

# Computerized Exudate Detection in Fundus Images Using Statistical Feature based Fuzzy C-mean Clustering

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**Abstract:** Diabetic retinopathy(DR) is considered as the root cause of vision loss for diabetic patients .One of the greatest concern and immediate challenges to the current health care is the severe progression of diabetes. Diabetic retinopathy is an eye disease and appearance of hard exudates is one of its earliest signs. The accuracy of the automated disease identification techniques should be high .Besides being accurate; the techniques need to possess a quick convergence rate enabling them to be suitable for real-time applications. In order to lessen the cost of these screenings, modern image processing techniques are used to voluntarily detect the existence of abnormalities in the retinal images acquired during the screenings. Hard and Soft exudates (Cotton wool spots) are a major indicator of diabetic retinopathy that can possibly be quantified automatically. Automatic computerized screening should facilitate screening process, reduce inspection time and increase accuracy. In this paper an automated method to detect exudates from low-contrast digital images of retinopathy patients with non-dilated pupils using feature based Fuzzy C-Means (FCM) clustering technique with a combination of morphology techniques and pre-processing to improve the robustness of blood vessel and optic disk detection. Pre-processing involve colour, normalization ,contrast enhancement and brightness preserving dynamic fuzzy histogram equalization whereas addressable features are converted colour spaces, intensity, standard deviation, edge strength, size, colour, texture and entropy. The detection accuracy is calculated with comparison to expert ophthalmologists' hand-drawn ground-truths and the results are comparatively analysed.

**Keywords:** Cotton wool spots, Diabetic Retinopathy (DR), Exudates, Feature, Fuzzy C-Means (FCM), Fundus image, Soft and hard exudates, Real time applications.

## I. INTRODUCTION

Diabetic retinopathy is a serious complication of diabetes mellitus and a major cause of blindness worldwide. Only in Finland there are 30 000 people diagnosed to the type 1 maturity onset diabetes in the young, and 200 000 people diagnosed to the type 2 latent autoimmune diabetes in adults. In addition, the current estimate predicts that there are 200 000 undiagnosed patients [1]. Early detection and timely treatment of diabetic retinopathy can halt or reverse the progression of the disease and prevent blindness. In Finland, only 10% of the total health care costs of diabetes arise from 70% of early diagnosed patients while the remaining 90% arise from the patients having poor treatment (30%) [2]. Fundus imaging has significant role in diabetic monitoring since presence of retinal abnormalities are

common. Diabetic retinopathy is asymptomatic. It is advised to all diabetic patients to have their retina in both eyes examined at least once every year even if they have no visual symptom. A fundus camera is used to capture images of the retina that are then read and graded by doctors. Given the number of diabetic patients screened yearly, the number of retinal images generated is large and the majority of them are normal. Automated detection of abnormal retinal images can reduce the workload of doctors reading the images and improve the follow-up management of diabetic patients.

Exudate is a primary sign of diabetic retinopathy (DR) which is a common retinal complication associated with diabetes and the most main cause of blindness. Singer DE et al. presented that hard exudates (HEs) have been found to be the most specific markers for the presence of retinal edema, the major cause of visual loss in non-proliferative

forms of DR and one of the most prevalent lesions during early stages of DR. Automatic segmentation of hard exudates (HEs) in fundus images is clinically significant for the prevention of vision loss with an early screening process. With this motivation in mind, in this paper, we propose an efficient and robust framework for automatic HEs segmentation.

The retinal images are classified as exudates and non-exudates which are further classified as Hard exudates and Soft exudates. Hard exudates apparently yellow with distinct margins and varying size. Micro vascular occlusion in DR results in infarction of the retinal nerve fibers and a white fluffy opaque lesion is formed which is known as cotton wool spots. Cotton wool spots are also known as Soft exudates or micro-infarctions [3]. The bright circular region spreading the blood vessels is called the optic disc.

Statistical features can be extracted from the images using disease based features. Color Fundus images are employed by ophthalmologists most of times for the detection and diagnosis of Diabetic retinopathy[4]. Figure 1(a) depicts a normal retinal image. 1(b) shows abnormal diabetic retinal image and 1(c) shows different feature of retinal image.

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

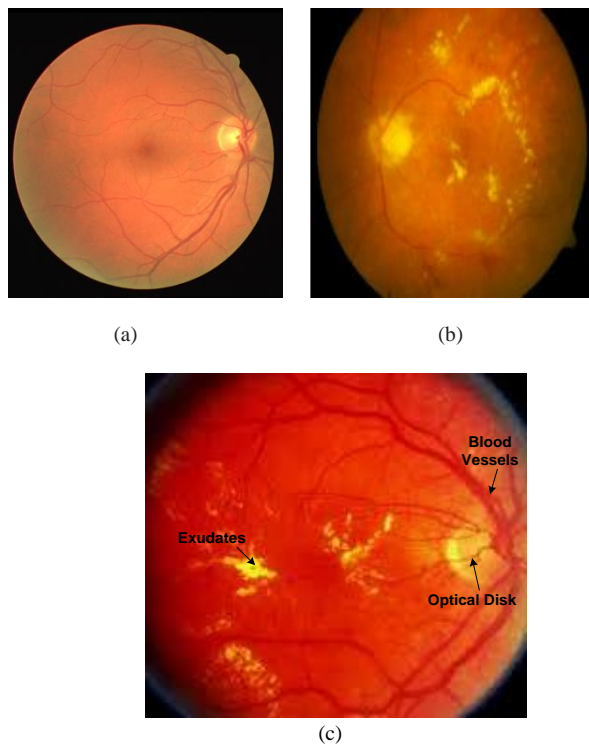


Fig. 1. a) Normal Retinal Image, b) Retinal image with exudates, c) Structural elements of a normal fundus.

a dataset is grouped into  $n$  clusters with every data point in the dataset belonging to every cluster to a certain degree. The automated disease identification system is not a single process. This system consists of various modules. The success rate of each and every step is highly important to ensure the overall high accurate outputs. The rest of this report is organized as follows: (a) Image pre-processing, (b) Feature extraction, (c) Segmentation using Fuzzy C-Means. This system combines computational intelligence and pattern recognition to analyze diabetic retinal images. Through this system, the abnormal retinal images are automatically discriminated from normal images, and an accurate assessment of retinopathy severity is obtained at pixel level.

