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Texture Feature Analysis in Fundus Image in Screening Diabetic Retinopathy

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Abstract

Diabetic retinopathy is an eye ailment caused due to the impairment of nerve fibres in retina, which leads to the risk of blindness.Early diagnosis and treatment help to considerably lower the impact of vision loss. Retinal digital image captured by the fundus camera plays a vital role in supporting cost effective method of analysis and for the subsequent treatment of diabetic retinopathy. The proposed system identifies and extracts the yellow bright lesion called exudateswhich is one of the clinical factorsassociated with diabetic retinopathy. The Haralick texture features which facilitates to accurately classify the data as presence of exudates or absence of exudates are extracted. The extent of the lesions present in the retina designates the severity of the disease. A screening simulation system has been designed to extract the exudates from the retinal image automatically.The proposed system was evaluated on publically available dataset and the performance was substantial.

Keywords—Exudates; Diabetic Retinopathy; K-Means clustering; Haralick features; Retinal Fundus Image;

I. Introduction

Retina is the sperical anatomic structure of innermost layer of the eyeball. Any damage to the retina results in vision impairment and its severity depends on the level of damage caused. Diabetic Retinopathy (DR) is a retinal vascular disease and it is associated with the deterioration of blood vessels in retina. It influences the vision of the person and may perhapslead to irreversible blindness if the pattern persists without treatment.The individual may not observe any wide variations in his perception up until the disease progresses.Besides blindness, it also results in multiple deformations in the body. Thisretinal ailmentdistresses the personswho have a long-timediabetes mellitus[1]. The psychosomatic disorder is due to either inadequate insulin secretion or absorption of insulin.The very first inflammatory signs that can be ascertained in the case of DR employing fundus examination are micro aneurysms.Micro aneurysms lead the blood vessels to seepage in retina.They appear as relatively small swells of blood on the retina which resembles red dots.Lipids and liquids spill from the blood vessels and form lesions as the disease progresses.The lesions are bright and dark and they are the pathological symptoms of DR. Bright lesions called as hard exudates are caused due to the leakage of lipid and proteins which are bright yellow of different size and shape [2]. Macula and fovea are accountable for the central vision and if exudates are developed at these locations it will worsen or impair the central vision of the patient [1]. The sensitive blood vessels in the retina will burst when the blood sugar level rises, causing haemorrhage and exudating lesions to occur on the surface of the retina[3].Hard exudates are the predominate and influential feature or clinically visible symptom for identification. Hence in automatic recognition of DR, identification of hard exudate is essential.

Any impairment or abnormality identified at the earlier stage is easy for treatment and reduce the risk of damage at higher extent. Any damage to the blood vessel system leads to vascular distortion and can be viewed by ophthamoloscope during clinical examination.DR is a preventable eye disease and early signs of it can be detected by ophthalmologist either by visual observation of retina or automated mode of inspection.The imaging techniques like OCT, fundus image etc are commonly used. Fundus imaging technique is a non-invasive and inexpensive method of capturing image of the

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pathological area.The visual inspection is tedious and time consuming in mass screening activities.Hence an automated tool is helpful in locating and identifying the level of damage.The digital fundus image captured by the digital fundus camera is shown in Fig.1 (a) shows a healthy image and 1(b) shows an image with exudates.

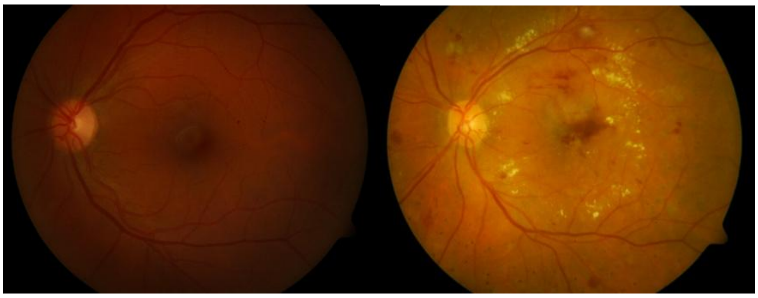

Fig. 1(a) Healthy Image Fig. 1(b) Image with exudates

Fig.2 shows the different severity levels of the disease, it depends on the prolonged ailment [4]. Severity levels depends upon the size and the number of exudates. Exudates are of hard and soft in type where hard of bright yellow and soft of whitish grey.

