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An Optimized Predictive Modeling for Screening and Grading Age-Related Macular Degeneration

M. Antony Ammal[1], Dr.D. Gladis[2]

[1]*Research Scholar, Presidency College (A), University of Madras, Chennai.*

[2]*Research Supervisor, Principal, Bharathi Women's College (A), University of Madras, Chennai.*

[1]*manto2k4@yahoo.co.in*

Abstract: Age related macular degeneration is a vision affliction that progresses to the threat of impairment and the damage is caused due to the degeneration of macula. The early detection and diagnosis help to considerably lower the impact of vision loss. Bright lesions called drusen are the cause of age-related macular degeneration. The area of the lesions present in the retina indicates the severity of the disease. The digital picture of retina captured by the colour fundus camera plays a central role for the cost-effective computer – aided screening, diagnosis and follow-up treatment of the mentioned ocular disease. A structured screening simulation method automatically spots and extracts the features from the fundus image and quantify the risk associated with it. The experiment's findings are compared with the ophthalmologist projection. The proposed framework was tested on publicly accessible dataset.

Keywords: Drusen, Macula, Age Related Macular Degeneration, Machine Learning Technique, Fundus Image.

1. INTRODUCTION

Age Related Macular Degeneration (ARMD) is an ocular disease which leads to vision impairment. ARMD affects the vision when the macula of retina degenerates. ARMD is one of the major cause of the loss of vision among older people[1]. ARMD's projection of people worldwide impact reaches 196 million by the end of 2020. Statistics in Indian population reveal a predominance of ARMD ranging from 1.2% to 4.7% which is caused by yellow lipids produced inside the macula region of the eye [2] called drusen and they are of small and discrete [3] in nature. Small drusen sign is not always the symptom of ARMD, as it develops in normal ageing phase but its risk factor is correlated with its incidence of clinical features frequency and size [4]. ARMD is a preventable eye ailment and if the disease progress without treatment the people may get irreversible blindness. It is unable to detect any noticeable changes in vision by themselves until the situation worsens and the majority loss the sight due to late diagnosis.

Any impairment or abnormality identified at the earlier stage is easy for treatment and reduce the risk of abnormality or damage. The ophthalmologists can analyse and confirm by either visual or automated inspection of the retina. But the visual inspection for large scale is a time consuming and tedious activity. Fig. 1(a) shows a healthy fundus image and Fig. 1(b) shows drusen affected fundus image.

Fig. 1(a) Healthy Fundus Image

Fig. 1(b) Drusen Affected Fundus Image

As per the ophthalmologist's society of India, availability of doctors to the population is less. So, an automatic screening system is advisable for early identification of the presence of drusen. The appearance of drusen is similar to exudate and care should be taken to differentiate them. The overhead can be reduced significantly by automatic identification and classification of drusen using the computerized analysis of fundus imaging. Digital fundus image processing and identification of the abnormality of ocular disease is less expensive when compared with medical tools which are expensive and high in accuracy rate. Fig. 2 shows the fundus image with different severity levels. In this paper an automatic method for detecting features using image processing technique and machine learning technique in fundus images is proposed as it enhances the screening capacity and can be a reality in mass screening activity. The system identifies and detect drusen in faster, easier and in cost effective manner. The paper is structured as, explanation of methodology is carried out in section II, followed by experimental results discussion in section III and conclusion in section IV.

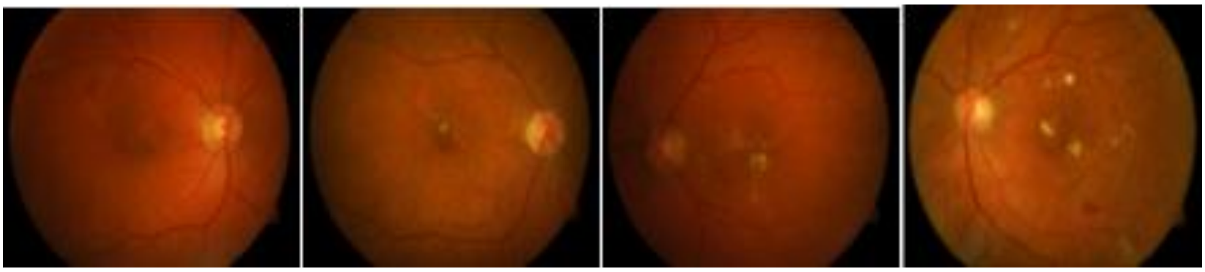

Fig. 2 Fundus Image with different Severity Levels

2. METHODOLOGY

Drusen is the visible clinical signal of AMRD predictor. The steps applied in drusen extraction from fundus image, the assessment process and evaluation of risk factor are elaborated below and the conceptual framework is shown in Fig. 3.

