CATARACT DISEASE DETECTION AND CLASSIFICATION USINGRETINAL IMAGE MODEL

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Abstract- *Among the most common blindness hasseveral causes that is cataract, especially among the elderly. According to WHO/NPCB surveys, India has approximately 12 million blind persons, with cataract accounting for 80.1 percent of those cases. Therefore detecting a cataract in the early stage is a very important as well as difficult task. There are different types of image models currently being used by researchers for problems related to eye. The utilization of five different imaging modalities specifically for automated cataract detection is presented. More focus is given to the retinal images for the cause of cataract detection as it is considered better for extraction of the macula, lesion, blood vessels, optic disc, fovea, and macula are all components of the macula are all featuresto look for. Detecting these features accurately can solvemany problems related to eye disease including diagnosis and grading of cataracts automatically. In this research article we explore the potential of different retinal imaging methodologies currently employed by many of the researchers along with their advantages and disadvantages. Through the research an automated approach for segmenting retinal images has been developed. The segmentation is achieved by an iterative region expanding approach that merges the contents of numerous binary images produced by vessel width dependent morphological filters. Finally, the suggested work's experimental results and evaluation are shown, which reveal promising results.*

Keywords: Cataract, retinal image, feature extraction, segmentation, morphological filter

1. INTRODUCTION

The eye is a complicated system that serves as a vital component of our bodies. The retina, iris, pupil, and optic nerve are all interconnected elements of the eye. Glaucoma, trachoma, age-related macular degeneration, pathological myopia, retinitis pigmentosa, and diabetic retinopathy are all disorders that have an influence on the eye. Patientsare sometimes unaware of the severity of their illness. It is incredibly difficult to appropriately impair eyesight due to late identification of eye disorders. [1].

After an eye exam with various technologies such as a slit lamp, retinal examination, or visual acuity tests, an ophthalmologist or optometrist diagnoses eyeproblems [3]. A printed chart or a sequence of smaller characters read with a viewing device are used to perform visual acuity tests [3]. The ophthalmologist examines the eye under magnification with a strong line of light using a slit lamp [4]. During a retinal examination, the pupil is dilated using drops to help widen the eye lens and analyse eye movements and papillary response.

However, these procedures need the use of expensive medical equipment that can only be used by ophthalmologists with extensive experience. Because these processes are manual, they are both time- consuming and subjective based on ophthalmologist experience. As a result, academics have made various attempts in recent years to automate the identificationof eye diseases.

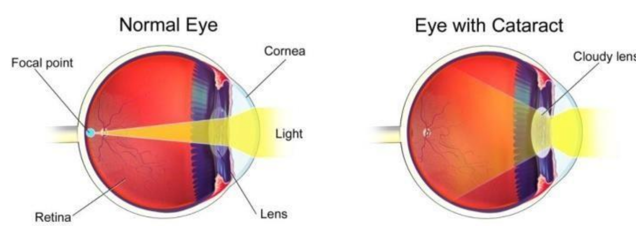


Fig 1: Normal eye versus Cataract eye [7]

Cataracts are the cause of 47.8% of all blindness cases in the world. Advanced age is the most significant risk factor for cataract development. Over 314 million people are blind or partially blind around the world. Sixty-seven percent of those who are blind are blind owing to cataracts.

More than 90 percent of the world's blind population live in developing countries. The World Health Organization (WHO) defines a cataract as a clouding of the eye's lens that inhibits light from passing through due to protein clumping together as people age. These proteins grow up only when the older cells compress into the lens's centre, resulting in a fuzzy view of the retina. [5].

Early diagnosis of cataracts is a little-discussed area forongoing research, despite the fact that it is one of the most common eye illnesses and the main cause of blindness worldwide. Nuclear cataract, cortical cataract, and posterior subcapsular cataract are the three types of cataracts that can arise depending on where they form or how they form [2]. The most frequent type of cataract produced by age is nuclear cataract (NC). The hardening and yellowing of the nucleus, the centre component of the eye lens, is the most common reason [8]. Cortical cataract (CC) is a type of cataract that develops in the lens cortex and appears as white wedged-shaped and directed opacities that move from the lens's border to the centre in a spoke-like pattern [8]. PSC (posterior subcapsular cataract) appears as little breadcrumbs or sand particles beneath the lens capsule. It is especially common in steroid-addicted and diabetic people [8]. The numerous types of eye cataracts are depicted in Figure 2.

