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MOBILE & WIRELESS HEALTH

An Effective Detection Mechanism for Localizing Macular Region and Grading Maculopathy

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Abstract
The eye disease is prominent in many nations including India and is said to affect up to 80% patients having diabetes. Diabetic Retinopathy is the medical term for denoting the damages to retina caused due to diabetes mellitus. Implying K means Clustering algorithm for coarse segmentation, hard distils are identified with better accuracy than the classical approaches. The variance based methods for segmenting hard distils are reviewed in the surveys and had to be improved. To remove the background features from the picture and conserve computational costs, a mathematical morphological method is used to reconstruct the image features for better segmentation. The results obtained for 96.4% sensitivity and 97.2% specificity. Along with this advantage, a graphical user interface is developed which will simplify the usage of this system. This model will divide the fragments into regions of interests having lesions and normal regions carrying normal features. After this segmentation, ophthalmologists will utilize the results to grade diabetic retinopathy and devise a treatment plan.

Keywords Retinal images · K-means clustering macular region · GUI

Introduction

Macula, the region of human eye, is responsible for sharpening our vision for purposes like reading, recognition and focusing on a single object. Damage to macula is termed to be diabetic maculopathy and this is a result of retinopathy [1, 2]. Leakage of proteins or other fluids into the macular regions will block the normal vision. When these fluids of fat and cholesterol deposit, the next symptom is leading to hardening of retina and accumulation of distils in close immediacy to the retina. The following Fig. 1 shows how macula will be expressed in colour fundus images [3, 4].

Many patients affected by diabetic maculopathy sensed no difference after the disease started and symptoms were found in very late stages of the disease [5]. Diabetic maculopathy has a history of affecting in a slow and steady pace. Without symptoms in early stages, medical practitioners need to identify a method for faster detection [6–8]. If the disease is left unattended for an extended time, the damage caused to retinal vasculature tissues cannot be diagnosed at all, leading to blindness. Hence from the reported cases, diabetes infected patients should undergo regular check-ups and mandatory medical opinion for preventing extreme damage [9–11]. The time taken for this number of records will usually delay the diagnosis process. This deficiency has resulted in demanding an automated system for retinal images optic disc detection, macular region localization and identifying the extremity of the disease. The next Fig. 2 illustrates how the automated system will work and grades the disease into mild, moderate and extreme cases of disease.

Hard distils identification

Presence of lesions with abnormal features in the eye of a diabetic patient will be due to diabetic retinopathy.

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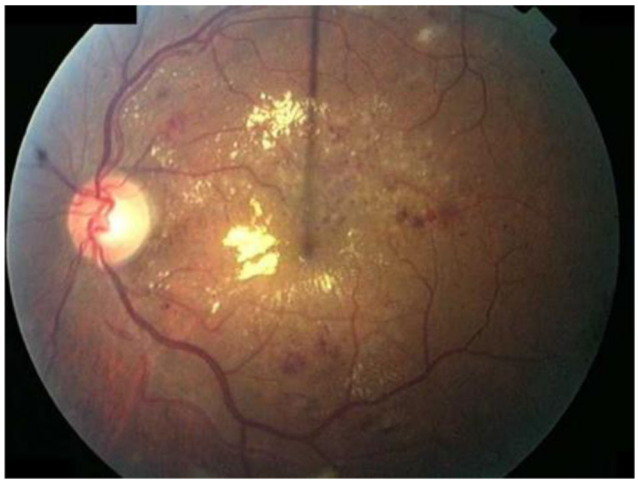

Fig. 1 Retinal images of diabetic maculopathy

Damage to a healthy eye will be in form of patches of fluids, fat, cholesterol and other retinal vasculature components [12]. The process of segmentation is achieved in two steps. K Means clustering technique is applied to group the patches if they are found to satisfy a condition [13]. Then a mathematical morphology technique is applied, to confirm that the hard distil regions are reconstructed. The challenge in this technique is that both the optic disc and distils follow the same characteristics and intensity values and the automated systems should be able to distinguish between the normal and abnormal features. To ensure that optic disc is not misjudged to be a hard distils, it is masked when the process is undergone [14].

