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Detection of Exudates in Digital Fundus Image for Diabetic Retinopathy

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ABSTRACT

Diabetic retinopathy (DR) is one of the leading causes of blindness in the world among patients suffering from diabetes. It is an ocular disease and progressive by nature. It is characterized by many pathologies, namely micro aneurysms, hard exudates, soft exudates, hemorrhages, etc, among them presence of exudates is the prominent sign of non-proliferative DR. Both hard and soft exudates play a vital role in grading DR into different stages. In this project we present an efficient method to identify and classify the exudates as hard and soft exudates..In proposed system we enhance the DFI images to find soft and hard exudates using k-means clustering technique. It is implemented to the MD algorithm which is given better histogram result in the existing system. the existing system has an investigation of three enhancement methods namely, Histogram Equalization(HE),Contrast Limited Adaptive Histogram Equalization(CLAHE) and Mahalanobis Distance (MD). The result shows that the MD is the best algorithm for the application of blood vessels image enhancement. Finally, the exudates are classified as hard and soft exudates based on their edge energy and threshold. The proposed method has yielded encouraging results.

Keywords: ***Diabetic retinopathy, Exudates, DFI, k-means clustering, blood vessels***

INTRODUCTION

Diabetic retinopathy is a complication of diabetes and a leading cause of blindness. It occurs when diabetes damages the tiny blood vessels inside the retina in the back of the eye.Diabetic retinopathy progresses from mild non proliferative abnormalities, characterized by increased vascular permeability-results in formation of micro aneurysms, to moderate and severe non-proliferative diabetic retinopathy (NPDR), characterized by vascularclosure-results in formations of exudates.

To proliferativediabetic retinopathy (PDR), characterized by the growth of new blood vessels on the retina [2]. According to ophthalmologists, both hard and soft exudates play vital role in grading the DR and tracking the progress of treatment. Hence, not only identifying the exudates but also classify them is important.

Exudates are normally detected and graded manually by ophthalmologists, which is timeconsuming and is susceptible to observer error. A computer aided detection of exudates could offer fast and precise diagnosis and then assist the ophthalmologist to treat the proposed for classifying the exudates as hard and soft exudates automatically.Several methods for the detection of exudates from fundus eye images have been reported in the literature.Digital fundus images (DFIs) are images obtained throughfundus photography, capturing the retina, optic disc, macularregions and the posterior surface of an eye.

These regions areused by ophthalmologists during diabetic eye screening anddiabetic retinopathy (DR) grading [1]. DR is an eye conditioncomplications faced by diabetic patient which may contributeto blindness. In few cases, pathological effects such as

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bloodvessel raptures may present in patient's retina. There are a fewcharacteristics in fundus images being used to detect the DRgrades such asexudates, micro aneurysms, hemorrhage and theblood vessels [2].

Regular diabetic eye screening is animportant step in detecting DR. Patients with sight-threateningDR might be identified during the screening process so thatnecessary treatment to prevent blindness could be given [3].The best method to obtain perfect contrast in analyzing thefundus surface is using the images obtained from FluoresceinAngiography (FA). However, FA is an invasive method since itis obtained by injecting a yellow dye (fluorescein) into thepatient's body to enhance the RV and choroid duringphotography and has its side effects which includephysiological problems such as Urticaria, severe seizure attack,myocardial infarction and anaphylactic attacks [4]. Accordingto [5], the DFI method does not need such invasive procedurebut the contrast is much lower than those of FA.

DFI is known to have very low contrast between the retinal vasculature and the background and it varies within the image which makes visualization and analysis of small retinal vasculatures difficult [6]. The illumination is very frequently uneven or non-uniform which causes the presence of local luminosity and contrast variability in the images that may lead to difficulty to a human observer to visualize and diagnose lesions in certain areas. This in turn can seriously affect the diagnostic process and its product [7]. Therefore, to guarantee visualization of the retinal blood vessels is at its best, image enhancement is required. Normalization method for DFIs is depending on the frequency domain and space [8].