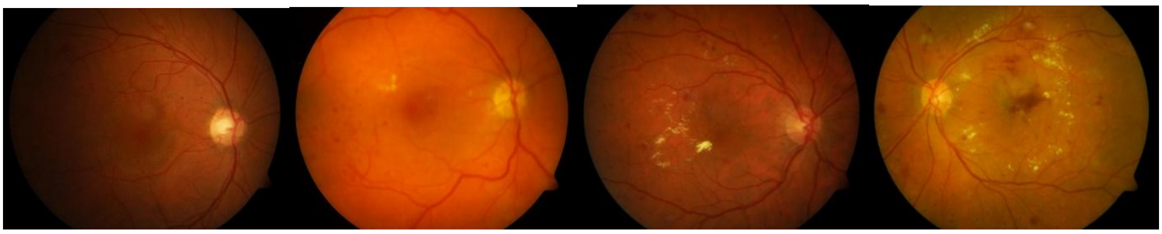

Fig.2 Colour fundus images with different severity levels

Manual analysis depends on the expertise of the person,which may lead to ambiguity in interpretation. This system is aimed to eliminate the inconsistency in diagnosis and also useful for the follow up process. So appropriate segmentation technique is needed. This work is focused to analyse the digital fundus photograph to support clinical diagnosis in extracting and classifying the DR levels using k-means clustering techniqueand is structured as follows. The methodology is discussed in section II which elaborates about the pre-processing, segmentation, feature extraction and classification phases, followed by Experimental results discussion in section III and conclusion in section IV.

II. Methodology

The digital fundus photograph has a definite role in clinical diagnosis in non-invasive manner because of its simple acquisition method and best image quality. In addition,it is a cost effective technique for healthcare treatment by retinal examination mode as it well suits for documentation and to analyse later. The methodology explains the feature extraction of exudates which is the anatomical landmark essential to identify DR. The detailed implementation phases of the proposed method are shown in Fig. 3. The input to the system is a 2D retinal fundus image captured by the fundus camera. The other phases include pre-processing, segmentation, optic disc removalfollowed by classification.

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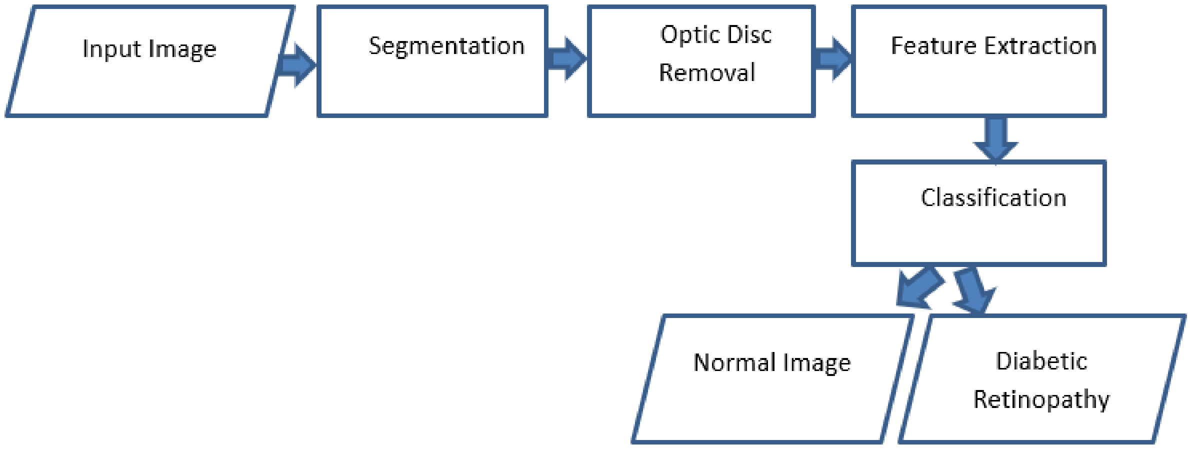

Fig.3. The work flow diagram of the proposed model

Pre-processing

Preprocessing plays a pivotel role in any image processing systems and the level of preprocessing depends on specific application and the algorithm applied. The image acquisition technique, the lighting conditions like non-uniform illumination, reduced contrast etc. affect the quality of the image. Gray level transformation, intensity adjustment, contrast enhancement are some of the preprocessing practices applied to enhance the efficiency of the system.The input retinal images are of size 700 x 605. If the images are processed as such the computational complexity will be high.To maximize the efficiency of the operation, the 2D fundus image is re-scaled to 256x256 and it is shown in Fig. 4.