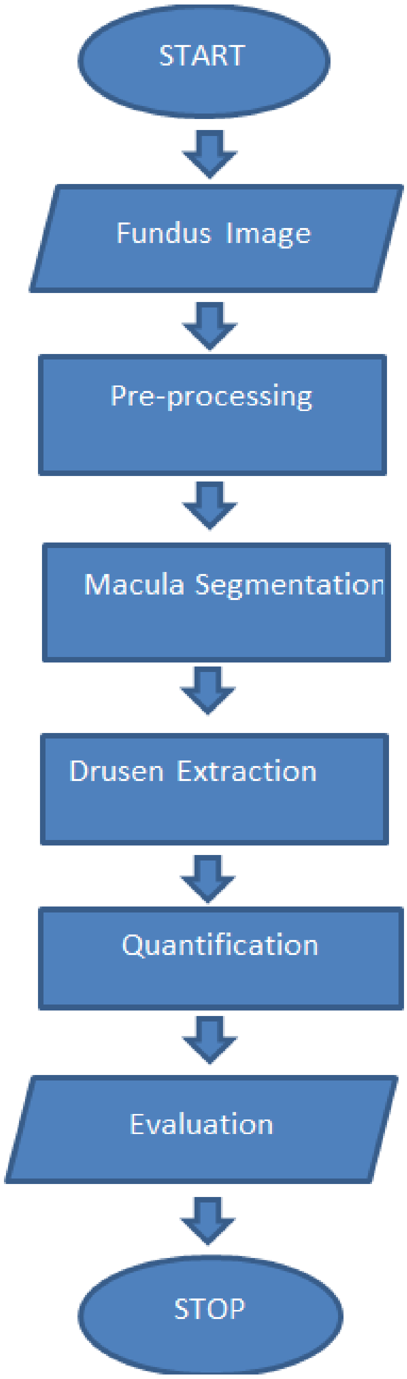

Fig. 3 Flowchart for Drusen Evaluation Process

Image Pre-processing

Preprocessing is a fundamental and important stage in any image processing techniques, which when applied normalize the image and remove noise and thus enhances the performance of the system considerably. The steps involved depends upon the application.

The macula is the region of interest as it indicates the presence of drusen, segmentation of macula is performed. LAB color space conversion applied to the segmented macula and the preprocessed image is shown in Fig. 4.