Several methods for the detection of exudates from fundus eye images have been reported in the literature. FerouiAmel et al [3] used k-means clustering algorithm and mathematical morphology to detect hard exudates (HEs) in retinal images. They reported a sensitivity of 95.92%, predictive value of 92.28% and accuracy of 99.70%. Li et al. and O. Chutatape [4] proposed a method based on dividing the image into 64 sub-images followed by applyinga combination of region growing and edge detection to detect exudates. C. I. Sanchez, M. Garcia, et. Al., [5] proposed a method based on mixture models to separate exudates from background followed by edge detection technique to distinguish hard exudates from soft exudates Garcia et al., et al.,[6] proposed a combination of local and lobalthresholding to segment exudates followed by investigating three neural network classifiers to classify exudates.

METHODOLOGY

For the enhancement tests, 40 images obtained from the DRIVE database were used. Each image was captured using 8 bits per color plane at 768 by 584 pixels using the Canon CR5 non-mydriatic 3CCD camera with a 45 degree field of view (FOV) and it is circular in form with a diameter of approximately 540 pixels [11].

Each of the images in this database has been cropped around the FOV area and was givena mask image to delineate the FOV. As mentioned previously, the three enhancement methods considered are

1) Histogram Equalization (HE),
2) Mahalanobis Distance (MD) and
3)ContrastLimitedAdaptiveHistogramEqualization (CLAHE).

Step by step procedures for this experimental work are asshown in Figure 1. In RGB DFI, the green channel typically shows the best contrast between the background and vessels whereas the other two hannels produce more noise [12]. As such, the grayimages from the green channel are used since the retinal blood vessels in these images are more visible. Upon extraction, the images are processed using the three methods mentioned by the application of the respective algorithms.

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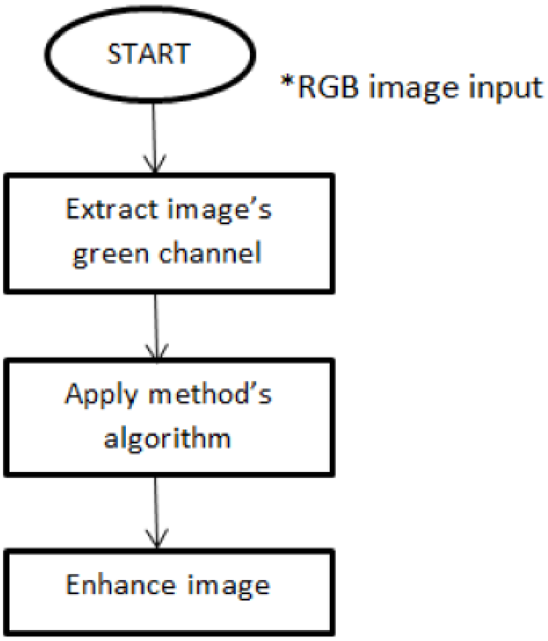

Fig.1 Step-by step procedures of digital fundus image enhancement

Mahalanobis Distance (MD)

Image enhancement using the MD method is carried out byidentifying the background image pixels and eliminating them,leaving only the foreground image. It is based on theassumption that in image nighborhoodN, the backgroundpixels has significantly different intensity value than those ofthe foreground pixels [13].

For each pixel(x.y)in the image, the mean $\mu_N(x,y)$and standard deviation$\sigma_{N}(x,y)$ of the statistical distribution ofintensities in N are estimated. The sample mean$\hat{\mu}N$is used asthe estimator for $\mu_N(x,y)$and the sample standarddeviation; $\sigma_N(x,y)$ the estimator for $\mu_N(x,y)$, If the intensity ofpixel (x,y)is close to the mean intensity in(x,y),it is consideredto belong to the background set β. As defined mathematicallyin Eq. 1, the expression implies that pixel (x,y)belongs to β ifthe stated condition is satisfied

$$d_M = \left| \frac{I(x,y) - \hat{\mu_N}}{\sigma \hat{N}} \right| < t$$

Histogram Equalization (HE)

