# DETECTION OF EXUDATES AND FEATURE EXTRACTION OF RETINAL IMAGES USING FUZZY CLUSTERING METHOD

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**Abstract:** Diabetic retinopathy (DR) is the micro vascular changes that cause detectable changes in the optic disc. This paper aims at the detection of retinal exudates and other features such as blood vessels and optic disc from fundus image. The two methods are implemented for the detection of exudates they are morphological method and FCM clustering method. Contrast limited adaptive histogram equalization (CLACHE) is used to extract the green component in the image. In blood vessel extraction, blood vessels are extracted by top hat transformation followed by connected component analysis. The optic disc centre is found using Circular Hough Transform (CHT) and propagation through radii method is employed and the entire optic disc region is blackened and removed. Exudates detection is the important characteristics of diabetic retinopathy and its varies depends upon the severity of the DR. The FCM method used to detect exudates. The overall sensitivity, specificity and accuracy are calculated and 98% accuracy obtained

**Keywords:** Retinopathy, Exudates, Optic disc, Blood vessels, Hough transform, histogram.

## INTRODUCTION

Diabetic Retinopathy (DR) is a lingering disease which eventually leads to blindness. Diabetic Retinopathy is damage the retina caused by diabetics mellitus. Continuous screening is necessary to prevent blindness. During the screening colour images are obtained by fundus camera and are required for manual analysis and diagnose the diabetic retinopathy. Sometimes fundus images are not clear to see because of abnormality of eyes, non-illumination and noise in a fundus image. It is suitable for automatic screening system. In an automatic system the normal features like optic disc, blood vessel and exudates in the retinal images are automatically detected. Depending upon the stages of the disease the effect of diabetic retinopathy on vision varies. There are two types of retinopathy non-proliferative diabetic retinopathy and proliferative diabetic retinopathy. Non-proliferative diabetic retinopathy consists of cotton-wool spots, intraregional haemorrhages, hard exudates, micro aneurysms. Proliferative diabetic retinopathy causes visual impairment where there may be sudden haemorrhage from the unstable new vessels resulting in total or partial visual loss or from preretinal haemorrhages.

Many techniques have been previously employed in this work. In the work of Sophrak et.al the method uses feature selection and exudates classification using naive Bayes and support vector machine (SVM) classifiers [3]. Morphological methods using watershed transformation has been studied by Thomas Walter in order to localize the optic disc [11]. The counters of the optic disc were detected using Watershed transformation. S.Kavita et.al proposed a method which uses an automatic detection of diabetic retinopathy exudates in color fundus retinal images. Candidate exudates employing a multi-scale morphological process were identified by Fleming A.D. et al. [7]. Based on local properties, the probability of a candidate being a member of classes' exudates, drusen or background was estimated. Ahmed Wasif Reza et al. have presented an approach to automatically segment the Optic Disc and exudates [1]. Akara Sopharak et. al have proposed an automatic method to detect exudates from low-contrast digital images of retinopathy patients with non-dilated pupils by a Fuzzy C-Means (FCM) clustering [3]. An effective framework to automatically segment hard exudates (HEs) in fundus images was proposed by Guoliang et.al based on a coarse to fine strategy, as a coarse result is obtained frost allowed of some negative samples, then eliminate the negative samples step by step . A new method for the detection of exudates using adaptive thresholding and classification is proposed by Hussain et.al in which the retinal structures are used to remove artefacts from exudates detection results [8]. The location of the optic disc is an important issue in retinal image analysis as it is a significant landmark feature, and its diameter is usually used as a reference length for measuring distances and sizes. A deformable contour model (or Snake) with gradient vector flow (GVF) (Viranee et.al, 2009) can be used as an external force for optic disc detection using segmentation [12]. S. Sekhar et.al used the morphological characters of an image. Morphology is used to locate the brightest region within the image and a Hough Transform is used to detect circular features within the gradient image of the resulting region of interest [10]. A geometrical parametric model was proposed by Foracchia et.al to describe the general direction of retinal vessels at any given position in the image. In this two of the model parameters are the coordinates of the OD centre [9]. Blood vessel segmentation is the basic foundation while developing retinal screening systems, since vessels serve as one of the main retinal landmark features. Osareh et.al proposed an automated method for identification of blood vessels in color images of the retina [5]. Adam Hoover et al used a novel algorithm called fuzzy convergence to determine the origination of the blood vessel network [2]. This method used the convergence of the blood vessel network as the primary feature for detection, in conjunction with the brightness of the nerve as a secondary feature .Di Lou et al proposed an automated blood vessel detection scheme based on adaptive contrast enhancement, feature extraction, and tracing [6]. Feature extraction of small blood vessels is performed by using the standard deviation of Gabor filter responses. Tracing of vessels is done via forward detection, bifurcation identification, and backward verification. In the work done by A.Kaupp et.al, a method was presented to segment a retinal image into arteries, veins, the optic disk, the macula, and background [4]. The method is based upon split-and-merge segmentation, followed by feature based classification. The features used for classification include region intensity and shape. The primary goal of the paper was vessel measurement; the nerve was identified only to prevent its inclusion in the measurement of vessels.