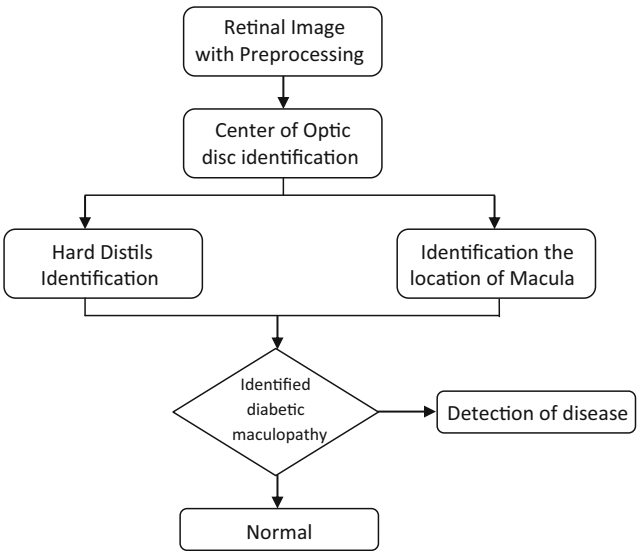

Fig. 2 Computerized system for detecting diabetic maculopathy

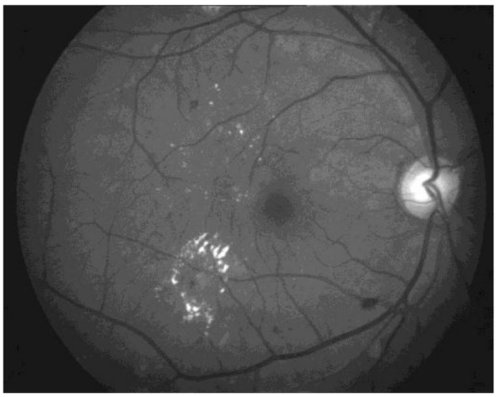

Fig. 3 Using clustering techniques with Intensity difference image for green channel

Hard distils segmentation

The bright regions in the retinal images are hard distils, for segmenting the same, a common threshold cannot be utilized. This cannot be applicable to all retinal images due to the changes in characteristics and features. Before segmentation a process of increasing the contrast of the entire image is done. Though this process is to enhance the visibility of lesions, it is applied uniformly to an entire image [15, 16]. This will result in chances of false positives, as some pixels will be mistaken as hard distils. After applying this technique, regions which obey to the predefined conditions are termed to be hard distils, cotton wool spots, drusen and pixel information surrounding the optic disc. Now the region after segmentation has to be classified into regions of hard distils and no distils. K-Means Clustering technique is employed for this classification process. To simplify distils' identification, RGB channelization is applied and Green colour channelized image is considered for identifying the brighter regions., it is preferred for hard distils segmentation. A pixel square of 15×15 is applied as a median filter to address the randomly distributed illumination into evenly spreading illumination [17, 18].

Fig. 4 Intensity difference image with subtraction is applied for clustering techniques

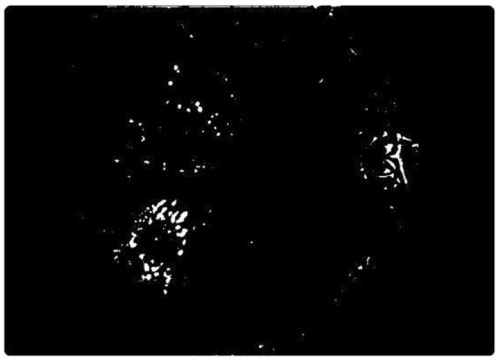

Fig. 5 Background image partition using clustering with hard distils segmentation method

Clustering operation will be done in the image after median filter applied image is subtracted from green channelized image. The background is eliminated in this process and features are enhanced in intensity [19, 20]. With all the necessary information in the intensity difference images, clustering operation is facilitated much better. This operation is shown in Figs. 3 and 4. The Fig. 3 shows how green channel is targeted and the Fig. 4 shows how the subtraction is applied for the technique.