HE is an operation that is based on histogram specification or modification to obtain new images. The objective of this contrast enhancement technique is to obtain a new enhanced image that has a uniform histogram that simply plots the frequency at which each gray-level happens from 0 (black) to 255 (white) [14]. Each histogram represents the frequency of occurrence of all gray-level in the image, which also tell us how the distribution of the values of individual pixel in an image.

$$(\gamma_{k)=n_{k/N}}$$

Whereγ_k, is the intensity level and $n_k$is the number of pixels in image with intensity. HE is to re-assign the intensity values of the pixels to create a uniform intensity distribution to reach the utmost value [15]. It is noted that HE can enhance thecontrast of an image but has the tendency to its brightness. This means that HE technique is a global operation so it does not preserve the brightness of image. [16]

Contrast Limited Adaptive Histogram Equalization CLAHE

Adaptive histogram equalization (AHE) transforms each pixel in a gray-scale image using a transformation function thatis derived from a neighborhood region. Simply, each pixel is transformed based on the histogram of a square surrounding the pixel. The transformation function derived from the histograms is similar to those of the ordinary HE, where the transformation function is proportional to the pixel values cumulative distribution function (CDF) in the neighborhood. AHE enables information with various intensities to be analyzed simultaneously [17]. This method is also automated and reproducible. However he results of AHE are image dependent and limited to images with low contrast variation only.

CLAHE uses RGB images directly and as such, the noise content of an image is not excessively enhanced in the resulting image, nevertheless visualization of the structures within the image is made by the sufficient contrast enhancement. This is achieved by limiting the

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contrast enhancement of AHE when the contrast amplification around a given pixel value is obtained according to the slope of the transformation function [18]. Thus, limiting the slope of the CDF is done by CLAHE when it limits the amplification by clipping the histogram at apredefined value before computing the CDF. The clip limit depends on the size of the neighborhood region and the normalization of the histogram. Images tend to appear more natural when processed with and can facilitate the comparison of different areas of the image [19]. However, the ability of an observer to detect the presence of some significant gray-scalecontrast may be hindered because of the reduced contrast enhancement of CLAHE [20].

Outputs of existing system:

As seen from the above figures, CLAHE and MD produce an approximately similar curve to the ideal Gaussian-shaped curve and also the resultant images by the two methods are more enhanced to facilitate blood vessel detection. The blood vessel using both algorithms are more visible compared to HE. histograms for CLAHE and MD have been normalized using the scales of 0 to 255 and 0 to 1, accordingly.

As HE and CLAHE use the neighborhood-based approach on the pixels, the background also contributes to the overall performance. This also means that any noise that is presence will be enhanced as well into atefacts which would later on effects further processing steps. Their neighborhood-based approach also means that the two algorithms are image dependent, implying that the results can be inconsistent even using the same set of database. On the contrary, the MD approach works on every pixel and only enhances the foreground pixels, producing a better contrast between the background and the blood vessels. It is observed that the optic disc is enhanced without tampering the blood vessel nearby. In addition, this selective enhancement of MD creates fewer artefacts for further processing when compared with HE and CLAHE.