## II. LITERATURE REVIEW

Huiqi Li et al proposed a technique for extraction of exudate using edge detection techniques. Principal component analysis (PCA) is used to detect the optic disc and shape of the optic disc is detected by a modified active shape model [5].

Sinthanayothin et al. used the Recursive Region Growing diabetic Segmentation algorithm (RRGS) of a window size of  $10 \times 10$  for the detection of the diabetic retinopathy on digital fundus images [6]. Wanget al. proposed a method which classify pixel into non-lesion or lesion classes using the color features in a Bayesian statistical classifier [7].

Sanchez et al. used the color and fine edge features for the detection of exudates. First the yellowish objects are detected, then objects that have the fine edges in the image are detected using Kirsch's mask. The results of yellowish objects with fine edges are used to detect the exudates [8].

Huan Wang et al. [9] detected exudates by using a minimum-distance discriminant classifier based on statistical pattern recognition and used local window for classification.

Lili Xu et al. uses a segmentation method to differentiate the contrast in larger and thin blood vessels. Adaptive local thresholding is used to produce the normalized image and to extract larger vessels. Thin vessel segments are classified using support vector machine [10].

Different stages of Diabetic retinopathy disease severity are detected by Some morphological operation and Texture Analysis methods applied on retinal images was found by [11]. The statistical features are extracted and classified using Bayes Minimum Distant Discriminant (MDD) classifier and the classifier is compared with original and brightness enhanced image is shown in [12].

Niemeijer et al. [13] proposed a method to differentiate the bright lesions such as exudates, cotton wool spots and drusen from color retinal images. Sinthanayothin et al. [14] developed a Recursive region growing segmentation. Huiqi Li and

OpasChutatape [15] have presented a method to detect exudates using region growing and edge detection techniques. He also detected optic disk using principal component analysis. Using a modified active shape model the shape of optic disk was detected.

Usher et al. used the Recursive Region Growing diabetic segmentation algorithm (RRGS) and adaptive intensity thresholding for the detection exudates regions [16]. Gohet al. proposed a method that used the minimum distance discriminant for the detection of the exudates. First computed the spectrum feature center of exudates and background and then the distance from each pixel to class center is computed. If the pixel falls within the minimum distance then it is classified as exudate [17]. Ege et al. used median filter for removal of noise. Bright and dark lesions are separated by thresholding. A region growing algorithm is used to extract the exudates. Bayesian, Mahalanobis and K-Nearest Neighbor classifier were tested. From different experiments, the Mahalanobis classifier yields the best results [18]. Walter et al. have proposed a method for the detection of exudates that using morphological reconstruction technique [19]. Niemeijer et al. have proposed a machine learning-based technique to detect exudates [20].

The Fuzzy C-Means (FCM) clustering is a well-known clustering technique for image segmentation. It was proposed by Dunn and improved by Bezdek [21]. Osareh et al. Used color normalization on and a local contrast enhancement in a pre-processing step. The color retinal images are segmented using Fuzzy C-Means (FCM) clustering and the segmented regions are classified into two disjoint classes – exudate and non-exudate patches – using a neural network [22]. The comparative exudate classification using Support Vector Machines (SVM) and neural networks was also applied. They showed that SVM are more practical than the other approaches [23].

Xiaohui Zhang and Chutatape Opas used local contrast enhancement preprocessing and Improved FCM (IFCM) in

Luv colors space to segment candidate bright lesion areas. A hierarchical Support Vector Machines (SVM) classification structure was applied to classify bright non-lesion areas, exudates and cotton wool spots [24]. Akara Sopharak proposed an automatic method to detect exudates from low-contrast digital images of retinopathy patients with non-dilated pupils using a Fuzzy C-Means (FCM) clustering is proposed.

Contrast enhancement preprocessing is applied before four features, namely intensity, standard deviation on intensity, hue

and a number of edge pixels, are extracted to supply as input parameters to coarse segmentation using FCM clustering method [25].

M. PonniBala detected exudates from the fundus image by thresholding and removal of optic disk using connected components analysis. Finally, an automated Fuzzy Inference System (FIS) is used for classifying

the retinal images as exudates and its severity and non-exudates [26]. S. Kavitha used diffusion segmentation to encapsulate the variation in exudates and lesion boundary criteria pixels. To prevent the optic disc from interfering with exudates detection, the optic disc is detected and localized with the aid of region props and color histogram. Exudates are detected with the aid of thresholding color histogram, which is used to classify the hard and soft exudates pixel from the color fundus retinal image.[27]

Many techniques have been developed for exudate detection, but they have limitations. Bad quality images affect the separation result of bright lesions and dark lesions using exudate feature extraction in Recursive Region Growing diabetic Segmentation (RRGS) algorithm, while most classification techniques require intensive computational power. Furthermore, some of techniques mention above worked on images taken when the patient had dilated pupils. Good quality retinal images with large fields that are clear enough to show retinal detail are required to achieve good algorithm performance. Low quality does not give good results even when enhancement processes are included. The examination time and effect on the patient could be reduced if the automated system could succeed on non-dilated pupils. Here, we aim to investigate the effectiveness of computational intelligence toward automatic detection and identification of exudate pathologies. In this way, we have constructed a large dataset. Color normalization, contrast-enhancement and Brightness preserving dynamic fuzzy histogram equalization are performed in preprocessing steps, The retinal images are segmented based on a combination of color representation in color spaces and an efficient coarse to fine segmentation using fuzzy c-means (FCM) clustering. Algorithms are exploited to select the most appropriate features from the segmented regions and to classify these regions into exudates and non-exudates. Morphology and templates are evaluated to remove the optic disk and blood vessels.