The blood vessel can be detected by wiener filter where the noises if present are eliminated [13]. Features like exudates are obtained by enhanced minimum distance discriminant classifier which uses NTSC based mapping [15].

This paper aim at detection of retinal image features such as retinal exudates, blood vessels and optic disc from the fundus image. The fuzzy clustering is a clustering algorithm where each point may have various degrees of membership. Fuzzy means clustering is used in the exudate detection. The main causes of exudates are proteins and lipids leaking from the blood into the retina via damaged blood vessels. This paper aims at detecting exudates using fuzzy means clustering. The detection of exudate consists of four modules. They are green plane extraction, blood vessel extraction optic disc detection and exudate detection. In green plane extraction only green component are extracted from RGB component. These green components are extracted from RGB component. These green components consist of all the features of the image compared to red and blue. Contrast limited adaptive histogram equalization (CLAHE) is used to extract the green component in the image. In blood vessel extraction, blood vessels are extracted by top hat transformation followed by connected component analysis. Diabetic retinopathy (DR) is the micro vascular changes that cause detectable changes in the optical disc. Optical disc detection is the only brightest part in the retinal images and next to it comes the exudates. The optic disc centre is found using Circular Hough Transform (CHT) and propagation through radii method is employed and the entire optic disc region is blackened and removed.

## METHODOLOGY

### Preprocessing

The image is captured by the high resolution fundus camera. The retinal imager is resized into 256x256 which is better for further processing. Then the retinal colour image is pre-processed .i.e. only green component are extracted since green image component are more clear than red and blue component.

After green plane filtering for contrast enhancement a contrast limited adaptive histogram equalization (CLAHE) is applied. This CLAHE equalization enhances the hidden features present in image function. This image has four features

i. Intensity image after CLAHE operation
ii. Standard deviation of $I_{CLAHE}$
iii. Saturation
iv. Approximate detection of edges of the exudates regions

The edge features are obtained using the gradient magnitude of the original image by sober filter function.

### Blood vessel detection

In retinal colour image the blood vessel has a network like structure. The blood vessels originate from optic disc and spread over the different branches. Blood vessels appear as a dark shade. To decreasing correlate information the retinal colour image is converted into gray scale. The fundus image is first pre-processed to standardize its size to 576x720. The intensity of the green channel is then inversed before adaptive histogram equalization is applied. The optic disc appears as a black patch after adaptive histogram equalisation. To detect the blood vessel morphological operation is used with top hat transformation. The morphological top hat transformation gives two types of information one is blood vessels (high contrast) and other is totally dark region. The image is converted into binary image. To reduce the noise image is connected to component analysis and obtain the arbitrary shape of blood vessels

The algorithm steps are as follows

i. Resize the input RGB fundus image to 576×720.
ii. Take green channel image and do intensity inversion.
iii. Perform adaptive histogram equalization.
iv. Do morphological opening and remove optic disc by subtracting the result of step (iv) from step (iii).
v. Convert to binary the result of step (iv).
vi. Remove all the small connected components to avoid noise.
vii. Do step (iii) 3 times and repeat step (v) and (vi) to obtain blood vessels with reduced noise.

viii. Take the gray scale image from step (i) and adjust the brightness.
ix. Obtain the optic disc location by searching for the brightest pixels and create mask of the optic disc.
x. Combine the blood vessel image from step (vii) with the mask from step (ix).
xi. Create the circular border and remove the circular border from the gray scale image of step (viii).
xii. Perform logical AND operation with the images of step viii and ix to further remove the noise.
xiii. Combine the results of step xii and xi to get the final blood vessels. The result of blood vessel extraction is shown in Figure .1