The retinal images display their properties through some gradient and intensity features. When the clustering method is employed over these colour fundus images, sets of data points are grouped together based on the specific condition they obey [21]. The centers of each cluster are agreed and the distance of each property in close range for a particular cluster centre is one significant way of identifying the similarities between the attributes of retinal images. With respect to intensity based images, the difference is identified based on the change in terms of two pixels' intensity. These clusters will primarily indicate that the retinal image is composed on background and foreground features. The background attributes constitute the darker components of the images and foreground features will indicate the features that are bright and thus needed for computations in an automated retinal image processing system.

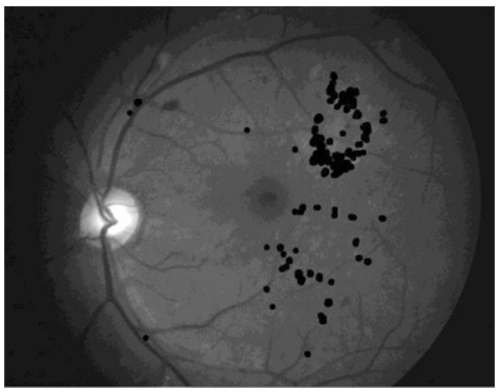

Fig. 6 Segmentation of hard distils with marker image

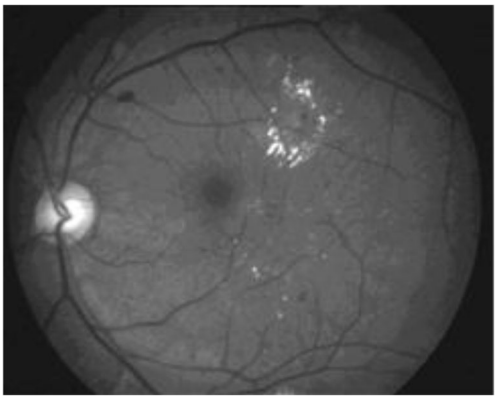

Fig. 7 Segmentation of hard distils with mask image

The algorithm to define how clustering is performed is explained as follows. The foreground cluster is marked as K_f and background cluster is denoted as K_b. Since the intensity of attributes in a foreground features are higher than all others, it is set to max. And the background features with less intensity is denoted by min. In an intensity differentiated retinal image, the difference is estimated by the following technique.

1) During the first iterative step, i = 1 it is set as $K_f(i) = \max$ and $K_b(i) = \min$
2) For intensity values IN, $p = 1,2,3\ldots..$ axb, p denotes the pixel position
   IN_p is the value of intensity at the corresponding pixel.
   $L1 = \text{distance}(IN_p, K_f(i))$.
   $L2 = \text{distance}(IN_p, K_b(i))$.
   If L1 < L2.
   Pixel with IN_p belongs to distil clusters.
   Else.

