</u>
² PG student, Department of Electronics and Instrumentation Engineering, Kongu Engineering College. Perundurai, Erode.<u>rajikavi5398@gmail.com</u>
³Department of Electrical and Electronics Engineering, M.Kumarasamy College of Engineering, Karur. <u>mariasindhuja.eee@mkce.ac.in</u>
⁴Department of Computer Applications, PSNA College of Engineering and Technology, Dindigul. <u>nandhu.be2010@psnacet.edu.in</u>

Abstract

Glaucoma is the prominent retinal diseases which amends the Optic Nerve Head in the retina of human eye. It cannot be completely treated, but earlier diagnosis prevents vision loss. In the medical domain, broad array of applications can be carried out using an image processing techniques. Diagnosis of retinal diseases is the major employment in image processing techniques. Recently the new non-invasive modality called Optical Coherence Tomography Angiography which could be applied for better analysis of eye diseases such as Age Related Macular Degeneration, Glaucoma and Diabetic Retinopathy. This paper deals with the exploit of Deep Learning techniques for Glaucoma diagnosis and its automated diagnosis system that helps the physicians to lighten their task crucially.

Key words-Glaucoma, Fundus Image, Retinal Nerve Fiber Layer (RNFL), Angio-OCT images, Vessel density, Deep Learning Techniques

1 Introduction

Glaucoma is one of leading retinal diseases results in visual impairments and its predicted to affect more than 118.2million people by the year 2040 [1]. Earlier diagnosis can prevent the vision loss. Thus, it is essential to do eye screening for detecting the glaucoma at earlier stage[2]. The major reason for Glaucoma is the frequent thinning of Retinal Nerve Fiber Layer(RNFL)[3]. Reducing the Intra Ocular pressure(IoP) is the promising treatment for better progression [4]. The typical treatment comprises of regular optometrist checkup, doubtful persons needs to perform a supplementary tests for final verification[5,6]. The entire study usually includes entire record of a patient and comprehensive eye examination [7]. However, these techniques has major drawbacks that it is a time consuming process and its available only in high cost[8].Currently, the fundus images, OCT modality and Angio-OCT images are commonly employed modality for examining the optic nerve.

The ratio of optic cup and optic diskis the main parameter to assess the Optic Nerve Head (ONH). When the optic nerve fibers gradually disappears, it may leads to glaucomatous stage. Fundus images intended feature such as Cup to Disk Ratio for classifying severity level of Glaucoma[9-11]. OCTA modality intended features such as Capillary, parafoveal density, vessel density and RNFL thickness measurements. OCT measured thickness parameter for classifying normal and eyes with mild to severe Glaucoma[12,13].Parafoveal density shows good progression with excellent accuracy. Parafoveal superficial vessel density in healthy eyes is(48.10±2.82%) whereas in glaucomatous stage vessel density

may reduce[14-16].

The prime objective of the analysis is to examine the better modality for screening and detecting severity level of glaucoma. Section 2 describes the different Retinal Imaging Techniques. Section 3 describes about the types of Glaucoma. Section 4 describes the Glaucoma diagnosis method and treatment for glaucoma. Section 5 provides information about the Glaucoma databases. Section 6 describes about the deep learning techniques and section 7 describes about the conclusion.

2. Different Retinal Imaging Techniques

Bio-medical applications such as MRI, CT scan and X-rays were used as modalities to visualize interior anatomy of the organ. Various parameters are evaluated and the results are acceptable if the results are predicted same as that of clinical results recommended by an ophthalmologist. OCT, OCTA and fundus images are the imaging modalities used to diagnosis the Glaucoma[17]. These tools are immense todiagnose and treat in advance to prevent the vision loss.

2.1 Optical Coherence Tomography

OCT imaging modality is a non intrusive technique based on the law of low coherence interferometry and allows ophthalmologist to map and measure the retinal thickness[18,19]. However, this helps in early detection many ophthalmic disorders such as, macular edema and Glaucoma [20]. Optic Cup is the white region and its is slightly brighter region in the center of disc [21]. Disk and Cup region depicts in Figure 1.

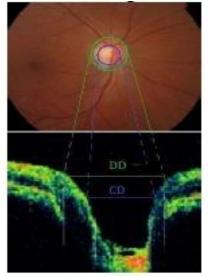


Fig 1.Fundus(above) and OCT(below) images [22]

2.2 Fundus Imaging Technique

Fundus imaging modality are the frequent methodology to capture retinal images[23]. In this modality, the optic disk comprises of bright and center area i.e., Optic cup depicts in Figure 2.

