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Cataract Classification and Grading: A Survey

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ABSTRACT: This survey paper basically focuses on different approaches for detecting cataract in digital fundus images. Cataract is clouding or dullness of the lens in the eye which causes visual loss and blindness. One can detect and classify image using various image processing techniques. This paper explains various algorithms for detecting red lesions and cataract in retinal fundus images. Basically cataract classification includes three main stages namely preprocessing of image, feature extraction and classification. Initially, the image is preprocessed by applying image processing techniques, then various features of retina (microaneurysms, hemorrahages, optic disk, blood vessels) are extracted. On basis of these extracted features, image is classified into cataract and non-cataract image by means of various classification techniques.

KEYWORDS: Cataract, fundus images, image processing, classification, retina, grading

I. INTRODUCTION

Cataract is clouding of the lens in the eye which is painless and developed gradually over a long period. Cataract is an eye disorder which occurs when some of protein at lens clumped together that makes it dull and increases opacity of the lens, causing some loss of vision. On the basis of area where cataract develops, cataract is classified into three types namely, nuclear cataract, cortical cataract and posterior sub-capsular cataract. Nuclear cataract develops deep in the nucleus of lens. It is associated with aging. Cortial cataract occurs in the lens cortex, which is the part of the lens that surrounds the central nucleus. Posterior sub-capsular cataract occurs at the back of the lens. People with diabetes or those taking high doses of steroid medications have a greater risk of developing this type of cataract.

Cataract is the leading cause of visual impairment in the world today and is responsible for up to 50% of blindness globally [1]. From the report of WHO in 2004, it is cleared that there are 53.8 million people in world suffering moderate to severe disability caused by cataract, 52.2 million of whom are in low and middle income countries [1].

The retina is the light-sensitive tissue at the back of the eye which is responsible for changing light into nerve signals that are sent to the brain. The fig.1 shows the fundus images of non-cataract and cataract image respectively. Automated cataract classification system mainly consists of three steps: preprocessing, feature extraction and classification. In preprocessing step, the RGB image is converted into green channel image and by applying image processing techniques, the contrast is enhanced and noise is removed. Then from the resultant image, features of retina are extracted by means of various operators and algorithms.

Based on extracted features, classification step is carried out. For classification, supervised and unsupervised learning algorithms are used. After that, grading step comes. Clinically, ophthalmologists evaluated the degree of cataract by comparing the picture observed through camera with a series of standard photographs, which is termed as clinical grading. Fig 2 shows the standard photographs of the Lens Opacities Classification System III (LOCSIII) [3]. The clinical grading is quite subjective. In order to improve the grading objectivity, human graders are trained to classify cataracts based on photographs or digital images, which is termed as grader's grading. But now-a-days researchers are making studies on automated grading system which will help to reduce the burden of ophthalmologists.

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Fig.1. Non-cataract and Cataract fundus image

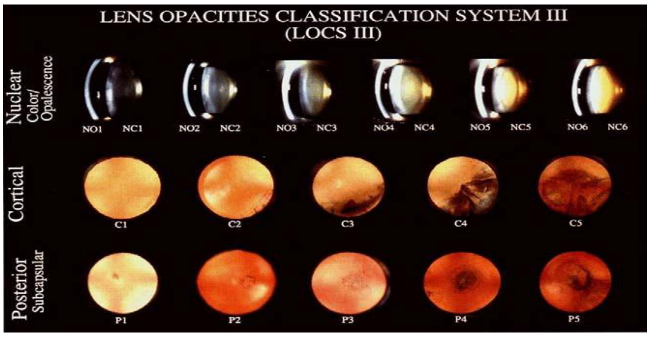

Fig. 2. The LOCS III Grading System [3]

II. LITERATURE SURVEY

Research on fundus image analysis for detection of retinal features and retina related disease has been made for years. Segmentation and localization of retinal features such as retinal lesions, blood vessels, optic disc, and fovea have been widely studied. Researchers are trying to develop the automated diagnosis system for retina related diseases such as diabetic retinopathy [16-20, 39], age-related macular degeneration [21, 40], glaucoma [22-25], cardiovascular diseases [26].