### III. MATERIAL AND METHODOLOGY

To develop exudate segmentation system, the first important thing is to obtain an effective database. This helps to verify results under different circumstances and helps in overall calculation of result. Fig.2 is the block diagram outlining the proposed method to automated detection of exudates from retinal images

#### A. Image Acquisition

To realize this and also for facilitating comparison with the existing methods, publicly available data-bases are used. Almost 500 images are used for implementation mostly images are from DIARETDB0. Images are captured using fundus camera and image size is 1500X1152 each. Some images are of 582X565 dimensions.

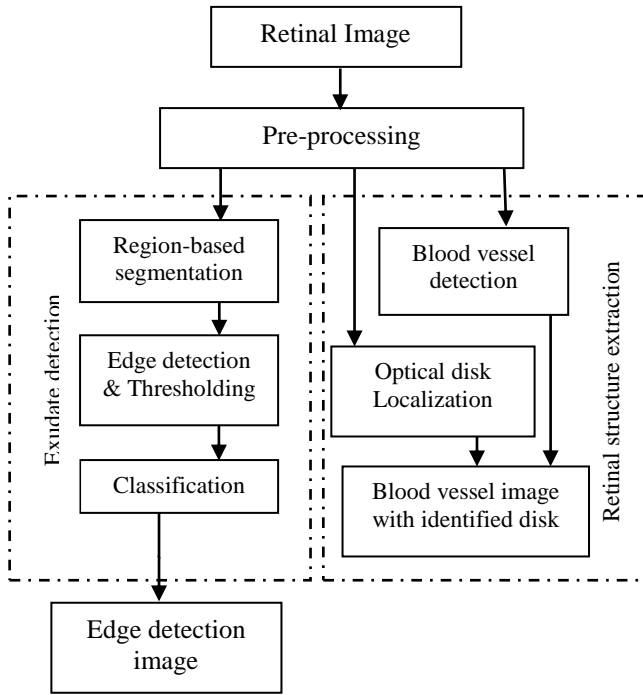


Fig.2. A Block diagram outlining the proposed method steps

**B. Pre-Processing**

The retinal images in the dataset are often noisy and poorly illuminated because of unknown noise and camera motion or incorrect setting.

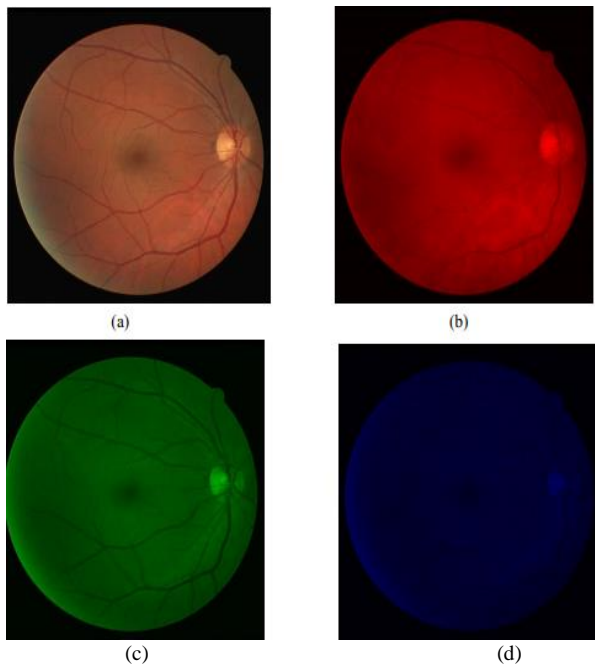


Fig. 3. a) Normal Retinal Image, b) Red, c) Green ,d) Blue component images

There is a wide variation of color of retina from patient to patient as well. Thus the images need to be cleaned and process-able. These noisy images are subjected to

various preprocessing steps, which include green channel extraction, histogram equalization and contrast enhancement. The retinal images and the preprocessed images for normal, mild, moderate and severe stages of exudates are shown in Fig.4. The exudates appear bright in the green channel compared to red and blue channels in RGB image as shown in Fig.3 Hence green channel is used for further processing by neglecting other two components. Brightness preserving dynamic fuzzy histogram equalization and contrast enhancement are used to increase the contrast between the exudates and the image background.