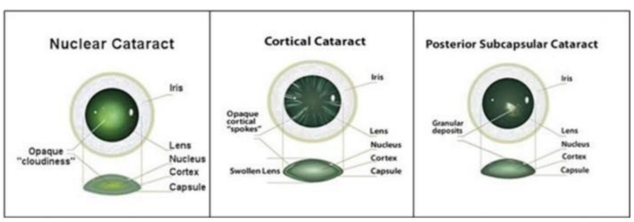


Fig 2: Types of Eye Cataract

Cataracts are diagnosed by an ophthalmologist by examining the changes in the eye lens. After cataract detection, grading can be done by comparing slit- lamp pictures to a collection of standard images using various grading systems. The most often used grading techniques are the Lens Opacities Classification System III (LOCS-III) [9] and the Wisconsin Grading System (WGS) [10].

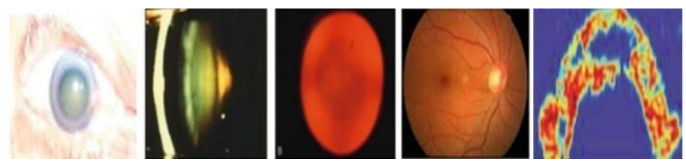
2. IMAGEMODELS

2.1 Digital Images

The use of digital camera photos for cataract screening becomes intriguing when considering the health services in underdeveloped countries. A digital camera is also a simple and easy-to-use instrument when compared to a slit lamp and othercomplex medical equipment used for cataract diagnosis.

2.2 Slit-Lamp Images

Nuclear cataract is typically detected using slit-lamp imaging. Because nuclear cataract affects the nucleus of the eye lens, characteristics from the nucleus area are extracted for automated identification and grading. [9,10].



(a) (b) (c) (d) (e)

Fig 3: Sample images of each image model

(a) Digital image **(b)** Slit-lamp images **(c)** Retro-illumination image **(d)** Retinal image **(e)** Ultrasonic image

2.3 Retro-illumination Images

A non-stereoscopic image obtained using a "Neitz CT-R cataract camera to concentrate on the anterior/posterior cortex of the lens"[10] is recognized as retro-illumination. Cortical and posterior subcapsular cataracts are examined using a retro imaging.

2.4 Ultrasonic Images

Ultrasound is a popular technique for diagnosing ocular disorders. For cataract diagnosis, ultrasound A-scan signals are collected using an ultrasound scanner equipped with 30–60MHz ultrasonic transducers from porcine lenses. B-scan and Nakagami images are created using the acoustic parameters velocity, attenuation, and backscattering signals [22].

2.5 Retinal Images

The diagnosis of eye-related disorders such as macular degeneration, diabetic retinopathy, and glaucoma has long relied on retinal fundus imaging. [11–13]. Although retinal (fundus) scans of the eye haverarely been used for cataract diagnosis and grading, several studies have attempted to identify cataract using these images andhave achieved a high accuracy rate.

The fundus camera is simple to use and can be operated by technologists or even patients. Retinal pictures have been employed widely in the diagnosis of ophthalmological illnesses such as glaucoma [16- 17], age-related macular degeneration [18–19], and diabetic retinopathy [20–21] since the invention of the fundus camera in 1910. Furthermore, this technique has been investigated in an attempt to automatically quantify cataract severity [22–23]. Some attempts at detection in smartphone-based systems have also been made [15]. Figure 4 shows four typical retinal pictures, exhibiting non-cataract, mild, moderate, and severe cataracts. Figure 4(a) shows a healthy retina with clearly visible main vessels, optic disc, choroid, and even capillary vessels. Figure 4(b) shows an image with a mild cataract, with the main vessels and optic disc visible,but the choroid and capillary vessels only faintly visible. Only the main blood veins and the optic disc are seen in Figure 4(c). Furthermore, in Figure 4, there are essentially no retinal structures visible (d). It can be assumed that more severe cataracts revealfewer retinal structures.

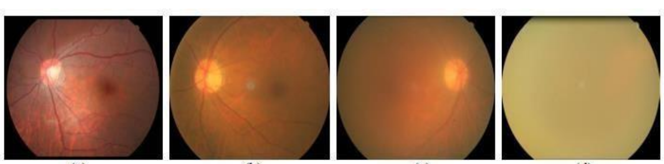


Fig 4. Retinal images: (a) non-cataract, (b) mild cataract, (c) moderate cataract, and (d) severe cataract.

A cataract is a slow-growing eye condition that can be partial or total, stationary or progressing. Patients with various degrees of cataracts require different therapies. Patients with light cataracts might delay degeneration by wearing antiglare sunglasses [24], whereas intermediate and severe cataract patients require surgical intervention [25]. It is feasible to discern the different levels of severity by extracting suitable information from retinal pictures.