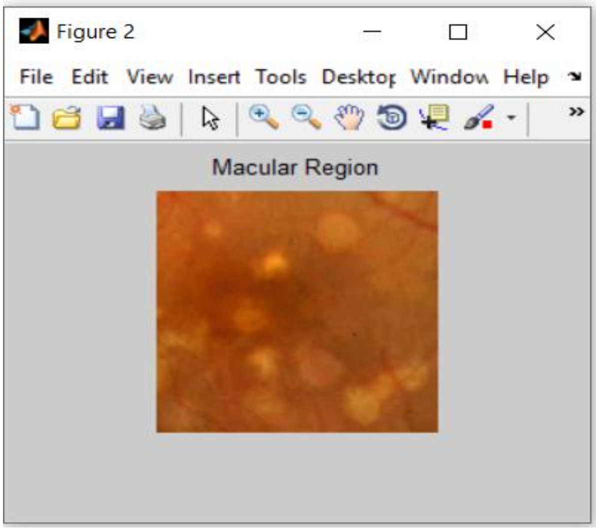

Fig. 4(a) Macular Region

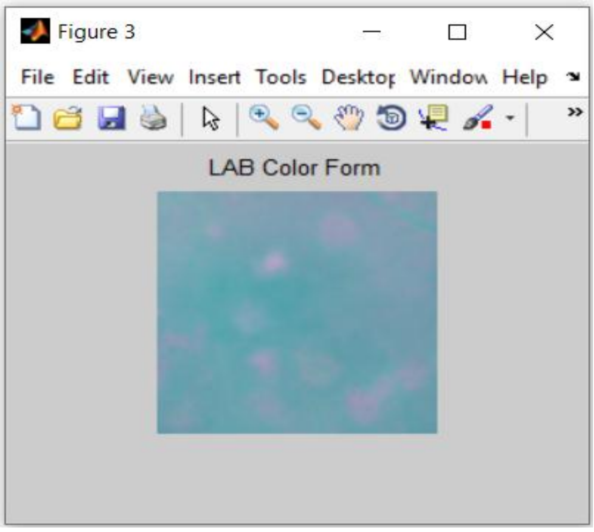

Fig. 4(b) LAB Color Space

Drusen Extraction

K-means clustering is an unsupervised machine learning technique applied in drusen extraction. It is a pixel-based clustering process. Based on the characteristics of drusen, the drusen candidate pixel is labelled. The nearest pixel with less intra cluster distance to the cluster center share the same cluster[6] and grouping is based on method of Euclidean distance(1) calculation and hence the boundary is well separated. The optimal choice of k in (1) results in assigning right pixel to each cluster based on the centroid C_j for cluster j. The extracted drusen is shown in Fig. 5.

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (1)$$

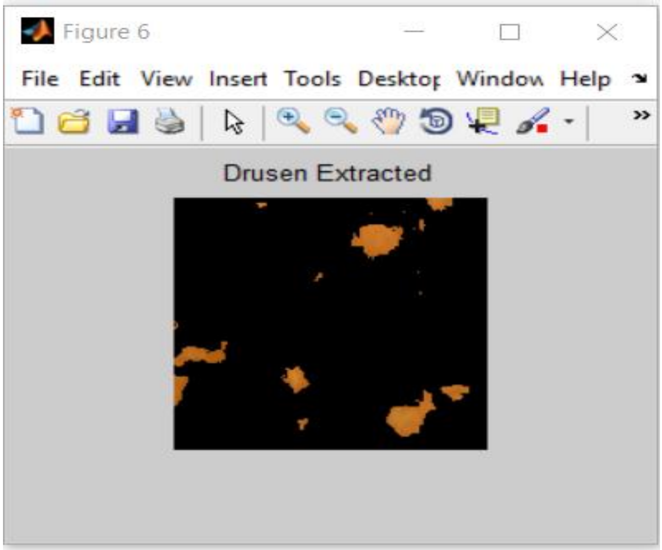

Fig. 5(a) Drusen Extracted

Post Processing

The processed image is subjected to post processing to improve the quality of the extracted image. If there exist a difference in intensity level between foreground and background by the threshold value T, as specified in (2) the pixel is identified as false positive and eliminated [1].

$$(x, y) = \begin{cases} o, & g(x, y) < T \\ 1, & g(x, y) \geq T \end{cases} \qquad (2)$$

Also, if the height and width of the drusen is less than a specified threshold T1 it may be identified as suspicious and can be eliminated as it may be due to noise. The drusen extracted image is shown in Fig. 5(b) and the drusen localization using bounding box technique is shown in Fig. 5(c).