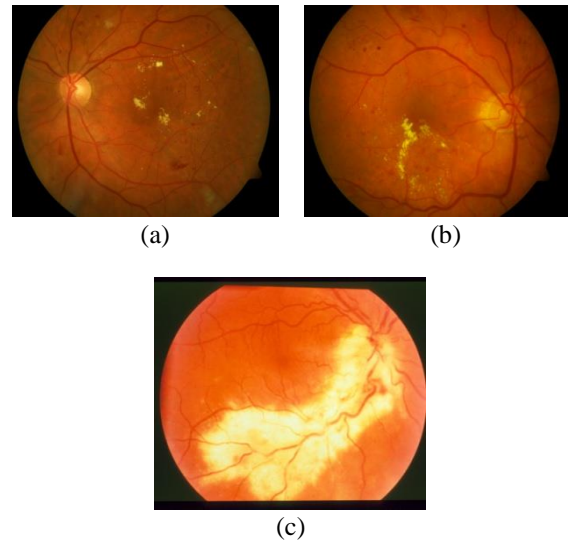


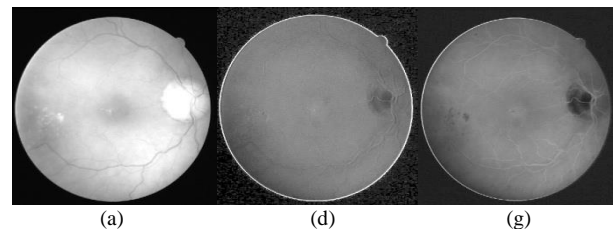
Fig. 4. Different Stages of Exudates in Retinal Image, a)Mild, c) Moderate, d) Severe (cause blindness).

**1) Rgb to Gray scale Conversion**

The RGB input image is first converted to equivalent gray scale image

**2) Brightness Preserving Dynamic Fuzzy Histogram Equalization**

Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) uses fuzzy statistics of digital images for their representation and processing [28]. Representation and processing of images in the fuzzy domain enables the technique to handle the inexactness of gray level values in a better way, resulting in improved performance. Execution time is dependent on image size and nature of the histogram, however experimental results show it to be faster as compared



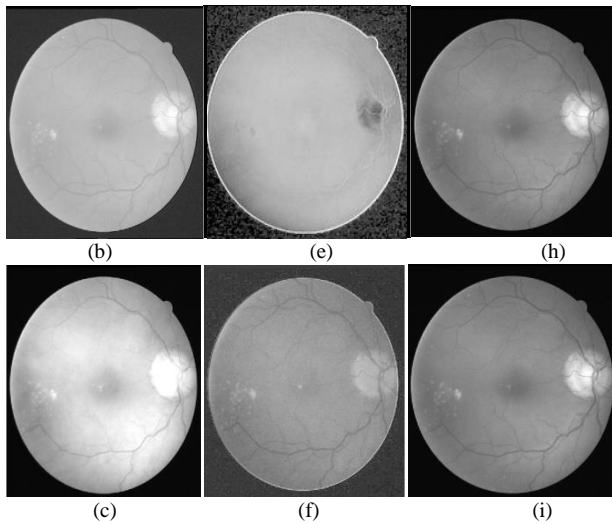


Fig. 5. Colour Space Conversions, a)V component in luv space, b) V component in hsv space, c) V component in hsi space, d) Saturation image in his space, e) Saturation image in hsv space, f) L component in luv space, g) U component in luv space, h) Hue, i) intensity image.

to BPDHE. The BPDFHE technique comprises of these functional steps as show below:

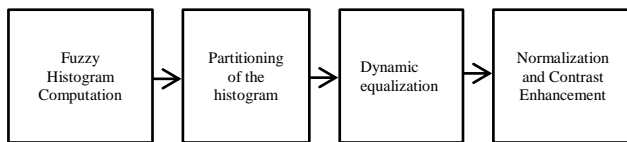


Fig. 6. Stages of Brightness preserving dynamic fuzzy histogram equalization

Fuzzy histogram is generalization of ordinary crisp histograms. Fuzzy histograms can be used to combine a high level of statistical efficiency with a high level of computational efficiency. FHs are very similar to the double kernel estimators. For a random sample of size ‘n’ from a distribution with probability density function (pdf) as  $f(x)$ . A FH estimates  $f(x)$  as follows

$$f(x) = \sum_i \frac{p_i \mu_i(x)}{\int \mu_i(x) dx'} \quad (1)$$

Whereas  $p_i$  is given by

$$p_i = \frac{1}{n} \sum_{j=1}^n \mu_i(x_j) \quad (2)$$

The membership function  $\mu_i$  in (1) and (2) must describe a fuzzy partition, which means that they must satisfy

$$\sum_i \mu_i(x) = 1 \quad \forall x \in \mathfrak{R} \quad (3)$$

Partition histograms in two Sub histograms based on image parameters such as median mean gray level and gray scale threshold used for partitioning. To further improve the mean image brightness preserving capability histogram is further portioned using features as local

peak or valley points act as markers for partitioning of the histogram. Contrast Limited Adaptive Histogram Equalization helps to improve contrast in different blocks on image homogeneous areas is limited to avoid amplifying any noise. Histogram of each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by a distribution [29].