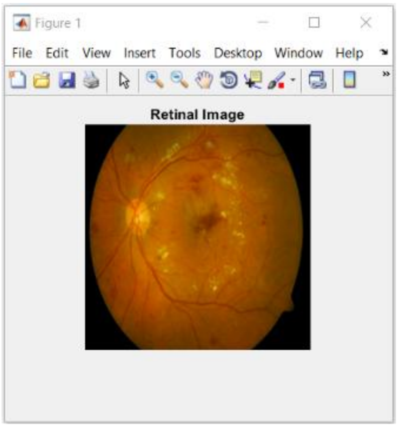

Fig. 4 Resized Image

Segmentation Technique Applied

Image segmentation is one of the significant step in image processing based applications and the accuracy of prediction results mainly rely on the efficiency of the segmentation process.Exudate is the clinical indicator and the feature identifier for DR. There are number of approaches existing in segmenting a portion of interest from the imageand K-means Clusteringis one such algorithm.

K-means Clustering Algorithm

K-means clustering is a popular unsupervised algorithm which is used in a variety of applications which categorize the data into groups based on certain similarities. Clustering group the similarities based on the characteristics of image based on light, shape and colourin order to extracts the features with maximum efficiency. The cluster results depend on the cluster values and hence the features grouped vary with varying number of cluster values.Euclidean distance method is applied to assign a

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pixel to a cluster such that the intra cluster distance is minimum so that well delineated boundaries can be obtained. K-means clustering aims to minimize the objective function (1)[5].

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

The segmented exudates extracted from the retinal image is shown in Fig. 5. As the anatomical structure of the retina called the optic disc is a bright portion similar to the intensity of the exudates, it is also extracted from the retinal image and it is visible in the Fig.5.

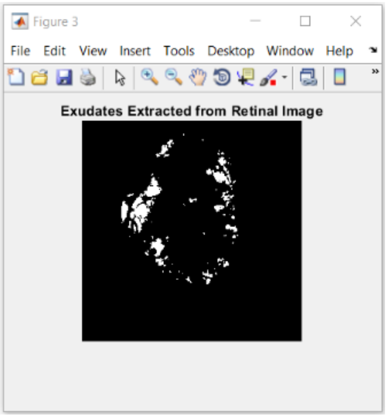

Fig. 5Exudates with Optic Disc

Optic Disc Localization and Elimination

Optic disc (OD) is a bright circular region on the retina where the blood vessels originate and if not eliminated earlier, and if extracted with the exudates, leads to misclassificationprocess. Hence an appropriate OD localisation and removal process is essential in order to extract the right features to classify the DR level.Circular Hough Transform which makes use of intensity and shape features well suits the need and is applied to locate high intensity values with low resolution level and a circular shape object of specified width as radius is localized and removed.Based on the Circular Hough Transformformula given in(2), the OD is located and eliminated from the segmented image[6]and Fig. 6 shows the process of localization.

$$(x-a)^2 + (y-b)^2 = r^2 \tag{2}$$

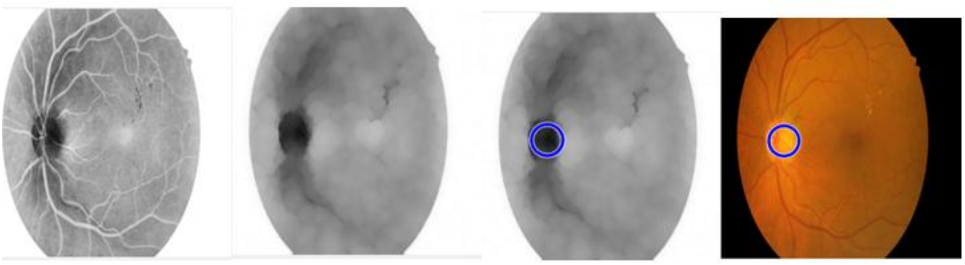

Fig. 6. OD Localization Process

The precision of the classifier was enhanced using the process of OD localization and removal. The segmented image after OD removal isshown in Fig. 7.