A. *Segmentation of Retinal Features:*

The retinal mainly includes retinal lesions (such as microaneurysms, hemorrhages, exudates), blood vessels, optic disc, fovea, macula. Following subsections contains the literature review of these retinal features.

- Retinal Lesions –
  Niemeijer et al. detected red lesion candidates in diabetic retinopathy images by using pixel classification. The detected candidate objects were classified using all features and a K-Nearest Neighbor classifier [4]. The system achieved a sensitivity of 100% at a specificity of 87%. In [5], an efficient approach for automatic detection of red lesions in fundus images based on pixel classification and mathematical morphology was proposed. Morphological top-hat transformation was used to detect red lesions candidates in fundus images, then by using SVM classifier, candidates are classified in red lesion areas and non-red lesion areas with sensitivity of 100% and specificity of 91%.

- Blood Vessels –
  In [6], J. Soares et al. presented a method to segment retinal vessels using 2D Gabor wavelet method and Bayesian classifier to classify each image pixel into vessel and non-vessel pixel based on pixel's feature vector. Gabor wavelet was used for noise filtering and vessel enhancement. Bayesian classifier with GMM (Gaussian Mixture Model) and LMSE(Linear Minimum Squared Error) classifiers was used for segmentation. Opas Chutatape et al. [7] detected and measured the diameter of retinal vessels in fundus images using Amplitude Modified Second-Order Gaussian Filter. For vessel detection, matched filter was used. This method gave 94.3% accuracy on fundus images.
  James Lowell et al. [8] presented an algorithm for measuring the vascular diameter. The overall process was made up of detecting and segmenting vessels, sampling points along vessels; measuring diameters; and drawing conclusions about vascular health. The diameter measurement was based on a two-dimensional difference of Gaussian model, which was optimized to fit a two-dimensional intensity vessel segment. Authors had been shown that the inclusion of a Difference-of-Gaussians model improved performance over a single Gaussian where there is a visible light reflex. In [9], Joes Staal et al. proposed the system which was based on extraction of image ridges, which coincide approximately with vessel centerlines. Authors grouped the ridge pixels which belong to same ridge to form a line element and then these line elements were subdivided into patches. Features were extracted and selected by applying sequential forward selection method. KNN classifier was used for classifying extracted features.

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- Optic Disc –
  Sinthanayothin et al. [10] proposed methods to localize optic disc, fovea and retinal vessels from fundus images. For preprocessing of image, adaptive, local, contrast enhancement method was applied. Then optic disc was localized by identifying the area with the highest variation in intensity of adjacent pixels. Blood vessels were detected by using multilayer perceptron neural network for which inputs were taken from PCA of image and edge detection of first component of PCA. Fovea was detected by matching correlation together with characteristics of a fovea. Ghoneim et al. [11] implemented the simple matched filter to roughly match the direction of vessels at OD neighbourhood. After generating vessels direction map of segmented retinal vessels, vessels were thinned and filtered using local intensity to represent OD center candidates. The difference between the proposed matched filter resized into four different sizes, and the vessel's directions at the surrounding area of each of the OD-center candidates was measured. The minimum difference provides an estimate of the OD-center coordinates. OD center was detected correctly with accuracy 98.77% and 100% on the publicly available datasets.

  In [12], Thomas Walter et al. presented new algorithms based on mathematical morphology for the detection of the optic disc and the vascular tree in color fundus images. The OD was detected by means of hough transform and watershed transform. For detection of vascular tree, Gaussian filter and morphological top-hat transform was used. Muramatsu et al. [13] compared three methods namely, Active Contour Model (ACM), Fuzzy C-means (FCM) clustering, Artificial Neural Network (ANN). ACM and ANN method gave better accuracy than that of FCM method.

- Fovea -
  In [14], fovea in fundus angiographies was automatically detected by using Bayesian statistical methods. The contour of the fovea was modeled by means of a unidimensional Markov chain and the observed intensities were assumed Gaussian and statistically independent between pixels. Two algorithms were used in order to estimate the fovea contour: Simulated Annealing (SA) and Iterated Conditional Modes (ICM). In [15], KNN regressor was used to predict the distance in pixels in the image to ROI at given location in the image based on features extracted at that location. A distance prediction was made for a limited number of image locations and the point with the lowest predicted distance to the optic disc was selected as the optic disc center. Based on this location the search area for the fovea was defined. The location with the lowest predicted distance to the fovea within the foveal search area was selected as the fovea location. The method found the optic disc in 99.4% and the fovea in 96.8% of regular screening images and for the images with abnormalities these numbers were 93.0% and 89.0% respectively [15].