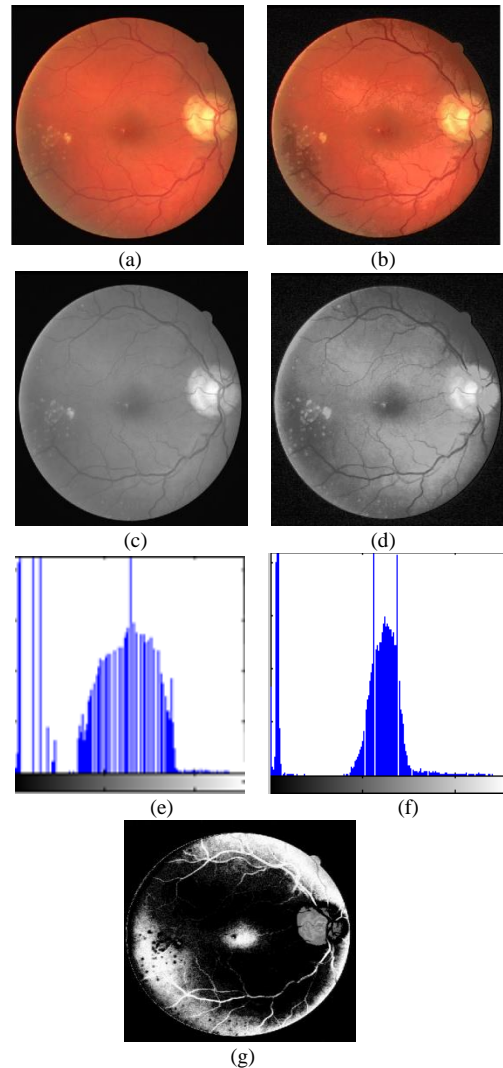


Fig.6. a) RGB input image b) BPDHE image, c) Gray scale input image, d) BPDHE image, e) Histogram of input image, f) After BPDHE, g) Difference image

### 3) CLAHE

Intensity image after pre-processing (ICLAHE) distinguishes pixels based on the intensity. The RGB plane (Red, Green and Blue) in the original image is transformed to HSI space (Hue, Saturation and Intensity). The equations used in conversion in RGB to HIS are:

Hue component is given by

$$H = \begin{cases} \theta & \text{if } B \leq G \\ 360 - \theta & \text{if } B > G \end{cases} \quad (4)$$

Where

$\theta = \cos^{-1} \left\{ \frac{1}{2} [(R-G) + (R+B)] / [(R-G)^2 + (R-B)(G-B)]^{1/2} \right\}$   
 Saturation component and Intensity are given in equation (5) and equation (6):

$$S = 1 - \left[ \frac{3(R+G+B)}{2} \right] \min(R, G, B) \quad (5)$$

$$I = \frac{1}{3} (R + G + B) \quad (6)$$

The Contrast-Limited Adaptive Equalization (CLAHE) is used for contrast enhancement. Before applying the (CLAHE) the intensity (I) band is filtered using median filter to reduce noise. The resultant image is shown in Fig. 6a

#### 4) De-correlation Stretching

The Decorrelation stretching technique involves a number of processes: 1) Extraction of the principle components of the image, 2) rotating and translating it along the principle components axes, 3) doing a contrast-stretch in the new domain to expand the dynamic range of the pixels, and finally, 4) re-transformation of the image to the original coordinates for display.

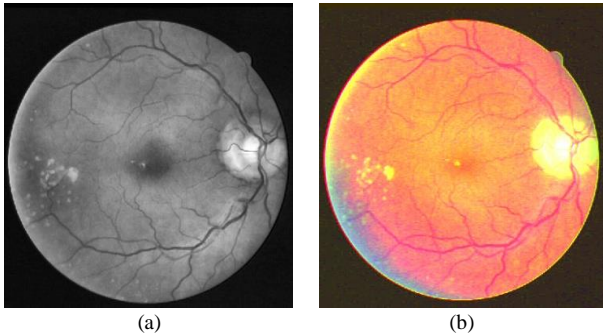


Fig. 7. a) CLAHE image, b) De-corrstretch image

This technique ensures that the contrast stretching procedure highlights the differences from one band to another. The technique has the added advantage of being able to deal with images from multiple bands at once which allows for creating various RGB composites for comparison. The resultant image is shown in Fig. 7b.

##### a. Optic disk and blood vessels elimination

Background subtraction is a commonly used in image processing to focus on the object and to remove the irrelevant details so that only pixels of interest are left for further analysis. This technique estimates the background surface from the image and subtracts it from the original image. Fig. 8 shows details of this process

The enhanced retinal image is converted to binary image by applying proper thresholding value. As the optic disk is circular in shape, a disk shape structuring element is used for morphology techniques. The optic disk is a component on the fundus from where optic nerves and blood vessels materialize. Localization of an optic disk is a vital step for accurate

exudate screening system. The optic disk is exemplified by the largest high contrast among circular shape areas. It is noticed to be in oval shape with an average diameter of 1.5 to 1.7. For this, again the segmented fundus image is converted into binary image. Then high intensity pixel is converted into white and other into region as black. The image BW is generally a logical array of some dimension. Color Histogram equalization technique is applied independently for each extracted regions and morphological operation is used to remove it from the original image and using the generated logical image.

Optic disk can also be removed using histogram matching process but that may involve large computations as compared to the morphological operations. Other techniques practiced at this step are using entropy feature on the ICLAHE image. Commonly used techniques for the detection of vessels include histogram matching, c-mean clustering and matched

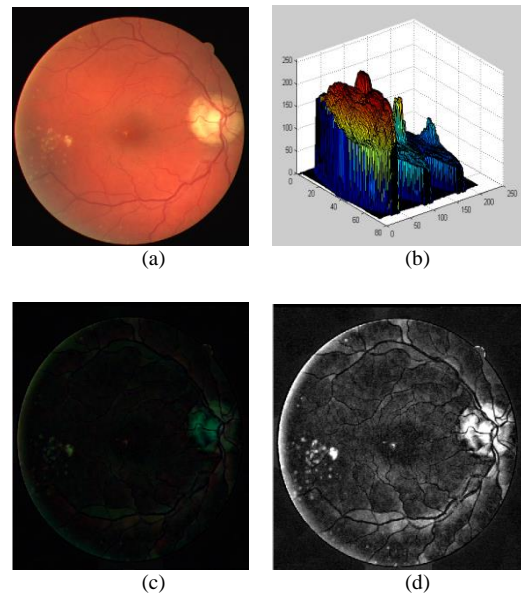


Fig. 8. a) Input image, b) Surface estimation, c) Background subtraction, d) Adjusted image

filters. We used Spatial Filtering by Kirsch's Templates which divide the image in a number of blocks and filter them accordingly for the candidate pixels of the blood vessels. Once optic disk and blood vessels is identified further feature extraction is performed to accurately find the exudates.