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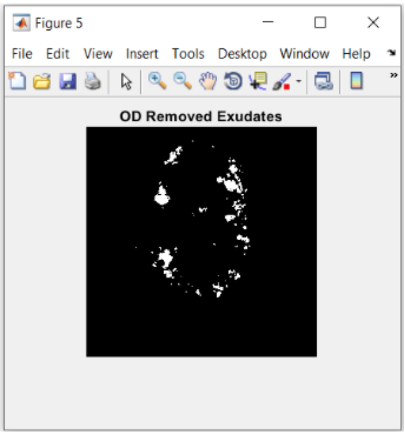

Fig. 7 Exudates

Feature Extraction by GLCM

Segmentation disintegrate the image into factorsto facilitate examination in a surpassing mode. Once the topic of attention is stratified the representation space can be transformed from image space to feature space. The texture feature is a method of measuring the relationship between pixels in the local region, representing changes in the gray levels of the image space.In estimating the disparity in intensity at the pixel of interest, texture function measurements use the contents of the Gray-level Co-occurrence Matrix(GLCM), a second order statistical method for texture analysis. The GLCM reflects the distance and angular spatial relationship of area of specific size over an image sub-region. Haralick texture features [7] like energy, entropy, contrast, correlation, homogeneity are calculated from the GLCM (3) and are tabulated in Table1.

$$c_{\Delta x,\Delta y}(i.j)=\sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & \text{if } I(p,q)=i \\ \text{and } I(p+\Delta x,q+\Delta y)=j \\ 0, \text{ otherwise}\end{cases} \tag{3}$$

Where i and j represents the intensity of the image, and p and q representthe spatial positions in inputimage. The classifcation accuracy of any diagnosing systems rely on the features extracted.The highest-ranking features were selected according to analysis of variance.

Table1.Haralick Texture Features

Features	**Description**
Area	Measures the maximum pixel count in the candidate area.
Contrast	Measures the spatial frequency of an image and is difference moment of GLCM.
Correlation	Measure of image linearity.
Energy	The sum of square of all pixel's intensities within candidate region.
Homogenity	Measures the distribution of elements in GLCM.
Mean	Measure of average value of pixel intensities in the region.
Standard Deviation	Measure of standard deviation of pixel intensities from its mean.
Entropy	Measure of randomness among candidate region pixels and neighboring pixels outside the region.
RMS	Measure of root mean square value of an image.
Variance	Measure of heterogeneity and is strongly correlated to first order

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	statistical variable.
Smoothness	Measure of relative smoothness of intensity in a region.
Kurtosis	Measure of peaks distribution related to the normal distribution.
Skewness	Third moment value of all pixels in square region including candidate region pixels and its neighbouring pixels.

Exudate Vs. Non-Exudate Classification

The measurement of extracted hard exudates and its classification is significant procedure in diagnosing the stages of diabetic retinopathy. GLCM features extracted are fed into the classifier.Though a greater number of features can be extracted from the image, to reduce the input size and to improve the accuracy the subset of relevant features are fed to the classifier. The extracted image is subjected to processing based on the support k-nearest neighbour (KNN) classifier.

KNN Algorithm

KNN is a machine learning technique-based classification algorithm, where K- denotes the number of nearest neighbours for the classifier to make its prediction. It classifies the objects in the feature space based on the nearest Euclidean distance[11]. KNN classifier is applied to classify the input patterns to the trained samples having minimum distance from the test feature vector [3]. It is a supervised classifier which discriminates different classes with different margin. If there is no pixel count, it indicates the absence of exudates and classified as class 0 for normal image and if there is a pixel count it indicates the presence of exudates and classified as class 1.