B. Cataract Classification –

Miguel Caixinha et al. presented a new approach for cataract classification based on ultrasound parameters obtained from porcine lenses with different cataract degrees. An extensive extraction and selection of acoustical parameters, i.e., velocity, attenuation and backscattering signals (B-Scan and Nakagami images), was performed in order to classify objectively and automatically the cataract severity [28]. Acoustical and spectral parameters were obtained from the central region of the lens. Image textural parameters were extracted from the B-scan and Nakagami images. Ninety seven obtained parameters were subjected to feature selection with Principal Component Analysis (PCA) and used for classification through a multiclass Support Vector Machine (SVM). Overall performance was 89%.

Miguel Caixinhaa presented a CAD system for the cataract classification based on ultrasound technique. For this, Ultrasound A-scan signals were acquired in 220 porcine lenses. B-mode and Nakagami images were constructed. Ninety seven parameters were extracted from acoustical, spectral and image textural analyses [27] and were used for feature selection by means of Principal Component Analysis (PCA). For classification, Bayes classifier, K Nearest-Neighbors (KNN), Fisher Linear Discriminant (FLD) and Support Vector Machine (SVM) classifiers were used. Out of these four classifiers, SVM classifier gave highest performance i.e. 90.62%.

C. Cataract Grading –

In [29], S. Fan et al. developed an automatic system for classification of nuclear sclerosis from slit-lamp photographs. Authors detected the visual axis and extracted important feature landmarks. Linear regression was used to select features and linear grading function using those features was fit using the Standards. Then they graded the severity of nuclear sclerosis based on the intensities of those landmarks. The system achieved accuracy

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of 95.8%. H. Li at al. developed an automatic grading system for nuclear cataract assessment [31]. To detect the lens contour from the slit-lamp images, bottom-up and top-down strategies were combined. Bottom-up strategy included lens localization using horizontal and vertical intensity profile clustering and Ellipse estimation of Lens. Top-down strategy used a modified ASM to detect contour of lens. The mean intensity inside the detected lens contour was used to indicate the opacity of the nuclear cataract. Authors showed that the difference between automatic grading and clinical grading is acceptable.

H. Li et al. implemented a computer-aided system to assess nuclear cataract automatically using slit-lamp images [30]. An enhanced Active Shape Model (ASM) was applied to extract robust lens contour from slit-lamp images. A Support Vector Machine (SVM) scheme was used to grade nuclear cataract automatically. This study showed that 97.8% of automatic grades are within one grade difference to human grader [30]. In [32], H. Li et al. developed an algorithm to detect cortical opacities from retro-illumination images, and to grade the severity of cortical cataract objectively. The combination of canny edge detection, Laplacian approach and convex hull approach was applied to detect the edge pixels. The detected pixels were further fitted to an ellipse by non-linear least square fitting. In order to detect cortical opacity specifically, the spoke feature was used to separate from other opacities such as PSC [32]. The detection results of local thresholding and edge detection in each direction were merged.

H. Li et al. developed an automatic system for PSC opacity detection in retro-illumination images [33]. The pupil detection was based on the edge detection and ellipse fitting. The features detected were intensity, edge, size and spatial location. The sensitivity and specificity were 82.6% and 80% respectively [33]. Chow, Yew Chung, et al. presented a new approach for automatic detection based on texture and intensity analysis to address the problems of existing methods [32], [33] (over-detection and under-detection) and improve the performance from three aspects, namely ROI detection, lens mask generation and opacity detection [34]. Image clipping was applied first to remove the bright spots in the retro-illumination image. Then the texture analysis was done to classify the image into two categories i.e. clear lens and lens with moderate or severe opacity. For clear lens, only texture filtering was applied to obtain the final result. While for nonclear lens, both global thresholding and texture analysis using local entropy were used to detect the opacity [34].