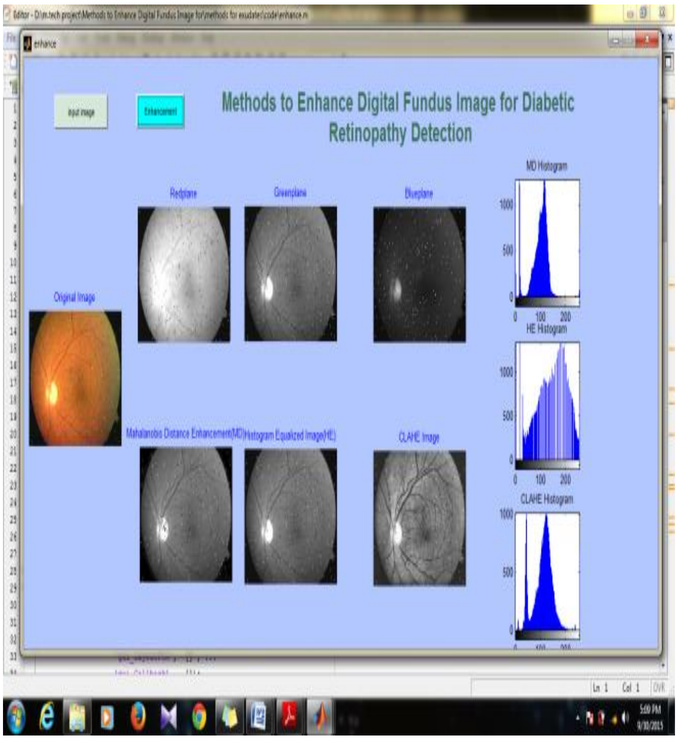

Fig-2: outputs of existing system for abnormal eye

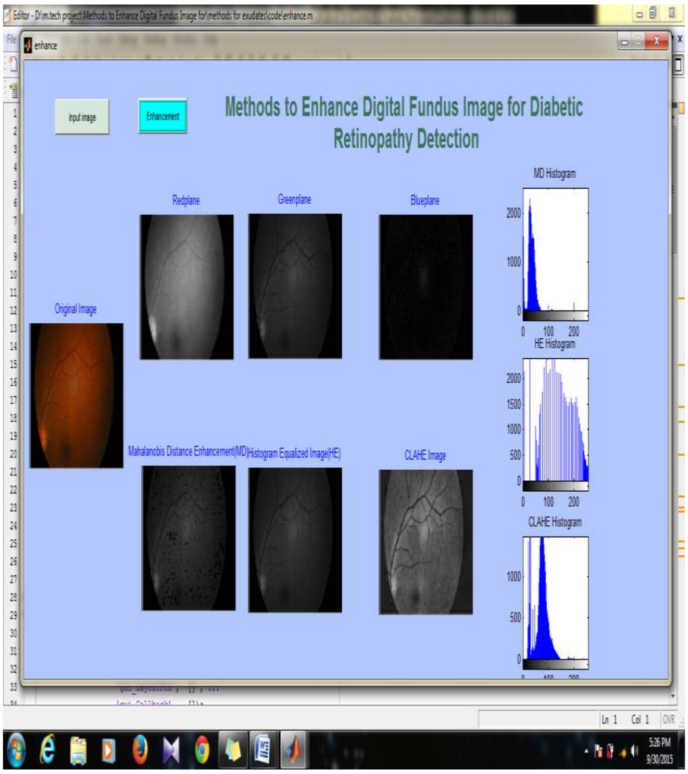

Fig-3: outputs of existing system for normal eye

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PROPOSEED SYSTEM:

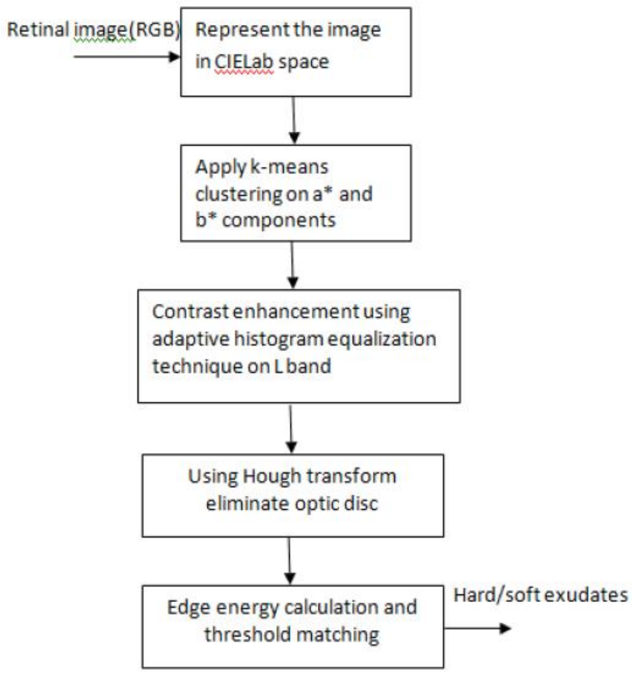
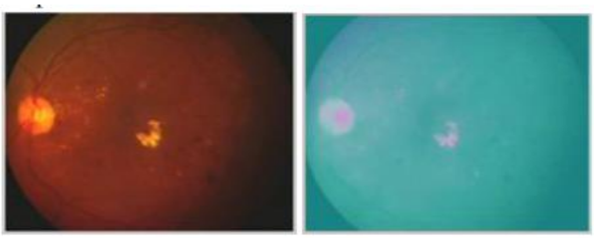