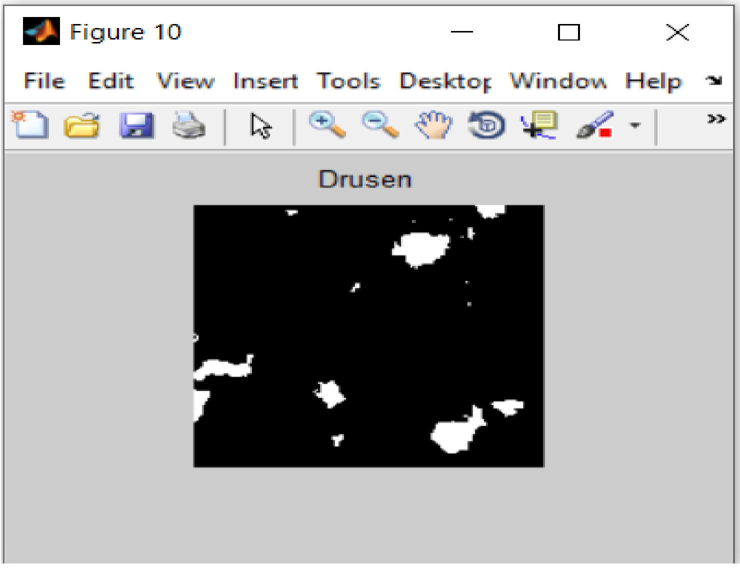

Fig. 5(b) Drusen Extracted Image

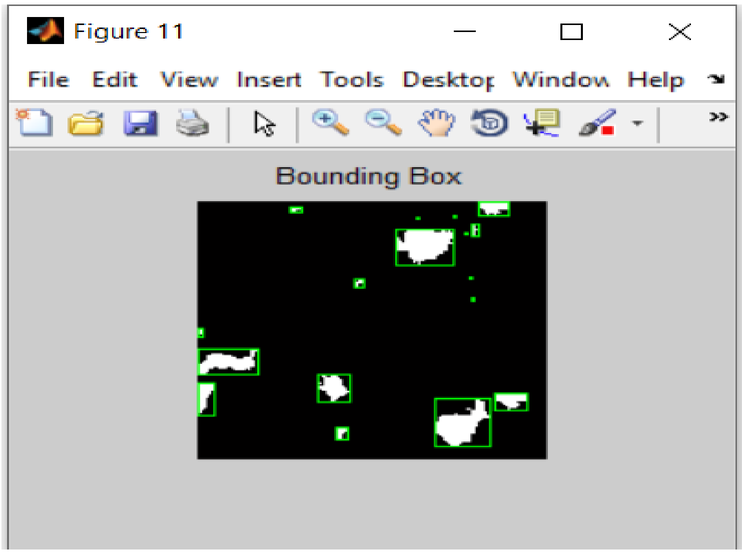

Fig. 5(c) Drusen Localization

Quantification

Table 1 indicates the clinical features like number, size, color and area[2] applied to evaluate and to assess the risk associated with ARMD.

Table 1: Clinical Features

Feature ID	Feature Name
F1	Number
F2	Size
F3	Color
F4	Area

The affected ratio of the macular region is the area of the drusen to the area of the macular region as in (3) and the connected component analysis is applied to calculate it. Appropriate measurement of these structures helps in effective evaluation[7].

$$Ratio = \frac{Area\ of\ drusen}{Area\ of\ the\ macula} \qquad (3)$$

Table 2 indicates the feature measurement based on textures like mean, energy, entropy, standard deviation etc.

Table 2: Features Measurement based on Texture

Feature	**Feature Name**
F1	Mean
F2	Energy
F3	Entropy
F4	Standard Deviation
F5	Smoothness
F6	Kurtosis
F7	Variance
F8	Skewness
F9	Contrast
F10	Homogeneity
F11	Correlation

Evaluation

The risk associated with the identified drusen has been studied by computer assisted learning algorithm by effectively measuring the clinical features and classified the image as either little risk or high risk. The ranking benchmarks for ARMD as per Cologne Image Reading Centre and Laboratory (CIRCL) protocol [6], are tabulated in Table 3. KNN classifier has been used to classify the image as healthy or not healthy. By assessing the clinical factors, the risk level associated with the unhealthy image is categorized as early, moderate or advanced risk level as shown in Table 3.

Table 3: CIRCL Protocol for ARMD Prediction

Feature		Prediction
Number of Drusen	Size μ m	
No Drusen		Normal Image
>10	<63	Early ARMD
>15	>63 and < 124	Moderate ARMD
>15	>125	Advanced ARMD
Not clear Image		Not Gradable

3. RESULTS AND DISCUSSION

For the evaluation of the proposed system the publically available dataset named as STARE [8] has been used. Extraction of desired features from digital fundus imaging is a challenging task. Some of the techniques were limited to extract the features and small size features may be missed out compared with large size features but K-means algorithm extract the features with maximum efficiency. Also, the quantifying factors as specified in Table 3 used for the assessment of risk factor depends on the quality of the image acquisition process. Visualization of grading the level of ARMD Images is tabulated in Table 3 and the standard deviation of the extracted drusen which helps in assessing the risk factor is graphically indicated in Fig. 5. The extracted drusen is measured by the features [3] calculated as per Table 4. The presence of at least one medium size or extensive small drusens is classified as AMD [2].

Table 4: Features measurement based on texture

Feature	Feature Name	Value
F1	Mean	86.14
F2	Energy	0.4416
F3	Entropy	7.11
F4	Standard Deviation	59.68
F5	Smoothness	1.00
F6	Kurtosis	1.74
F7	Variance	139.20
F8	Skewness	0.53
F9	Contrast	0.1038
F10	Homogeneity	0.9481
F11	Correlation	0.8288