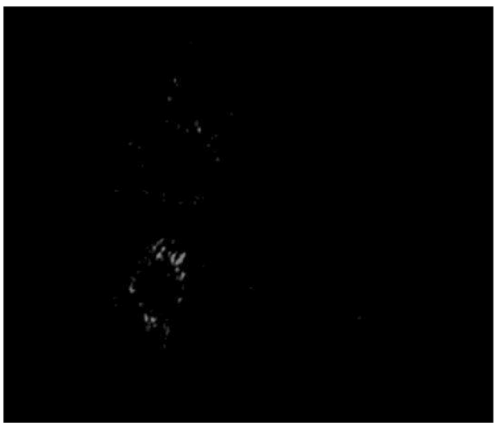

Fig. 8 Segmentation of hard distils with reconstructed image

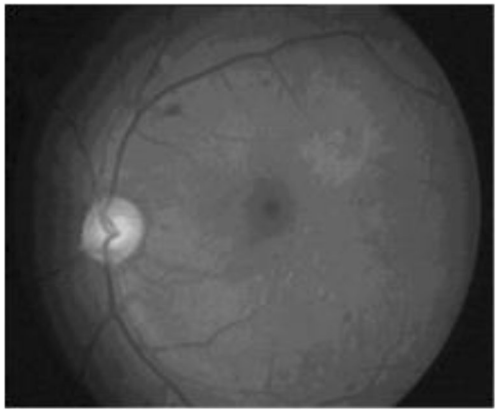

Fig. 9 Segmentation of hard distils with dissimilarity image

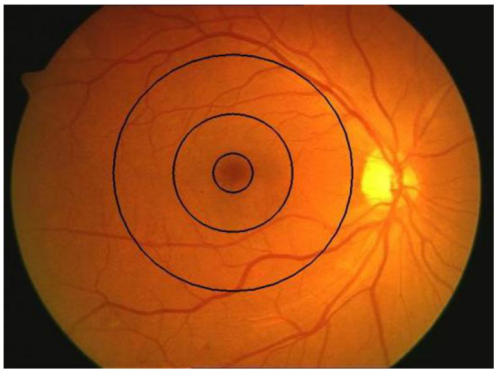

Fig. 10 Normal stage for extremity level reporting system

The pixel matches to the properties of background clusters

3) The clusters centers are updated to the next iterative position by incrementing the value of i.
4) Until axb is reached, i.e. until all the pixels are determined, these steps are repeated.

The stopping pixel for the above mentioned algorithm will be defined by the user themselves as this is assumed that the successive distance between two different cluster centers. When this algorithm was tested with a number of training images, it was calculated that maximum of three iterations was sufficient to distinguish the features between foreground and background (Fig. 5).

Refining the segmentation of hard distils

Clustering of the properties in a retinal image will result in possible regions of interest for segmentation. Yet this process of clustering will not be sufficient for segmentation processes. Hence a mathematical model for reconstructing the image features is applied to add accuracy to the previous technique. Now the regions of interest will be classified into regions having hard distils and regions which do not have them. This process will not be limited within a quoted number of steps, as the differences in input images varies according to individual patients' records. However an optimal number of iterative steps can be defined to achieve this segmentation. These recursive steps will be applicable in two set of images one being indicator image and other being pretense image by elongating the features. The indicator image is represented by T_i and pretense image is represented by P_m and the condition assumed here is $T_i \leq P_m$. The condition for elongating the features is given by the following equation.

$$E_i(T_i, P_m) = (T_i \oplus B)^n P_m \quad (1)$$

The indicator image will tend to expand their regions of interest while being protected by a limit introduced by pretense images. This process will be recursively executed the number of times until a criteria of $E_i = E_{i-1}$ with

Table 1 Universal table for macular edema extremity level detection

Extremity level of the disease	Observations
Absence of macular Edema	Presence of Hard Distils – Nil
Presence of Macular Edema	Presence of Hard Distils at Posterior Pole
	Type I – Mild: Hard distils found far from macular region
	Type II – Moderate: Hard distils almost touching the centre of macular region.
	Type III – Extreme: Hard distils found within the macular region.

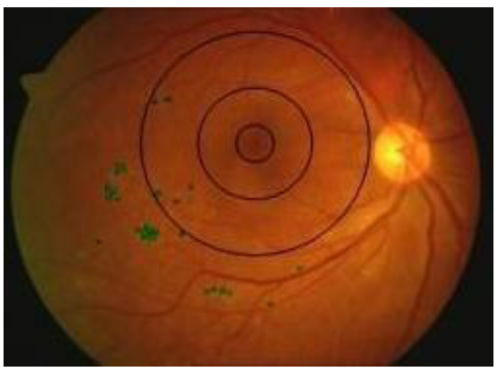

Fig. 11 Type I stage for extremity level reporting system

indicator and pretense images being the common parameters. In most cases the retinal images which are channelized into the green colour is selected as the pretense image. This states that the indicator image has significant properties and will be used for determining the regions of interests. The images will possess a similarity to conclude the mathematical morphology method is successfully implied and the output is desirable. Deriving the exact outline after using the indicator images as reference images, the segmentation of hard distils is refined. The following Figs. 6, 7, 8 and 9 represents the process of retrieving the difference features after the reconstructed image is subtracted from original image.

A colour fundus image is transformed into a pretense image with its boundary highlighted as already mentioned in Chapter 3. And this process is carried out for all colour fundus images. The pixels which lie inside the boundary of this pretense image will be considered for computations as distil regions. With the available information, a thresholding metric is to be defined. This will conclude the determination of hard distil regions in the pretense images. The thresholding metric cannot be common to all images as the context varies completely or to some extent.