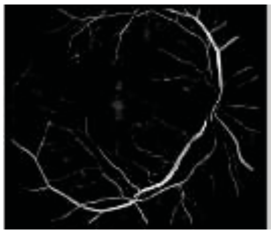

**Fig. 1** Blood Vessel Extraction

**Optic disc detection**

The optic disc (OD) is the brightest feature in the retinal Image. From the retinal colour image the blue plane extracted. The circle is marked by applying the circular hough transform radius and centre of the circle is found. After rounding off the detected circle centres initialise the disc filter with specified radius. From the centre of the optic disc get all the positions of the ellipse. Ellipse width and height is calculated by radius of the circle. In an array, store all the ellipse points using radius of the circle ellipse is cropped. Cropped ellipse is correlated with the initialised disc .Hough Transform can be extended to detect other shapes, such as, circles or ellipses. Unlike the linear HT, the Circular Hough Transform (CHT) relies on equations for circles. The equation of the a circle is,

$$r^2 = (x - a)^2 + (y - b)\text{................} \quad (1)$$

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

$$x = a + r*\cos\text{............................} \quad (.2)$$

$$y = b + r*\sin\text{............................} \quad (3)$$

A CHT relies on 3 parameters: r, a and b. r is the radius of the circle while a and b is the centre in the x and y direction. The parameter space of a circle belongs to $R^{3.}$ This requires a larger computation time and memory for storage, increasing the complexity of extracting information from the image. The points lying on the circle are represented by a single point in the three dimensional (3D) parameter space (a,b,c) with an accumulator of the form A(a,b,c), which is also known as the Hough space. Here, (a, b) is the centre and c is the radius of the circle. The procedure to detect circles in an image involves the following steps:

1. Obtain a binary edge map of the image.
2. Set values for a and b.
3. Solve for the value of c that satisfies the equation for circle
4. Increment the accumulator that corresponds to (a,b,c). Propagation through radii is employed is employed to find the exact edge of optic disc [14].

**Optic disc elimination**

The intensity of optic disc is sometimes similar to exudate. To avoid false detection of exudates, the false detection of exudates, the optic disc is removed for blackened before exudate detection. The optic disc elimination is shown in figure 2.

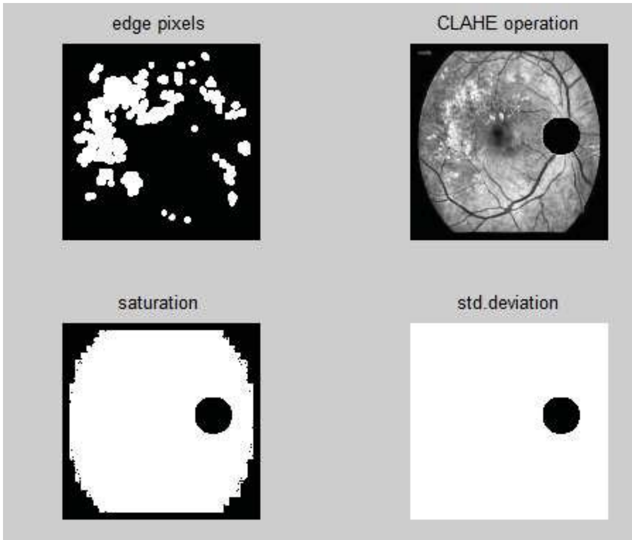


**Fig. 2** Selected features for clustering

**Exudate detection**

In color image segmentation the FCM clustering method is used. FCM clustering method classifies the pixels with various degrees of membership. Initially assumptions are made for the cluster centre which is intended to mark the mean location of each cluster. Initial assumption of the cluster normally incorrect, then FCM assigns a membership value for each point. By updating the membership grade using fuzzy which in turn updating the cluster centre. The edge pixels are determined, after CLAHE operation the standard deviation of the image these features are used for FCM clustering. Depending upon the cluster size the FCM clustering is performed with the input data as the array A cluster size of 8 is selected and the FCM clustering is performed with the input data as the array created and with the cluster size 8. The features selected for clustering are shown in figure 3. The output of the clustering operation involves the centre of each cluster matrix created, the final fuzzy partition matrix and values of the object function. The clustering is done to get a set of 8 classes or clusters. The pixels of each class are obtained by finding the maximum pixels in the final fuzzy partition matrix. Each class of pixels is assigned a specific value as the index number. Thus the pixels belonging to each cluster is assigned with an index .The array thus obtained is then reshaped to images, such that each image represents each cluster and 8 new images are obtained. A mask image having the size of the new image, with all zeros is created. The clusters selected are then combined with the mask created to generate the exudates regions. In order to eliminate further optic disc pixels, the image obtained is subjected to logical AND operation with the inverted optic disc image resulting in image with exudates only. Clustering of data is a method by which large sets of data are grouped into clusters of smaller sets of similar data. It is a mathematical tool that attempts discover certain structures or patterns in a data set, where the objects inside each cluster show a certain degree of similarity Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree It is based on minimization of the following objective function.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m \|x_i - c_j\|^2 \quad 1 \le m < \infty \quad ..... (4)$$