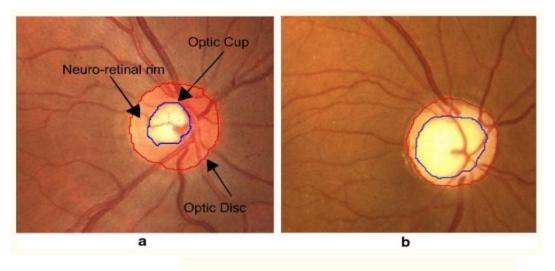


Fig.2 a) Normal Fundus image and b) Glaucoma iamge[24].

2.3 Optical Coherence Tomography Angiography

Angio-OCT images produces angiography images in seconds[25]. Angio OCT images provides detail report about both the structural and functional information[26]. This technique demonstrates the ability of visualize the blood flow in both choroidal and retinal levels with high resolution[27]. In addition to this choroidal and parafoveal vessel density can be quantified[28]. OCTA techniques has the potential to diagnose the variety of diseases such as Myopia[29].

3 Types of Glaucoma

The vessel density changes will be helpful for diagnosis of glaucoma and various types of glaucoma stages[30]. Thus, paying more attention on the vessel density parameters for earlier diagnosis[31,32]. Angio OCT modality helps to determine the vessel density effective for better diagnosis.[33,34]. Glaucoma comprises of several types among which majority percentage of the affected community suffer from Angle Closure Glaucoma[35,36][72][73]. Some other types of glaucoma are congenital, pigmentary, steroid induced types of glaucoma [37]. Table 1 shows the summary of Progression, Causes and symptoms of various types of Glaucoma.

| Author & Types of | | Evolution | Causes | Symptoms | |
|---------------------|------------|------------------------|-----------------------|------------------------|--|
| (Year) | Glaucoma | | | | |
| Philip, S., et al., | Open-angle | It is the common form | It has no symptoms | Peripheral vision may | |
| & (2019)[38] | glaucoma | and its pain free | at earlier stage. So | slowly damage tends to | |
| | | | it's known as 'Silent | vision loss | |
| | | | Thief of sight' | | |
| Rong., et | Angle- | Angle closure glaucoma | This form of | vomiting, | |
| al.&(2020) | closure | is more painful | glaucoma requires | obscured or | |
| [39] | glaucoma | compared to other | instantaneous | indistinct vision | |
| | | types. | treatment | | |

| Igarashi, N., et al.,&(2019) [40] Nakano, H., et | Low-tension glaucoma Exfoliative | This form of glaucoma has drawback that even eye pressure is normal but optic nerves may get damaged. | This occurs mainly due to lack of blood flow Laser treatment | More vulnerable in damaging theoptic nerves. It is difficult to classify Low tension glaucoma Excessive whitish |
|---|--|---|---|--|
| al.,& (2020) [41] | glaucoma | toexfoliation disorder. | prevents vision loss | fluidon the lens and retina blocks the eye drainage canal results in increased intra- ocular pressure |
| Simcoe, M.J., et al., & (2020) [42] | Pigmentary glaucoma | This type of glaucoma mainly affects the young and near-sighted | Iris get broken upand pigments leaked in the drainage system | slight agonyand hazy vision are the common symptoms for this type of glaucoma |
| Mursch- Edlmayr, A., et al., & (2020)[43] | Neovascular glaucoma | The drainagesystem may gets affect by diabetes that causes theintra-ocular pressure to increase | The fluid's drainage structure getsblocked | - |
| Badawi, A.H., et al.,&(2019) [44] | Congenital glaucoma | Occurs in eye frombirth. | This type of glaucoma can be analyzed in child age. | It occurs mostly for child especially boys. |
| Zhang, S., et al., & (2019) [45] | Secondary glaucoma | This type of glaucoma occurs when the pressure is increased. | Irritation in the eye and may cause damage | This type of glaucoma occurs frequently during a surgical time. |
| Goldberg, I.et al.,& (2020) [46] | Chronic glaucoma | Vision loss occurs suddenly | For preventing vision loss, early diagnosis is necessary | It cannot be cured. |
| Križaj, & (2019) [47] | Acute glaucoma | Liquidin the eye may totally obstructed. | This type of glaucoma does not cause any sudden pain | The symptoms for this type are red eyes and vomiting. |

4. Clinical Diagnosis for Glaucoma

Guidelines for diagnosis, organization and anticipation were given by the Australian National Health and Medical Research Council in the year 2010[48]. For earlier diagnosis, a blend of various tests may become valuable[49]. To analyse the severity of glaucoma at frequent levels, Optic nerve evaluation (ONE) and visual field testing (VFT) are proficient. It is essential to analyse the efficiency of the treatment to determine whether treatment is necessary or not [50]. The main objective of the inspection is to estimate the level of severity period increased within a certain period of time[51][70][71]. Figure 3

depicts the different tests employed in Glaucoma diagnosis.