Diabetic retinopathy for computerized extremity level reporting system

Diabetic retinopathy is the condition of finding abnormalities in human eye's vasculature tissues and if those abnormalities are found very near to the macula, it becomes a condition called diabetic maculopathy. The centre of macula is responsible for focusing on intimate details of smaller objects like reading. Depending on the presence of lesions from the centre of macula, extremity of the disease is graded by the ophthalmologist. When the blood vessels near the macular region are significantly damaged and huge deposits of fluids are found, it is mentioned as Clinically Significant Macular Edema (CSME). The hard distils rupture and leave the fluids leak in the regions close to fovea. When the line of sight for the macula is disturbed by these fluids and distils, focusing on a specific object becomes more difficult. This condition is also claimed to affect the vision very critically and lead to blindness. CSME has defined three categories of the disease based on their localization namely mild, moderate and extreme conditions. This is the universal standard used for grading maculopathy. The next Table 1 is the ground table for ophthalmologists, technicians, physicians and other experts authorized to handle this disease to

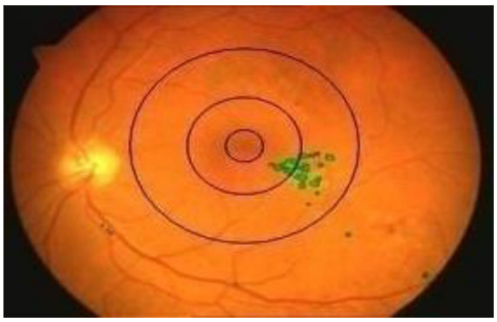

Fig. 12 Type II stage for extremity level reporting system

communicate in common terms. This table has defined a better way to understand the terms which were differently used in different areas. This ground table has been used as a reference in this proposal. The automated grading system for maculopathy follows the standards accepted by all practitioners. Another set of standards are defined as a metric in Early Treatment of Diabetic Retinopathy Study (ETDRS), based on the extremity level of diabetic retinopathy. This has defined the global standards for retinal images and their grading methodologies on patients' medical history. The evaluation is done on stereo retinal images from diabetic affected patients.

The techniques for correctly localizing the position of macular region with respect to the optic disc, as this is relatively common in all retinal images. Three marking positions are used to segment the identified macular region in every 1/3 radius of optic disc diameter (ODiD), 1 ODiD and 2 ODiD using macula as the centre point. If the hard distils are missing in any of the given input retinal images, they are considered to be healthy eye. Clinically Non-significant Macular Edema as shown in Fig. 10 is identified by the presence of hard distils beyond the 2 ODiD regions. This will represent the regions which are nowhere close to the centre of macular regions. If the hard distils can be found within the 2 ODiD regions, this is