Gao, Xinting, et al. presented the enhanced texture feature based on the grader's expertise of cataract and the characteristics of the retro-illumination lens images [35]. The statistics (such as mean, standard deviation, skewness and kurtosis) of the enhanced texture feature was used to train the linear discriminant analysis to detect the cataract. The accuracy of 84.8% was achieved. Xu, Yanwu, et al.presented a system to automatically grade the severity of nuclear cataracts from slit-lamp images. The system consists of three components: ROI and structure detection, feature extraction, and prediction [36]. The authors proposed a regression based framework with BOF group features and a group sparsity constraint for joint feature selection, parameter selection and regression model training [36].

Ruchir Srivastava et al. presented automatic grading of nuclear cataract (NC) from slit-lamp images using image gradients [37]. The system mainly consists of three steps namely, preprocessing, feature extraction and grade prediction. First, the lens region was localized automatically using horizontal and vertical profile clustering and then structure was detected using a modified version of active shape model (ASM). Features related to gradient aspects (such as Location, orientation, and magnitude) were extracted. These features are used in combination with prior features related to color and brightness.

In [38], Liye Guo et al. presented a computer aided system for automatic classification and grading of cataract on the basis of fundus image analysis. The system was built up with three main stages: preprocessing of image, feature extraction, cataract classification and grading. Image features are extracted by means of wavelet transform (Haar transform) and sketch based method in combination with discrete cosine transform. Multiclass discriminant analysis is used to classify the images into cataract and non-cataract images and then graded into mild, moderate and severe cataract. The correct classification rate for hybrid of wavelet transform and sketch based method classification and grading is 89.3% and 73.8% respectively [38].

This survey shows that many researchers studied cataract classification and grading on slit-lamp images, retro-illumination images and ultrasound images.

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III. DISCUSSION

For detecting retinal features from the fundus images, datasets used are DRIVE, DIRECTDB0, DIRECT-DB1, DRIONS-DB etc. In most of studies, the real-world images from the various Eye Hospitals are used. For cataract classification and grading, all the images of trained and tested dataset are acquired from Ophthalmic Hospitals. For preprocessing of images, green channel of the RGB fundus image is used in most of the research because it gives better contrast between the retinal lesions and the background of the image. Then noise is reduced by applying various image processing techniques.

From the survey, it is cleared that most of the approaches used the step i.e. pupil detection or lens localization. For this, canny edge detector and Laplacian detector were applied to the image. Then, the detected edge was filtered based on the convex hull. A non-linear least square fitting method was finally used to fit an ellipse mathematically to the edge points on the convex hull [32], [33].

But it is found that ellipse fitting is not robust to irregularly shaped lens, and Laplacian and Canny edge detections are susceptible to noise. This introduces the problem of over-detection and under-detection. Active shape model (ASM) is used by many researchers to locate the contour of lens. ASM is a parametric deformable model that combines point distribution model (PDM) and iterative refinement procedure. It can describe shape of non-rigid objects and is efficient in many applications especially in the extraction of anatomical structures which are complex and variable among individuals and where a high degree of priori knowledge is available. A modified ASM is used to extract the contour of lens. The strategy of the modified ASM mainly composes of five steps: initialization, matching point detection, pose parameter update, model update shape and convergence evaluation [30].

For feature extraction, intensity, edge, size and spatial location, color, texture, brightness features are used in most of studies. For classification of images, SVM, K- Nearest Neighbor, SVM regression, Probabilistic Neural Network (PNN), Artificial Neural Network (ANN), Fuzzy C-Means clustering, Bayesian network, Fisher Discriminant Analysis (FLD) classifiers are used.

IV. CONCLUSION

This paper focuses on the literature of the cataract classification and grading. All automatic detection systems used slit lamp images or retro illumination images. This survey paper mainly present the studies made on detection of retinal features, retinal diseases, cataract classification and grading systems. All these studies consist of: preprocessing of image, feature extraction and prediction. Automatic cataract classification and grading system reduces the burden of ophthalmologists. Also it solves problems regarding manual grading. From this survey, it is found that there is less work done for cataract classification and grading based on fundus images.

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