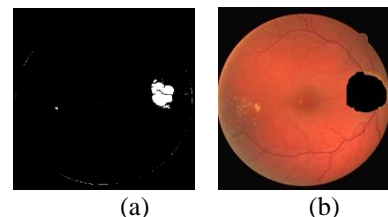


Fig. 9. a) Detection of optic disk, b) Eliminating optic disk

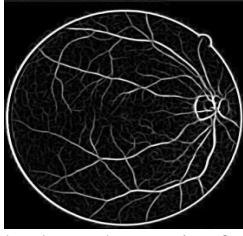


Fig. 10. Enhanced blood vessel extraction from original image

### b. Feature Extraction for Fuzzy Clustering

After the pre-processing of the original image, we'll extract four features to input to fuzzy c-means clustering. Color, shape and texture are the mostly used features by ophthalmologists to identify exudates. We investigate which feature can prove to be the best candidate feature for the fuzzy c-mean clustering.

In the fine stage, FCM assigns any remaining unclassified pixels (pixels from ambiguous regions) to the closest cluster based on a weighted similarity measure between the pixels in the image and each of C (e.g., exudates and non-exudates) cluster centers [ 20]. Local extrema of this objective function are indicative of an optimal clustering of the image. The function is defined as:

$$J_{FCM}(U, v; X) = \sum_{k=1}^n \sum_{i=1}^C (\mu_{ik})^m \|x_k - v_i\|^2$$

$$1 \leq m < \infty \quad (7)$$

Where  $\mu_{ik}$  in equation (7) is the fuzzy membership value of a pixel  $k$  to cluster  $i$  and  $X = x_1, \dots, x_n$  is a finite dataset  $\mathbb{R}^d$ .  $\{v = v_1, \dots, v_c\}$  is a set of cluster centers, where  $v_i \in \mathbb{R}^d$ ,  $1 \leq i \leq C$ , represents a  $d$ -dimensional  $i^{\text{th}}$  cluster center, and is regarded as a prototype. The objective function  $J_{FCM}$  is minimized when high membership values are assigned to pixels whose values are close to the centroid for its particular cluster, and low membership values are assigned when the pixel data are far from the centroid. Taking the first derivatives of  $J_{FCM}$  with respect to  $\mu_{ik}$  and  $v_i$ , and setting them to zero yields necessary conditions for minimizing the objective function. The parameter  $m$  is a weighting exponent that satisfies  $m > 1$  and controls the degree of fuzziness in the resulting membership functions. As  $m$  increases, the membership functions become increasingly fuzzy. In this paper, the value of 'm' was assumed to be equal to 2 it can be set to any number which shows the presence of the number of clusters, and the norm operator represented the standard Euclidean distance. For  $m > 1$ , local minimum can be defined using the equation (8) and equation (9):

$$\mu_{ik} = \frac{1}{\sum_{j=1}^C (\|x_k - v_i\| / \|x_k - v_j\|)^{2/(m-1)}} \quad (8)$$

$$v_i = \frac{\sum_{k=1}^n (\mu_{ik})^m x_k}{\sum_{k=1}^n (\mu_{ik})^m} \quad (9)$$

Where the positive-definite matrix  $U$  is the fuzzy C partition of the input image pixels over the set of C cluster centers treated as vectors and  $v_i$  represents the  $i^{\text{th}}$  class center. An important parameter in an FCM clustering algorithm is the number of classes(C) and their corresponding centers that are computed within the coarse segmentation stage. Hence class centers  $v_i$  are considered as sufficiently well approximated within the coarse segmentation phase. At this stage, pixels from ambiguous regions are assigned to the remaining cluster. Thus, for any unclassified pixel  $x$  with the feature vector  $k$ , the fuzzy membership function  $\mu_{ik}$  is computed, which evaluates the degree of membership of the given pixel  $t$  to the given fuzzy class  $v_i$ ,  $i = 1, \dots, C$ . The resulting fuzzy segmentation is converted to a hard segmentation by assigning each pixel solely to the class that has the highest membership value for that pixel. As most pixels are classified in the coarse stage, a significant computation time required for FCM is saved.

### 1) Feature 1(Enhanced Intensity image)

Intensity band is selected which is the one of the output feature of pre-processing (ICLAHE) as the exudate pixels can usually be discriminated from normal pixels based on their intensity. The RGB space in the original image is transformed to HIS (Hue, Saturation and Intensity) space. Before applying the (CLAHE) the intensity (I) band is filtered using median filter to reduce noise.

Normally exudates gather together in small clusters so they tend to have many edge pixels around the area. That is the reason why a number of edge pixels were selected as our last feature. However, during this feature extraction, we removed some irrelevant edge pixels, as described in the following algorithm.

### 2) Feature 2 (Hue)

The second input to FCM clustering is Hue, which is the feature that is extracted from HSI space, because hue

TABLE 1. POSSIBLE CANDIDATE FEATURES FOR THE FUZZY C-MEAN CLUSTERING

Feature	Description
1	Entropy of the image
2	Hue
3	Edge Strength
4	Enhanced Intensity image
5	Standard deviation
6	Perimeter of Region
7	Colour
8	Image size
9	Compactness of Region
10	Mean

components give the color information. From visual analysis, exudates look/seem differently in a yellow or white color.