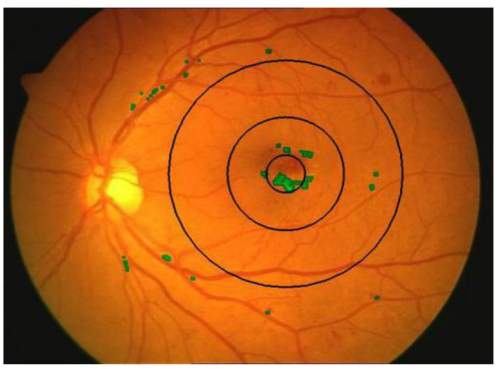

Fig. 13 Type III stage for extremity level reporting system

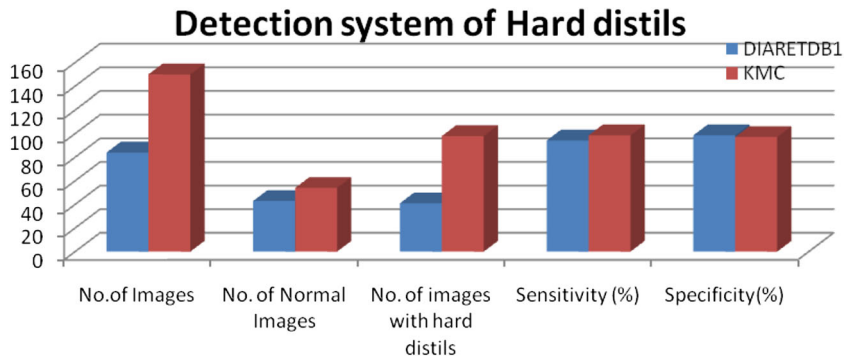

Fig. 14 Detection system of hard distils performance measurement

classified as Clinically Significant Macular Edema. The conditions of CSME are slightly more stringent when marking these classifications. Presence of hard distils outside 1 ODiD will be considered as mild cases of macular edema as shown in Fig. 11. When hard distils lie within the 1 ODiD region without interfering with the centre of macula or foveola, it is to be considered as a moderate case of maculopathy Fig. 12. The presence of lesions in very close proximity to centre of macula or within the 1/3 radius of macular centre is considered to be serious cases of maculopathy Fig. 13. Severe loss to sight and a condition which leads to blindness is the last stage of extreme maculopathy.

The figures illustrate how this automated system for grading maculopathy and classification is performed with the accuracy of an expert ophthalmology.

Simplified graphical user interface for usage

Matlab 7.0 has a dedicated toolkit for developing a user interface for the background operations, namely Graphical User Interface (GUI) Development Environment. The proposed interface will be composed of the following features.

1) As already mentioned, STARE, DRIVE and KMC databases of retinal images are selected for evaluation of the model proposed. STARE and DRIVE database images are preferred to test how the blood vessels network is extracted for further understanding.
2) Optic disc localization plays the next important role for any automated retinal image analysis system. The position, boundary, diameter are to be identified.
3) With respect to the position of optic disc, macular region is also identified, followed by tracing the outline of macular region. This process is also automated.
4) Sensitivity and Specificity of blood vessels network identification are to be stated. Applying Gabor filters, the performance has to be reported.
5) Presence of lesions throughout the foreground features is to be analyzed and marked.
6) Once lesions are detected, their extremity level has to be classified.
7) The results are stored with the identity of patients to monitor the progress and regress after medication.

Performance measurement and discussions

Diabetic maculopathy detection techniques were proposed in the previous sections and tested for validating this approach. This output is explained in the following Fig. 14. The images retrieved from KMC database showed

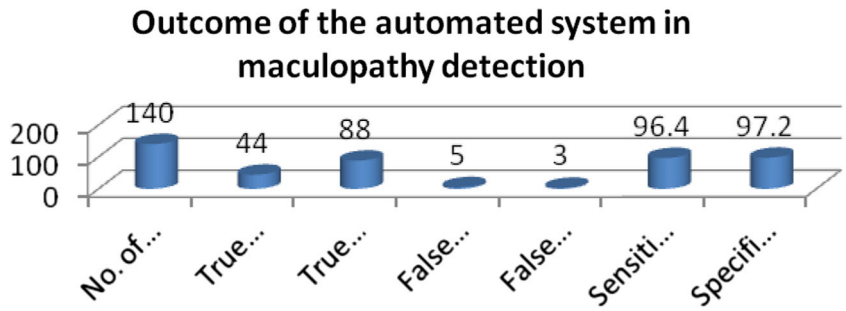

Fig. 15 Outcome of the automated system in maculopathy detection

Table 2 Extremity stages of maculopathy

Extremity	Hard Distils in Intensity Circles		
	Region 1	Region 2	Region 3
Type I Stage	Yes	No	No
Type II Stage	Yes/No	Yes	No
Type III Stage	Yes/No	Yes/No	Yes

successful results in 96 images producing a sensitivity value of 98.6%. Just two images out of 54 images were found to have lesions in them and the rate of specificity is 97.2%. Some images produced wrong results as they were prone to higher illumination of light, high brightness in these images masquerade the intensity of lesions. There were 5 images which do not satisfy the minimum quality requirements for automatic detection on maculopathy. These images are not considered for computations in the system. Even if they would be processed, their poor contrast will limit the quality of output obtained or inaccurate results.

The Fig. 15 summarizes the performance statistics of the automated system in maculopathy detection. The database offered a total of 140 colour fundus images in digitalized form. Images were found to possess a low contrast and illumination. Those five images are eliminated from computations to derive the best possible time. The system intends to remove such images in the very first step. 93 images were analyzed and graded accordingly, to the condition of maculopathy present in the images. Database also included retinal images from healthy patients and they accounted for about 47.