Fig-4: Block diagram for proposed system

Conversion from RGB color space to CIELAB colorspace

L*AB color space is a perceptual model of human visionand an absolute reference space for color [14]. Working inLAB is counterintuitive at best. All the brightnessinformation is in the L* channel while color is encoded inthe a* and b* channels. Preprocessing methods work moreefficiently and effectively in LAB space. For example, noiseremoval from the image can be achieved by applying filtersto either a* channel or b* channel without affecting theontrast which is stored in L*channel. Therefore, in theproposed method we choose LAB color space over RGBcolor space.



a *b*

Fig-6 (a)OriginalRGB Fundus image,(b)CIELAB Image

K-mean Clustering

Because of the computational simplicity of the k-means algorithm over other clustering algorithms we decided to use the k-mean clustering in the proposed work. The k-mean clustering algorithm is a special case of the generalized hard clustering algorithms. It is applied when point representatives are used and the squared Euclidean Distance is adopted to measure the dissimilarities between vectors xi and cluster representatives θj.

The k-means algorithm is given below.

Algorithm:

Step1: Choose arbitrary initial estimatesθj (0) for the θj's j=1,…,m.

Step2: Repeat

1. For i=1 to N
   Determine the closest representative, say θj for xi.Setb(i)=j;

End {for}

2. For j=1 to m
   Parameter updating: Determine θj as the mean of the vectors xi Ɛ X with b(i)=j.
   End {for}

Until no change in j's occurs between two successive iterations.

Fig-7:Clusterlabeled image

Contrast Enhancement

Contrast enhancement leads to enhancement ofseparability between exudates (foreground) and background. As CIELAB color space is been used in the proposed method, we know that L* channel contains all the information related to brightness. Adaptive histogram equalization technique is applied to this channel to facilitate enhancement of feature extraction.

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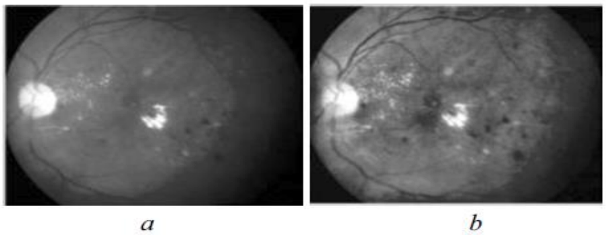

Fig-8(a)L channel image(b)contrast enchanced image

Blood vessel detection

To facilitate exudates extraction from the pre-processedimage, blood vessel network is detected and then eliminatedfrom the image using Morphological operations.Morphological operations can readily be used in medical mage analysis as it supports powerful tools to extractpathologies based on shape [17]. The morphologicaloperations used in the proposed work are given below.

1. Dilation: $X \oplus B = \{z | [(\hat{B})_z \cap X] \subseteq X\}$
2. Erosion: $X \ominus B = \{z | (B)_z \subseteq X\}$
3. Closing: $X \cdot B = (X \oplus B) \ominus B$

An important part of applying morphological operations is to decide on the shape and size of structuring element. In the proposed work, a ball shaped structuring element of size 8, was found to be optimal for eliminating the blood vessel network from the retinal images of local data base.