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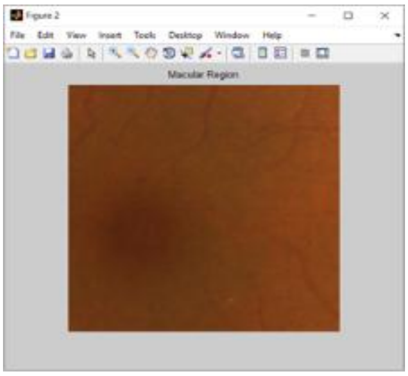
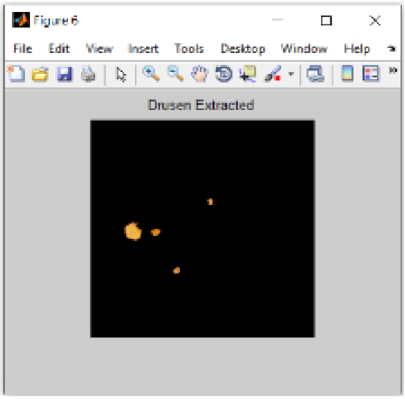
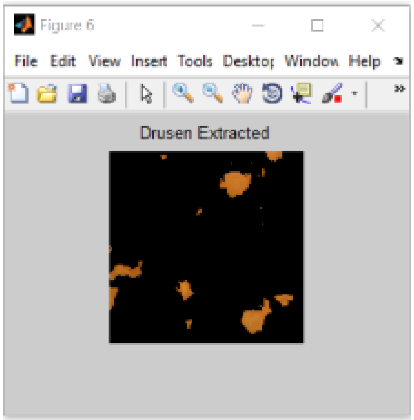
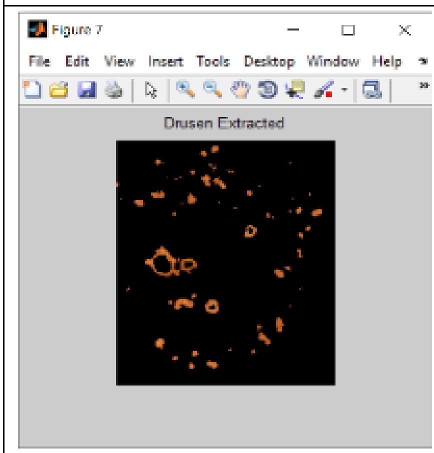
Table 5: Visualization of grading the level of ARMD Images

Image	Number	Ratio Affected	Inference
	Nil	Nil	No Drusen
	4	0.0242	Small Drusen
	17	2.8333	Medium Size Drusen
	59	8.4286	Large number of Small Drusen

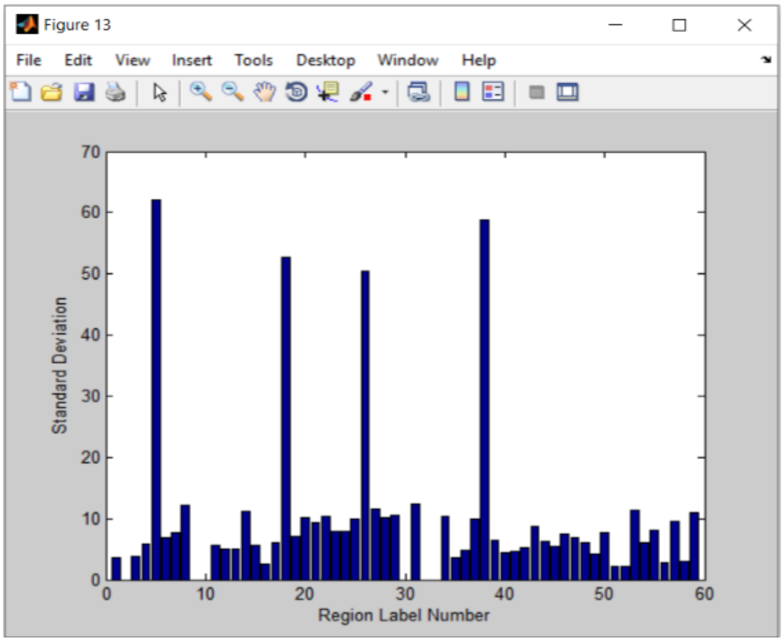


Fig. 6 Standard Deviation of Drusen

The individual person affected by ARMD may not feel the risk earlier and it is not apparent to monitor it before the vision level get affected, instead an eye checkup can throw light on the status [9]. Based on the level of degradation, the person may be warned and the follow up process of treatment can be started well in advance before the damage. As it is irreversible, prevention of the progression[10] is best action.

4. CONCLUSION

A screening system has been designed using Matlab2018a to effectively identify, quantify and classify drusen, as manual processing is intense for large number of images especially in eye awareness camps in rural regions, where the lack of ophthalmologists is apparent. Texture measurement features are analyzed to remove the false lesions and it classify the image and grade the level of damage as per the algorithm. The performance of this system is found to be effective and efficient in identification and grading. The results have been evaluated with the ophthalmologist's prediction. The application of machine learning technique generates promising results over publicly available dataset. The work can be extended in future to deal with real time data and deep learning technique.

5. REFERENCES

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