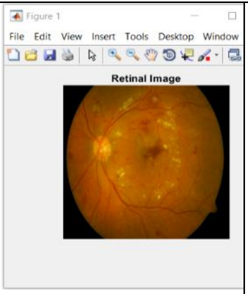
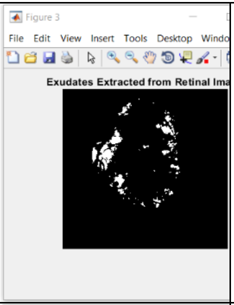
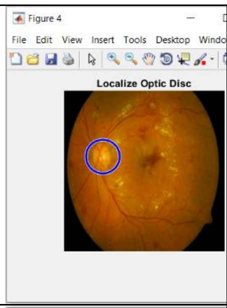
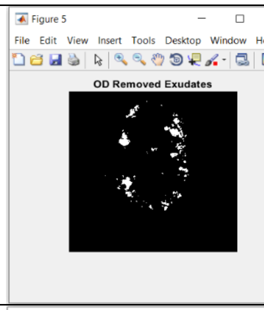
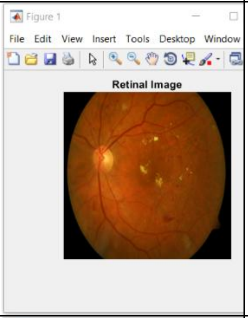
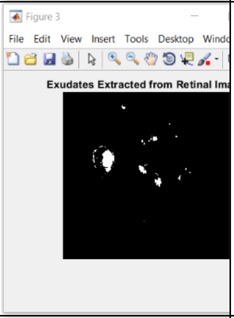
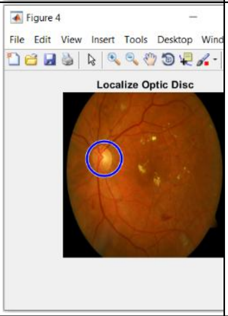
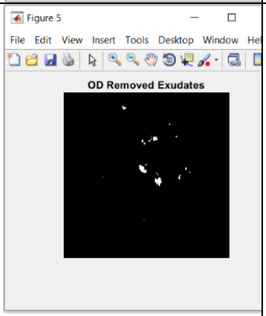
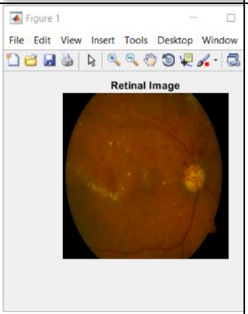
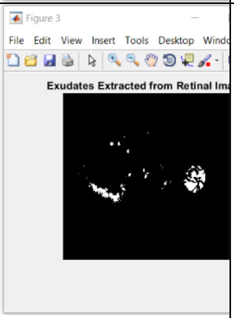
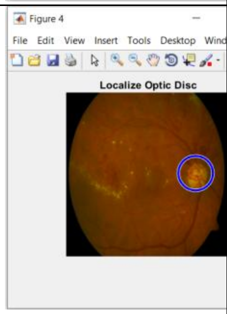
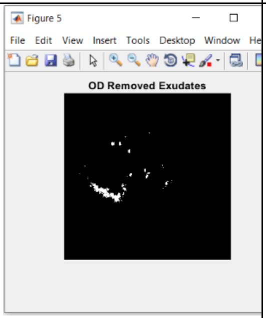
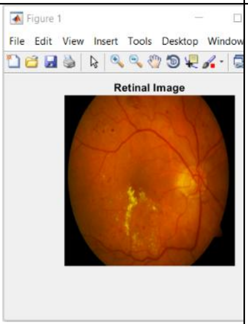
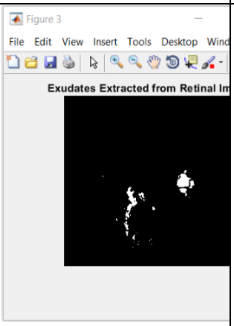
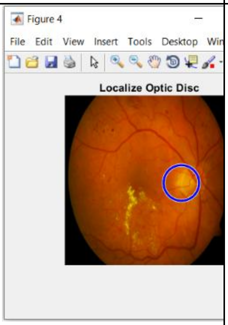
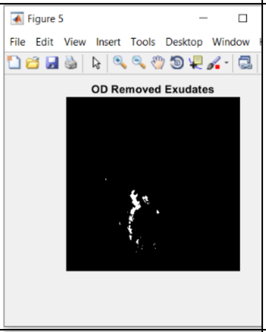
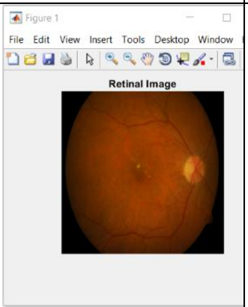
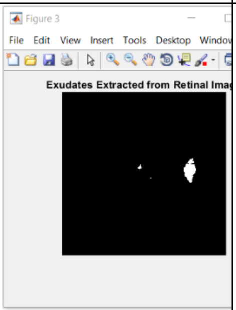
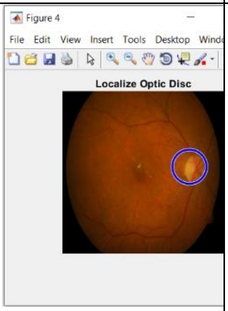
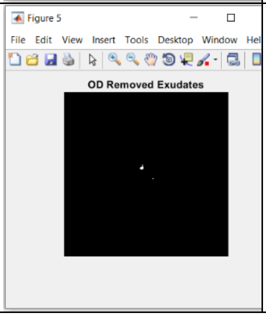
III. EXPERIMENTAL RESULTS