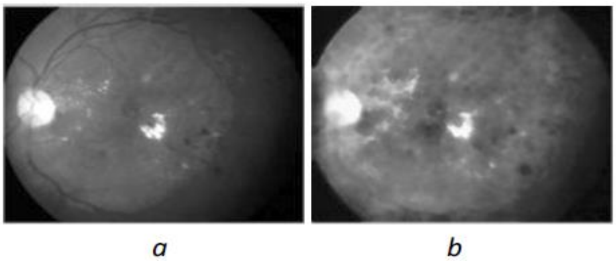

Fig-9:(a)L channel image (b)image after morphological operations

Hough Transform for circle

FerouiAmel et al[3], used mathematical morphologyand image reconstruction for removing the optic disk(OD). The technique empirically removes the OD but does not ensure that the correct part of the image is eliminated. Hence, we used Hough transform technique[16] to fit a circle to OD and ensure that the area located in the image is OD. The Circular Hough Transform (CHT) relies on equations for circles. The equation of the a circle is

$r^2=(x-a)^2+(y-b)^2$

Here a and b represent the coordinates for the center, and r is the radius of the circle. The parametric representation of this circle is

$$x = a + r * \cos(\theta)$$
$$y = b + r * \sin(\theta)$$

Circular Hough Transform Algorithm works is presented below.
Step1: Covert color retinal image into grayscale
Step2: Create a 3D Hough array (accumulator) with thefirst two dimensions representing the coordinates of the circle origin and the third dimensionrepresents the radii.
Step3: Perform edge detection using the Canny edgedetector.For each edge pixel, increment the correspondingelements in the Hough array.
Step4: Collect candidate circles, and then delete similarcircles.
Step5: Draw circles around the object.
In the proposed work, to assign the values for a and b,we first extract the portion of image that contain the opticdisk. This is achieved by performing optic disk localizationusing correlation coefficient. Then, the size of the ubimageis assigned to a and b and radius is fixed to rangebetween 45 to 55 pixels[15].

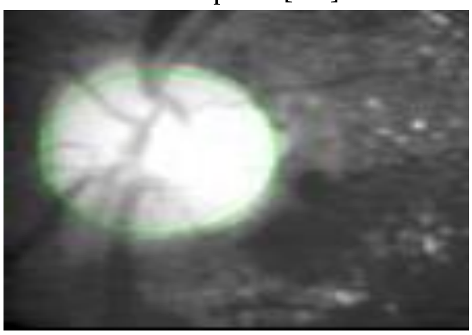

Figure 10. Optic disk marked using Hough Transform for circle

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Classifying Hard and Soft Exudates

The final step is to classify the exudates as hard and soft based on the threshold value and edge energy. Edge energy calculation is required to extract the exudates with sharp edges which are a characteristic feature of hard exudates. FerouiAmel et al [3], used Kirsch operator and green channel of RGB image to determine the edge energy.

Kirsch operator requires more computational time and the results are not better than canny operator. Hence, we preferred canny operator over Kirsch operator for edge energy detection. The hard exudates are extracted by combining this edge energy and a threshold value. To extract the soft exudates subtract the hard exudates image from the image that contains both types of exudates.

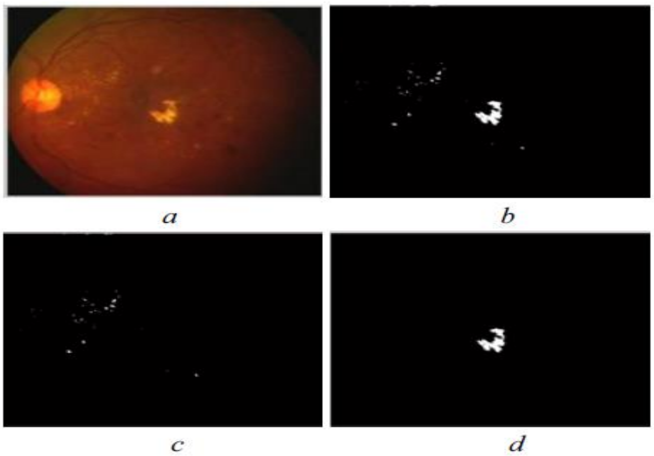

Fig-11: a. Orignal RGB image b. binary image with Exudates c. Binary image with only HE d. Binary image with only CWS