The extremity level of maculopathy in each image is explained in three circular regions from centre of macula. Three regions will accumulate all the lesions in the retinal images, based on the proximity they are graded with significance. With the number of lesion patches in each intensity circle, the following Table 2 gives ground information of extremity level of maculopathy. Based on the number of circles with lesions, maculopathy will be graded into mild moderate and extreme.

Lesions in all three regions Region 1, Region 2 and Region 3 are combined together to determine the overall damage done by the disease to the human eye. Analysis of Variance between three intensity circles abbreviated as ANOVA is done to get a quantifiable value for damage and extremity of disease. There is another concern in this approach that has to be addressed. The data fed into the system is not distributed by nature as the images in databases are a wide range of patients' history and devices. This has invited vast changes in pixel information in the images in different intensity circles. Hence, instead of ANOVA test, Kruskall-Wallis test with no parametric conditions is opted to rank the significance of these methods. Some test cases are prepared for the given sample sets and Kruskal-Wallis test is performed to determine the difference between the three sections. This is shown in Fig. 16. The data are prepared for all three extremity levels in the given sample set.

Figure 17 documents how Kruskal-Wallis test is performed on images for detection of maculopathy and grading them into mild, moderate and extreme cases of symptoms. From the documented results, it is evident that notable changes can be recorded between at least two intensity circles.

Mead et al., 2001 devised some set of standards which has to be met by all newly proposed methodologies of automatic retinal image analysis system. The expectation is whether at least 80% sensitivity is achieved and at least 95% specificity is achieved by new techniques. This is the minimum results that should be attained.

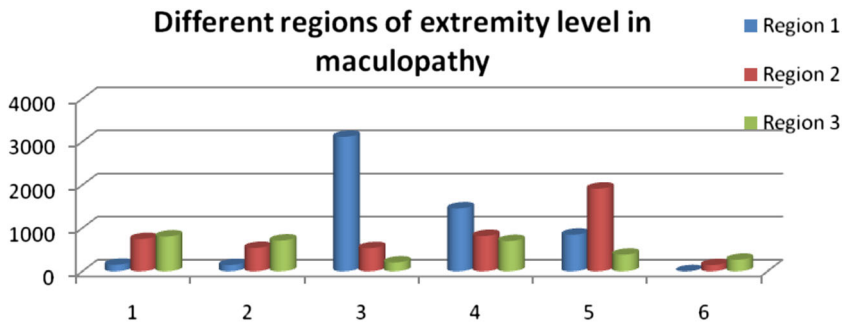

Fig. 16 Different regions of extremity level in maculopathy

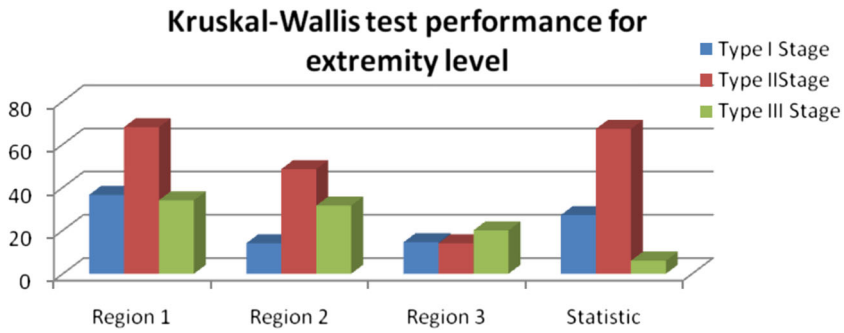

Fig. 17 Kruskal-Wallis test performance of extremity level of different regions

Conclusion

The different techniques used in the proposed automated system for maculopathy detection and the results grades the images into mild, moderate and extreme cases of maculopathy. Detection of maculopathy demands two important components in retinal images to facilitate the automated process.. The method proposed in this technique was K Means Clustering and this was more efficient than variance based technique in surveys. Cotton wool spots are also considered as lesions in variance method of segmenting and they were assumed to be hard distils. Automatic threshold was achieved by recurring and entropy based technique. This system will strive to provide an innovative and time saving solution for faster analysis and grading for maculopathy so that a serious vision threatening disease can be kept at bay.

Compliance with Ethical Standards

Conflict of Interests The authors declare that this article content has no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the author.

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