The developedsystemto detect diabetic retinopathy is centred on a sequence of parallel and sequential stagesand developed using MATLAB 2018a software of MathWorks [8]. For the assessment of the projected system the acquiescentlyaccessible dataset DIARETDB1 [9,10] a standard diabetic retinopathy database has been used, which is a public database for benchmarking diabetic retinopathy from retinal fundus image. It consists of a total of 89 colour fundus images of which 84 images are with atleast mild-proliferative signs of DR and 5 images are considered as normal as there is no sign of DR according to experts. Segmenting the exudates from the retinal image is a challenging task and the accuracy of the results relies on the performance of the segmentation algorithm. Few challenges exposed are the blurring effect of images during acquisition process, and shape and the intensities of the anatomical structure is analogous to exudates.

The performance evaluation of the method applied in segmenting the image have been discussed here.The algorithm was tested on images with exudates and also without exudates.Table2 shows the performance evaluation of the algorithm on the dataset.Classification has been carried out on the set of feature vectors that aids to categorizethe image based on the extracted features into two classes as class 0 and class 1.Class 0 represents the normal image in the sense that it is free from DR symptom and class 1 indicate the presence of exudates which indicates the DR.But the quantification of the exudates indicates the level of severity caused to the retina.

Table2.Classificationbased on GLCM features

Image	**Input Image**	**Segmented Image**	**OD Localization**	**OD Removed Image**	**Classification**

1	 Retinal Image	 Exudates Extracted from Retinal	 Localize Optic Disc	 OD Removed Exudates	1
2	 Retinal Image	 Exudates Extracted from Retinal	 Localize Optic Disc	 OD Removed Exudates	1
3	 Retinal Image	 Exudates Extracted from Retinal	 Localize Optic Disc	 OD Removed Exudates	1
4	 Retinal Image	 Exudates Extracted from Retinal	 Localize Optic Disc	 OD Removed Exudates	1
5	 Retinal Image	 Exudates Extracted from Retinal	 Localize Optic Disc	 OD Removed Exudates	1