where $m$ is any real number greater than 1, $u_{ij}$ is the degree of membership of $x_i$ in the cluster $j$, $x_i$ is the $i$th of d-dimensional measured data, $c_j$ is the d-dimension centre of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center.Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership $u_{ij}$ and the cluster centres $c_j$ by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad , \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad .... (5)$$

This iteration will stop when $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$, where $\varepsilon$ is a termination criterion between 0 and 1, whereas $k$ is the iteration steps. This procedure converges to a local minimum or a saddle point of $J_m$. The algorithm is composed of the following steps:

1. *Initialize U=[$u_{ij}$] matrix, $U^{(0)}$*

2. *At k-step: calculate the centers vectors $C^{(k)}$=[$c_j$] with $U^{(k)}$*

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad ............ (6)$$

3. *Update $U^{(k)}$, $U^{(k+1)}$*

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad ........ (7)$$

4. *If || $U^{(k+1)}$ - $U^{(k)}$||< $\varepsilon$ then STOP; otherwise return to step 2.*

The computation of the updated membership function is the condition for the minimization of the objective function. With fuzzy *c*-means, the centroid of a cluster is computed as being the mean of all points, weighted by their degree of belonging to the cluster. The degree of being in a certain cluster is related to the inverse of the distance to the cluster. By iteratively updating the cluster centres and the membership grades for each data point, FCM iteratively moves the cluster centres to the "right" location within a data set. The performance depends on initial centroids. For a robust approach there are two ways which is described below.

1) Using an algorithm to determine all of the centroids. (For example: arithmetic means of all data points)

2) Run FCM several times each starting with different initial centroids.

The FCM clustering has been used for the segmentation of exudates and their identification and the number of cluster and the detected exudates are shown in figure 3,4 and 5 respectively

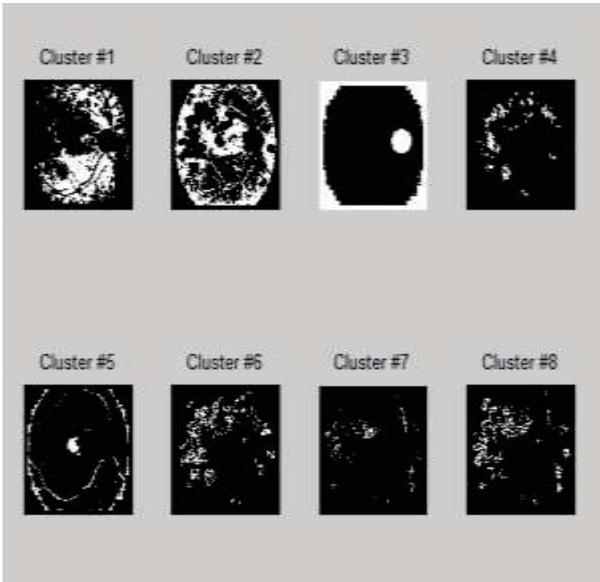


**Fig.3** Cluster images

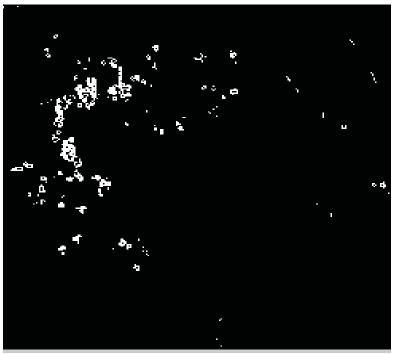

**Fig .4** Final exudates

**Fig.5** Exudates marked to color image

## IPERFORMANCE ANALYSIS

The performance of the method was evaluated quantitatively Sensitivity and specificity are chosen as the measurement of accuracy of the algorithms at the pixel level. This pixel based evaluation considers four values which are:

1) True positive (TP) – Number of exudates pixels correctly detected.
2) False positive (FP) – Number of non-exudates pixels which are detected wrongly as exudates pixels.
3) False negative (FN) – Number of exudates pixels that are not detected.
4) True negative (TN) – Number of non-exudates pixels that are correctly identified as non-exudates pixels.