3. RELATEDWORKS

Automatic cataract detection using retinal images has attracted significant attention, and was discussed in [26-28]. Various methods which can be used for cataract detection and classification using retinal image model is discussed further.

3.1 Transformation based approach: [29] offereda study for cataract detection utilising retinal pictures and the Fourier transform. Due to variable amounts of blurriness, the high-frequency component distributions of retinal pictures differ. The high-frequency component distribution curveis used to assess the cataract severity. The results show that the performance of this method has a good association with the LOCS III score, indicating that the retinal image-based method is genuine.

3.2 Global feature-based approach: In [30-31], the Haar wavelet and discrete cosine transformation (DCT) were utilised to investigate four-class categorization using retinal pictures. In both the discriminant analysis and the supervised technique, the results showed that the Haar wavelet feature achieves higher accuracy than the DCT feature. [32] employed texture and morphological data, and the findings showed that based on the BP-net, this strategy also produced pretty good accuracy. The performance of the Haarwavelet, DCT, and texture features were summarised in [33], which suggested an ensemble learning-based technique. The results showed that the Haar wavelet feature outperforms the DCT and texture features in terms of accuracy.

3.3 Local feature-based approach: In [34], the local standard deviation was employed. The local standard deviations of the coefficients and the other eight features were extracted after the blood vessels were strengthened by match filtering in different orientations. Retinal pictures with various cataract severities were effectively categorised using a decision tree [35].

3.4 Deep feature-based approach: In [36], deep CNN (DCNN)-based categorization was used, and the DCNN achieved somewhat better accuracy than the other approaches. However, when thetraining samples are near to 2000, the accuracy reaches a relatively high and steady level, necessitating significantly more photographs than other relevant efforts.

Table 1: Literature review table of methods usedin retinal image model for cataract detection andclassification

Sl No	Approaches	Methods	Authors	Advantages	Disadvantages
1	Transformation based approach	Fourier Transform	Abdul-Rahman et al.[29]	Exhibits strong correlation with the LOCS III score	Frequency component may differ for various levels of blurriness
2	Global features based approach	Haar wavelet	Fan et al. [30]	Low cost running detection procedures. This method can achieve the highest accuracy by applying different global features in less time and less memory overhead.	It cannot be used for some particular applications wherethe illumination level of images is very low.
		Discrete cosine transformation	Guo et al. [31]		
		Texture and morphological feature based method	Yang et al.[32]		
		Ensemble learning-based method	Yang et al.[33]		
3	Local features based approach	Local standard deviation	Xiong et al.[34]	Many features can be extracted locally so that it can be used as a good numerical ability for high order tasks.	The local standard deviation alone gives low accuracy, it needs some other methods to be fused together.
		Decision tree based method	Zhang et al.[35]		
4	Deep features based approach	Deep CNN	Zhang et al.[36]	Gives a slight higher accuracy than above methods.	Needs a large no of data set for training purpose thus use more cost, time and System overhead.

4. PERFORMANCEEVALUATIONMETRICS

To evaluate how accurate a system is, i.e. to measure its performance, many evaluation metrics can be used like Accuracy, Specificity, Precision, Recall, F1 score and mean square errorrate.

True Positive (T P: f + +): The number of instances that were positive (+) and correctly classified as positive (+).

False Negative (FN: f + −): The number of instances that were positive (+) and incorrectly classified asnegative (-). It is also known as Type 2 Error.

False Positive (FP: f − +): The number of instances that were negative (-) and incorrectly classified aspositive (+). It is also known as Type 1 Error.

True Negative (TN: f − −): The number of instances that were negative (-) and correctly classified as negative (-).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

5. CONCLUSION

The strain on ophthalmologists and clinicians is reduced by automatic cataract identification and grading. It also offers an objective approach to assess the severity of cataracts and aids in the reduction of visual loss through quick and precise diagnosis. This document provides an overview of the procedures and approaches used to identify and grade cataracts. The use of five different imaging modalities for automated cataract diagnosis using digital image processing is demonstrated. Slit-lamp images, retro-illumination images, retinal images, ultrasonic images, and digital eye images are examples of these sorts.. Retinal images are considered good for feature extraction so features like lesion, blood vessels, optic disc, fovea, and macula can be detected which can be used for automatic cataract detection and grading. The scale of the visible retinal structure is the most valuable information for evaluating cataract severity.

Also, if we consider among all the approaches used in retinal image model then global feature based approach specially texture based and morphological method is much suitable for cataract detection and classification as it is a low cost running detection procedure. Also, this method can achieve the highest accuracy by applying different global features in less time and less memory overhead.

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