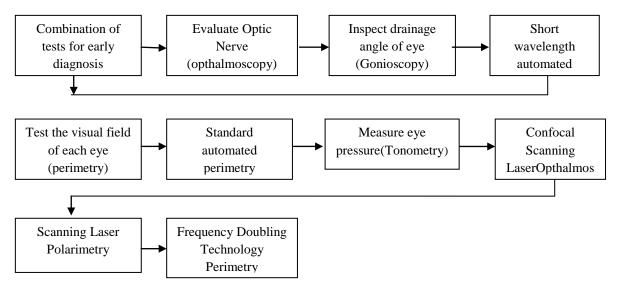
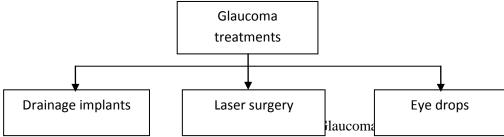


Fig 3.Various test used in Glaucoma diagnosis[37]

4.1Treatment for Glaucoma

The treatment involves trabeculectomy, laser surgery and implantation of drainage canal. Figure 4 shows the various types of treatments.



5. Database

Some of the freely accessible datasets available for diagnosis of glaucoma are discussed in Table.2

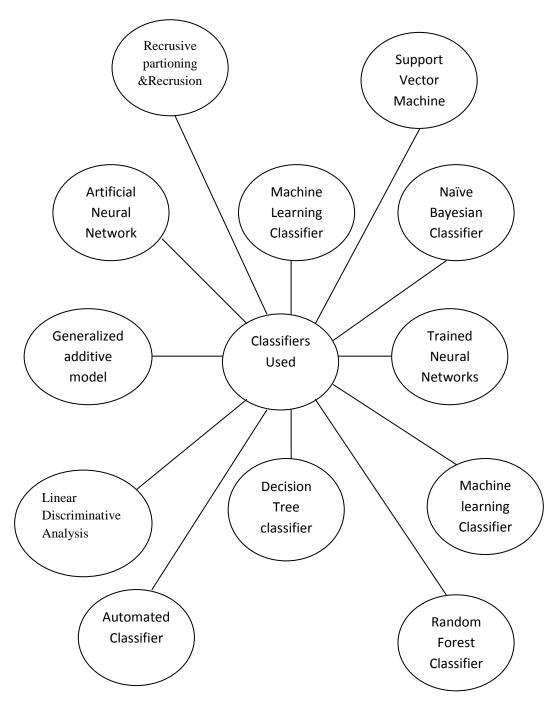
| Datasets | Total No. of images | Origin |
|----------|---------------------|--|
| DRIVE | 40 | Diabetic retinopathy research program, Netherlands |
| MESSIDOR | 1200 | French Ministers of research and defence |
| ORIGA | 650 | Singapore Eye Research Institute |
| REFUGE | 1200 | Zhongshan Ophthalmic Center, Sun Yat- sen University, China |

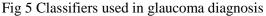
Table 2 Publicly available datasets for glaucoma diagnosis

| DRISHTI-GS | 101 | Arvind Eye hospital, Mumbai | | | | | |
|------------|-----|-----------------------------|--|--|--|--|--|
| | | | | | | | |

6. Deep Learning models for Diagnosis of Glaucoma

Several enhancement methodologies are employed for the accurate diagnosis[53][69]. Various types of databases have been gathered comprises by numerous amount of data. Therefore while applying several classifiers; the accuracy of the modalities can be determined. Figure 5 shows various classifiers employed in diagnosis.





The literature analysis on several segmentation and classification techniques over retinal imaging techniques and some of the performance are discussed in the Table 3. The performance metrics such as Accuracy, Sensitivity and Specificity are summarized for different methodologies. It is evident that each methodology has both merits and demerits. The clustering based approach works well in eliminating the noise. The Level based technique is generally employed for sharp corners and it acquires better efficiency. Even though it is efficient, it consumes much time and sometimes may consequences below or above-segmentation level. The threshold-based methodology is quick process. But threshold-based methodology cannot provide better results for wider level of pixels.

From the above analysis, clustering-based technique provides better results. The K-Nearest Neighbour algorithm is very efficient for training large datasets, but its calculation time is very high. Support Vector Machine (SVM) has high searching capability when compared to other classifiers, although it is not efficient for binary classification. Therefore the SVM provides better progression while examining all other classifiers. Though, every technique has its merits and demerits, but enhanced methodology need to be anticipated for the Glaucoma diagnosis.