### 3) Feature 3 (Standard Deviation)

Standard deviation shows how much variation exists from the average or expected value. A low standard deviation indicates that the data points tend to be very close to the mean whereas high standard deviation indicates that the data points are spread out over a large range of values.

After applying the CLAHE on the Intensity image then find out the Standard deviation and is selected as an input because distribution measurement of the pixel values would discriminate exudate pixels from the normal pixels since standard deviation shows the main characterization of the closely distributed cluster of exudates.

### 4) Feature 4 (Edge Pixel Image)

For Edge Pixel detection, we have followed 4 different steps to get the required enhanced image as the 4th input to the Fuzzy C-Means. These steps are:

- To detect the fast edges, a mask size of 3x3 pixels of sobel edge operator is used to compute the gradient magnitude.
- After the detection of the fast edges, thresholding is applied using low value to get more fine edge pixels.
- Some of the Edges obtained from the previous step are not the true representation of exudates. Some edges represent vessel edges and before moving to next step these vessel edges must be removed. decorrelation stretch is applied on the Red band for the fast detection of blood vessel. The decorrelation stretching is a process used to enhance or stretch the color differences found in a color image.
- Different types of exudates some are soft exudates that cannot be detected using a strong and fine edges. After the decorrelation stretch process red pixels are selected and then added with the previous step results because the soft exudates normally appear red. However, the optic disc also consists of pixels in red, which are need to be removed first. A number of neighboring white pixels of the resulting image from the above processes is counted using a window size of 17 x 17 to form our final feature.

$$Compactness = n\pi * (A) / (P)^2$$

- Where A is the area which is the number of pixels in the region and P is the perimeter, which is the total number of pixels around the boundary of each region and n can be a multiple of 2.
- Then we have applied laplacian filter to blur the final feature image. Laplacian filter is a standard

laplacian of Gaussian convolution. This filter is designed to measure changes in intensity without being sensitive to noise. The function produces a peak at change in intensity and then at the end of the change.

### 5) Entropy

Image entropy is a quantity which describes the 'business' of an image, i.e. the amount of information which must be coded for by a compression algorithm. Low entropy images, have very little contrast and large runs of pixels with the same intensity. An image that is perfectly flat will have zero entropy. Consequently, they can be compressed to a relatively small size. On the other hand, high entropy images have a great deal of contrast from one pixel to the next and consequently cannot be compressed as much as low entropy images.

$$Entropy = - \sum_i P_i \log_2 P_i \quad (10)$$

These extracted images are used as in the segmentation process as an input to FCM clusters. We have obtained 2 clusters in our case. The overall result is the dot product of the cluster's output image and decorrelated image. Entropy, standard deviation, edge strength and hue is used for fuzzy c-mean clustering and compared with other features in clustering.

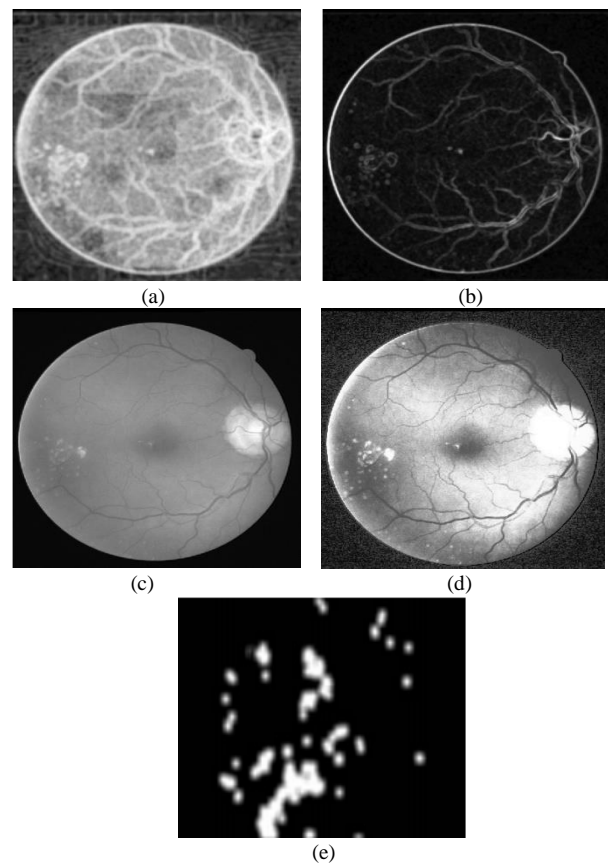


Fig. 11. a)Entropy , b)standard deviation , c)Hue ,d)intensity) Edge pixel image



#### IV. RESULTS

To evaluate the performance of the proposed method we used DIARETDB0 dataset. We have chosen this data set for performance evaluation because it contains both normal as well as abnormal cases. The proposed algorithm is coded in MATLAB version7.4 and run on a2.2GHz Intel Core duo2 Laptop with 4GB Ram. The proposed classification scheme including image pre-processing and FCM based segmentation has been tested on dataset. We will use the following image as running example to illustrate each step of the proposed algorithm.



Fig. 12. Original image used for performance evaluation of algorithm.

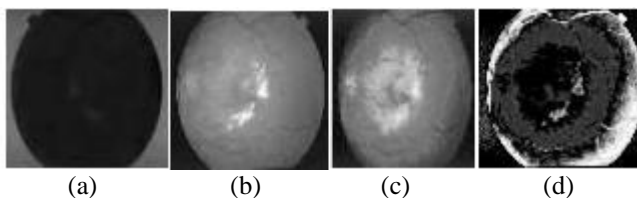


Fig. 13. The different stages of brightness preserving dynamic fuzzy histogram equalization (BPDFHE).