Sensitivity, Specificity and Accuracy are computed from these values using the equations given below.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad \text{.......... (8)}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad \text{.......... (9)}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad \text{........ (10)}$$

The percentage rate of pixels affected are determined by using the formula

$$\%\ \text{of exudates pixels} = \frac{\text{Total no of exudates pixels}}{\text{Size of the image in x and y direction}} \times 100$$

**Performance measurement**

The performance analysis is done on a set of 10 images and the results showing the true positive, false positive, true negative and false negative is shown in table 1 True positive versus false positive is plotted in figure 6

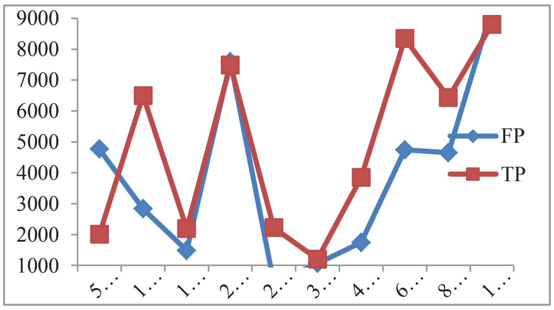


**Fig.6** True positive Vs. False positive

| Images | TP | FP | TN | FN | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| Image1 | 2006 | 4767 | 69403 | 773 | 82.18 | 93.57 | 92.8 |
| Image 2 | 6500 | 2832 | 72694 | 32 | 95.3 | 96.25 | 96.24 |
| Image 3 | 2190 | 1481 | 74476 | 40 | 98.2 | 98.05 | 98.07 |
| Image 4 | 7490 | 7597 | 67830 | 106 | 81.2 | 89.9 | 88.7 |
| Image 5 | 2222 | 439 | 71561 | 100 | 99.5 | 94.3 | 94.2 |
| Image 6 | 1200 | 1065 | 74991 | 360 | 96.9 | 98.5 | 98.6 |
| Image 7 | 3846 | 1739 | 35169 | 810 | 82.6 | 99.87 | 99.81 |
| Image 8 | 8343 | 4740 | 334259 | 675 | 92.51 | 99.64 | 99.60 |
| Image 9 | 6434 | 4648 | 342682 | 382 | 92.31 | 99.65 | 99.48 |
| Image10 | 8799 | 9309 | 32657 | 936 | 90.38 | 99.30 | 99.24 |

**Table 1**: Exudates Detection Results

**Percentage of exudate pixels**

The percentage of exudates pixels in each of the images is shown below in table 2.

| Image No. | Percentage of Exudates pixels (%) |
|---|---|
| IMAGE 1 | 15.40 |
| IMAGE 2 | 12.74 |
| IMAGE 3 | 9.83 |
| IMAGE 4 | 5.23 |
| IMAGE 5 | 8.52 |
| IMAGE 6 | 19.39 |
| IMAGE 7 | 13.65 |
| IMAGE 8 | 18.45 |
| IMAGE 9 | 23.9 |
| IMAGE 10 | 10.12 |

**Table 2**: Percentage of pixels

## CONCLUSION

Detection of exudates and the features such as blood vessel and optic disc are implemented using Morphological method and Fuzzy-C-Means clustering technique. The number of pixels affected with exudates is found using morphological method. Blood vessels are also extracted using this method and the optic disc is eliminated to detect the exudates pixels. The optic disc pixels are obtained by taking the brightest pixels and a mask is created to eliminate them The optic disc is detected using Circular Hough Transform and then blackened. Blood vessels are detected with the help of morphological operations followed by connected component analysis. Finally the exudates are determined using Fuzzy C-Means clustering and 8 clusters of images are formed and the exudates clusters are selected and isolated, to determine the final exudates images. Both of the above said methods are implemented on a set of 10 images. The overall sensitivity, specificity and accuracy obtained are as follows 91.108%, 97.95%, 97.67%. As an extension of the work done, soft exudates (cotton wool spots) can be detected and hard exudates and soft exudates are differentiated. The main problem faced in this work is the correct localization of optic disc, in certain images with high illumination. In such images with high amount of reflectivity some exudates pixels are wrongly identified and removed as optic disc pixels. In this work the circular feature and the brightness are the 2. The clustering method can also be improved by considering more exudates features and the number of clusters selected may be reduced to obtain better results.

## ACKNOWLEDGEMENT

The authors acknowledge Gayathri Dhas for her support during this work.

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