| Refer | Databas | Imagin | Technique | Perfor | mance I | Metrics | Remarks |
|-------|---------------------------|-------------------|--------------------------------------|--------------|-----------------|-----------------|--|
| ence | e | g modalit y | S | Accu racy | Speci ficity | Sensi tivity | |
| [54] | Rim-One Dhristi- GS | Fundus images | Fuzzy C- Means methodolog y | 93.47 | 91.56 | - | LARKIFCM methodology consumes less time and provides better progression |
| [55] | Messidor | Fundus images | Clustering- based approach | 90.00 | - | - | Residual noise appears even after segmentation process |
| [56] | DRIVE | Fundus images | Local Binary Pattern | 96 | 96 | 96 | Needs to extract more features to improve the classification |
| [57] | SCES | Fundus images | Disc-aware ensemble network | 84.29 | 84.78 | 83.29 | Earlier diagnosis of glaucoma by collecting contextual information of the Optic Disk |

Table 3Summary of Various methodologies for Glaucoma Diagnosis

| [50] | ORIGA | Fundus | Deer chiest | | | | Combination of |
|------|---|------------------|--|-------|-------|-------|---|
| [58] | dataset | images | Deep object detection network | - | - | - | localization and segmentation |
| | | | | | | | are done in a particular |
| | | | | | | | method |
| [59] | DRIVE | Fundus images | Adaptive thresholdin g and SVM classifier | 93.36 | 85.56 | - | This technique provides better progression in vessel extraction |
| [60] | Mendele y | OCT images | Structure tensors to extract candidate layer pixels, Convolutio n Neural Network Graph Set Theory. | 94.6, | 94.07 | 94.68 | Need to extend the segmentation of retinal layers to higher dimensional level. |
| [61] | DIARET DB1 | OCT images | clustering kernel density estimation and Support vector classifier | 97.25 | - | - | SVM dependent intelligence grounded on quadratic normalization |
| [62] | Local Dataset | OCT images | Local binary pattern and Support vector machine. | 99.30 | 96.64 | 98.83 | Performance based on all RGB channels. |
| [63] | Electroni c research & medical records, Duke Universit y Vision | OCT images | Segmentati on-free Deep Learning technique | 81 | 95 | 65.71 | Better progression than usual RNFL thickness parameters even diagnosis at earlier stage. |

| [64] | Mendele | OCT | Automated | _ | - | - | This study |
|----------------|----------------------|---------|--------------------------|----|-------|--------|---------------------------|
| [01] | y data | images | Segmentati | | | | reveals that for |
| | | & | on | | | | each OCT |
| | | Fundus | algorithm | | | | modality there |
| | | images | | | | | is a equivalent |
| | | | | | | | fundus |
| | | | | | | | modality with |
| | | | | | | | marginal note |
| | | | | | | | for |
| | | | | | | | understanding |
| | | | | | | | purposes |
| [65] | Zenodo | OCT | Extra tree | 95 | - | = | Extra tree |
| | | images | Classifier, | | | | classifier is |
| | | | Feature | | | | used due to the |
| | | | agnostic | | | | high amount of |
| | | | approach | | | | datas. |
| | | | | | | | |
| [66] | Dryad | OCT | Multiple | 98 | 98.3 | 97.1 | Developed an |
| | (Private | images | classifiers | | | | synthesized |
| | dataset) | | such as | | | | model from |
| | • | | Random | | | | original |
| | | | Forest and | | | | features and |
| | | | SVM | | | | yields an |
| | | | classifier | | | | higher |
| 5 (7) | x 1 | 0.075.4 | 1.56 | | 04.44 | 0.6.67 | accuracy. |
| [67] | Local | OCTA . | k-Means | 90 | 94.44 | 96.67 | Features such |
| | hospital | images | Segmentati | | | | as capillary |
| | | | on,SVM | | | | loss shows |
| | | | classifier | | | | better . |
| | | | | | | | progression |
| | | | | | | | compared to |
| | | | | | | | RNFL |
| [20] | A 11 town of | OCTA | Culit | 96 | | | thickness |
| [68] | All types of dataset | | Split Spootrum | 90 | - | - | Vessel Density is more |
| | | images | Spectrum A mplitudo | | | | |
| | from | | Amplitude Decorrelati | | | | changeable feature and |
| | Angio octa | | | | | | possibly |
| | modality | | on Angiograph | | | | reflects when |
| | modality | | y algorithm | | | | Intra Occular |
| | | | y argonum | | | | Pressure |
| | | | | | | | changes |
| | | | | | | | changes |
| | l | | | | | | |

7.Conclusion

This paper embraces various retinal imaging modalities, segmentation and classification techniques employed for the glaucoma diagnosis. Here we epitomized the disputations that came over while segmentation and classifications. Researchers examined numerous features for classification purposes but still more texture based features are required to increase the performance and diagnosis. From the analysis, for classification purposes deep learning techniques acquires better progression when compared to image processing methodologies. Finally thissurvey concludes that it is essential to incorporate hybrid techniques for segmentation and classification of Glaucoma images to attain better progression.

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