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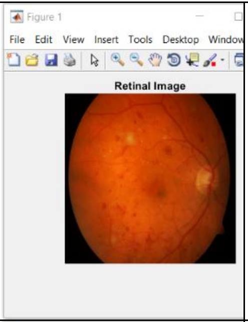
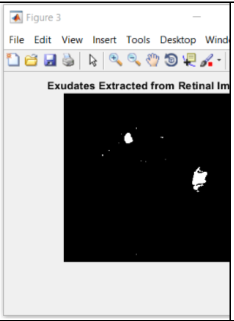
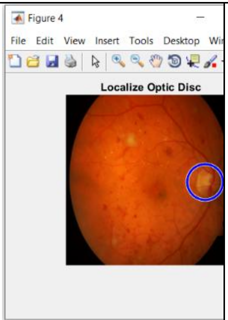
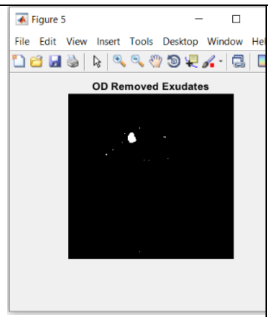
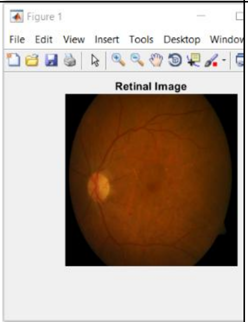
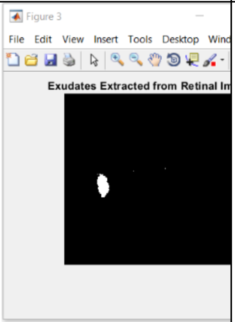
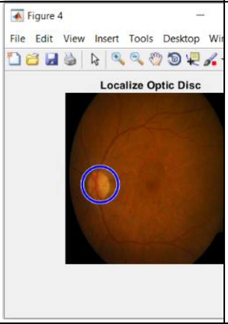
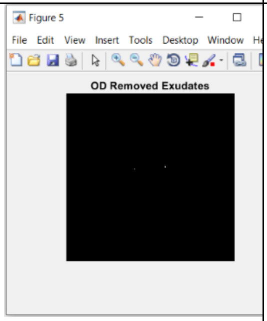
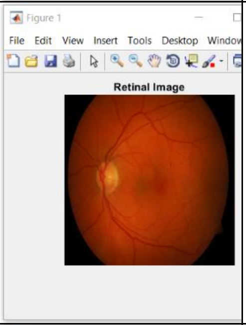
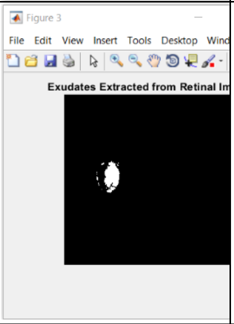
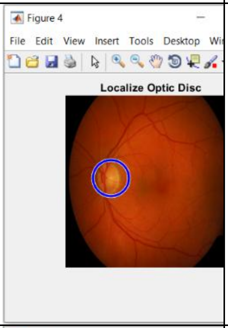
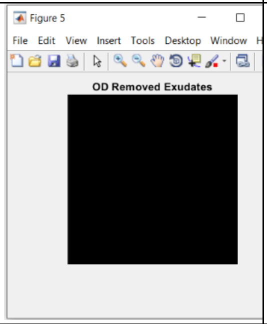
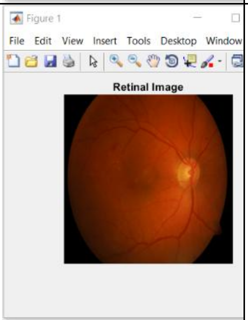
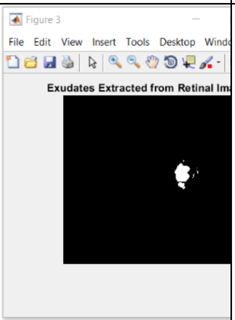
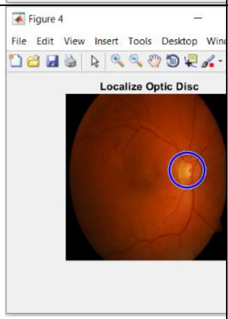
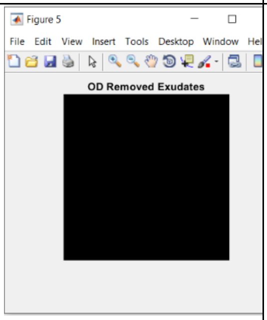
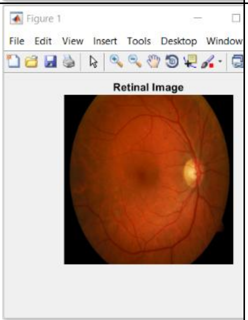
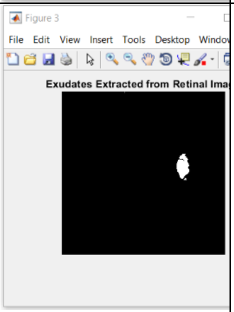
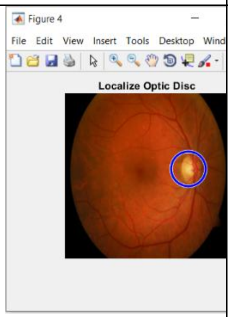
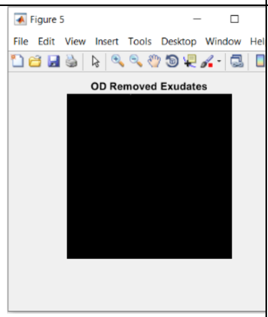
6					**1**
7					**1**
8					**0**
9					**0**
10					**0**

From the table it is apparent that the proposed technique is positively correlated. The method achieved better segmentation by k-meansclustering and classification by k-nearest neighbour using GLCM features with less computational time. The Haralick features extracted and their corresponding values for the above tested images are tabulated in Table3.