EXPERIMENTAL RESULTS

All the images have a full visible optic disk. Forthese images, using Hough transform technique, OD hasbeen eliminated with an accuracy of 100%. However, themethod fails for the images that have only a portion of opticdisk . The morphological operations for removingthe blood vessel network have yielded 100% results. Lastly,the exudates have been classified as hard and soft exudatessuccessfully based on edge energy and threshold value.

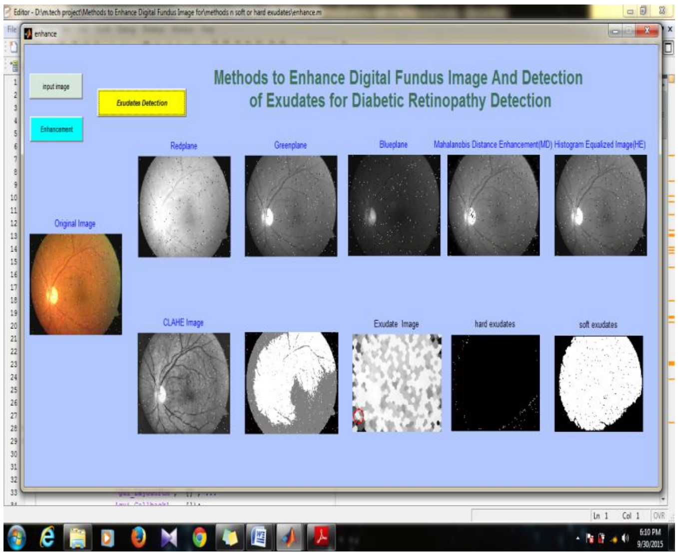

Fig-12:output for proposed system(abnormal eye)

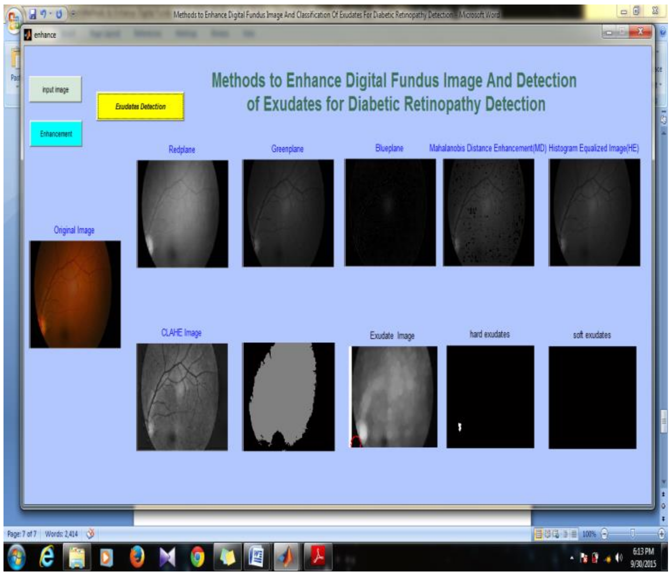

Fig-13:output for proposed system(normal eye)

CONCLUSON

Automatic detection and classification of exudates using k-means clustering algorithm has been presented in this project. The proposed method has yielded encouraging result. The proposed method has successfully classified the exudates as hard and soft exudates. Such classification helps the ophthalmologists in diagnosing the retinal diseases. Grading is possible by opthalmologists which is time saving and is susceptible to error free.

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