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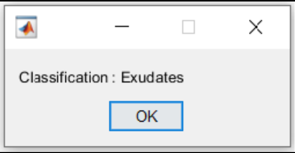
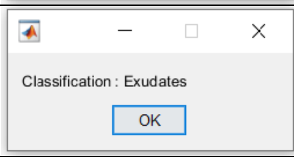
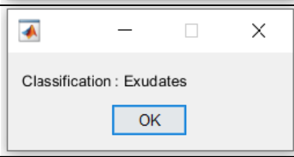
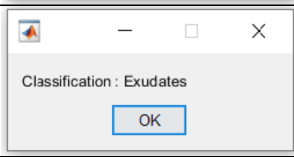
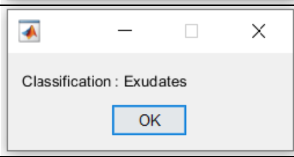
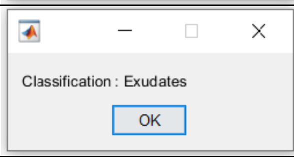
Table3.GLCM Features Extracted from Imges

Features	Image1	Image2	Image3	Image4	Image5	Image6	Image7
Contrast	0.0670	0.0735	0.0576	0.0740	0.339	0.607	0.0339
Correlation	0.9715	0.9579	0.9469	0.9690	0.9728	0.9739	0.9692
Energy	0.2869	0.3288	0.3259	0.2339	0.3280	0.2452	0.3441
Homogeneity	0.9668	0.9640	0.9712	0.9632	0.9831	0.9697	0.9830
Mean	63.0158	56.2586	44.0884	61.8161	45.8675	65.6055	41.4885
Standard Deviation	65.3060	57.5565	46.1697	69.6840	50.4553	73.1440	43.7313
Entropy	5.4516	6.4799	4.8216	5.3923	6.1384	6.8648	6.1602
RMS	9.8940	11.4103	9.5715	9.4359	10.5168	11.75	10.9410
Variance	637.3064	516.6338	281.8825	558.2368	368.9992	584.972	291.9751
Smoothness	1	1	1	1	1	1	1
Kurtosis	1.9597	2.4254	1.9589	2.2458	2.7178	2.4850	2.8234
Skewness	0.5310	0.7533	0.5558	0.7820	0.9177	0.9322	0.9029

Based on the existence of exudates in the extracted image the defected area is calculated, the image is classified and tabulated in Table4. The presence of a smaller number of exudates and the less affected area of the retinal image indicate the early stage and the risk of blindness can be treated earlier. On the other hand, if it is higher and the affected area is more, it indicates the advanced stage.

Table4.Classification using Defected Area

Image	Pixel Count	Defected Area	Classification	Inference
1	1420	9.9483	1	
2	303	4.5954	1	
3	565	6.2752	1	
4	469	5.7173	1	
5	28	1.3970	1	
6	173	3.4724	1	

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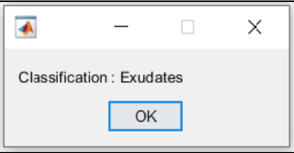
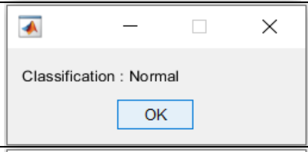
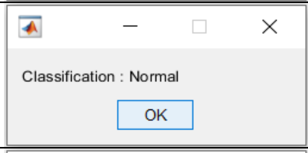
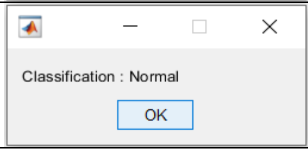
7	3	0.4573	1	
8	0	0	0	
9	0	0	0	
10	0	0	0	

Increase in number of exudates increase the risk of progression to visual impairment and hence early detection avoid permanent vision loss. It is better to do an annual eye examination, as the disease is silent in the beginning.

IV CONCLUSION

A screening system for the ocular disease, Diabetic Retinopathy has been simulated using MATLAB2018a software. The proposed work is carried out in two phases.Identification of hard exudates is of concern in diabetic retinopathy disorder. Hard Exudates that are existing in the DR afflicted fundus image have been detected using the k-means clustering algorithm developed in this work as the first phase followed by classification using KNN algorithm.The system can effectively assist in clinical diagnosis in mass eye screening programmes to identify, quantifyand classifythe image as normal or exudates. The system can aid the ophthalmologist to screen the disease rapidly as well as precisely. The system can be enhanced in the future by detecting the haemorrhages present in the retinal image with real data and deep learning techniques.

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