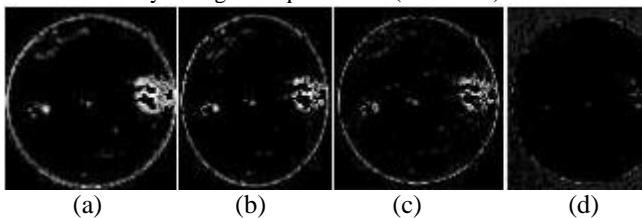


Fig. 14. Effect of changing the window size (a) 17x17 (b) 11x11 (c) 7x7 (d) 3x3

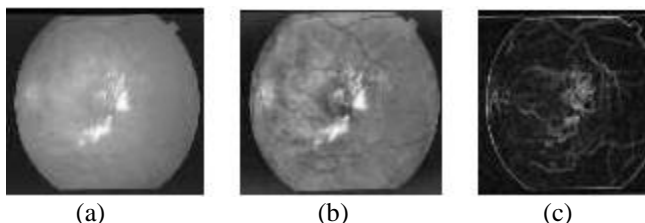


Fig. 15. (a) Intensity image (b) result of the ICLAHE (c) Standard deviation of ICLAHE.

Many images were tested on the MATLAB platform. Each image took approximately 3 minutes for FCM clustering. After fine segmentation using cluster based approach, most of the detected exudate regions are true exudate pixels, which give a smaller true positive value;

however, it also reduces the false positive value because misclassification of non-exudate pixels is also lower. The performance of our technique was evaluated quantitatively by comparing the result of extractions with ophthalmologists' hand-drawn ground-truth images. This approach aims to measure the correctness of the algorithms at the pixel level. After fine segmentation, most of the classified exudates regions are true exudates pixels, but some regions are of the optical disk and blood vessels. Fig.12 shows how exudates are detected. In this image when optic disk and blood vessel elimination which has achieved, is combines it makes a very robust system for exudate detection. Fig.13 shows the interactive graphical user interface system that allows selection of image and selects the best four features for further classification of the exudates .

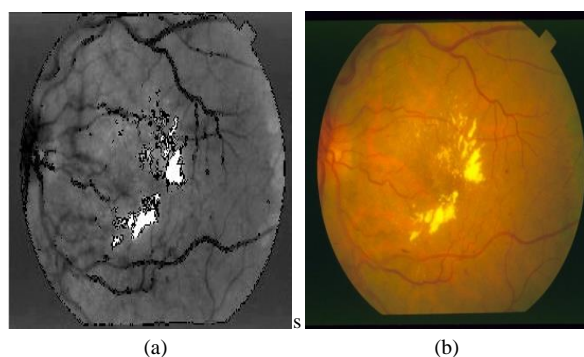


Fig. 12. a) End Result, b) Input image

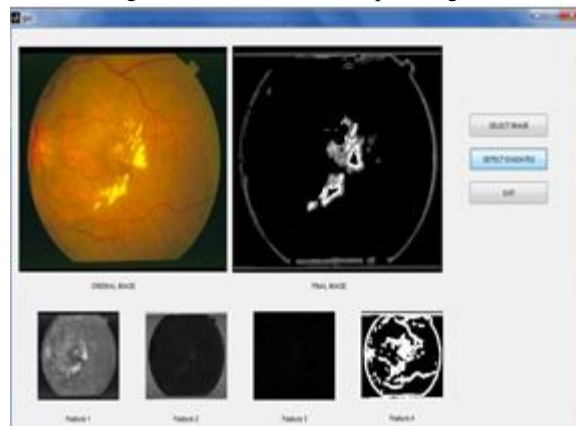


Fig. 13. GUI of the Exudate Detection System

#### V. CONCLUSIONS AND FUTURE WORK

In the diagnosis of diabetic retinopathy, image processing of color fundus images has a significant role to play. In this report, a method is presented for automatic detection of Exudates from the color fundus retinal image. The color fundus retinal images are subjected to preprocessing including RGB to HSI conversion. The paper methodology is based on the FCM clustering segmentation and morphological techniques. Four input features applied to the FCM, namely intensity, standard deviation, hue and number of edge pixels. Robustness and accuracy of the method have been evaluated on a

database of different images. The accuracy values increase when the FCM clustering technique is combined with morphological technique. There is some incorrect exudates detection which is due to artifacts, which are similar to exudates, artifacts from noise in the process of image acquisition, the exudates that are proximate to blood vessels or exudates that appear very faint. These missing faint exudates may have not affected the sensitivity much since even human experts are not sure about some ambiguous regions in the image. However, the performance of the algorithm can be improved if these set of low-contrast exudates can be detected.

#### REFERENCES

- [1] Finnish Diabetes Association. Development programme for the prevention and care of diabetes, 2001. ISBN 952 5301-13-3.
- [2] Finnish Diabetes Association. Programme for the prevention of type 2 diabetes in Finland, 2003. ISBN 952-5301-36-2.
- [3] Lars B. Bäcklund, "Early Diagnosis of Diabetic Retinopathy by Mass Examinations in Primary Health Care", PhD thesis, Karolinska Institutet, Sweden, 2000. ISBN: 91-628-4224-2.
- [4] Tomi Kauppi, Valentina Kalesnykiene, Finland. DIARE TDB0: Evaluation Database and Methodology for Diabetic Retinopathy Algorithms, CA. [Online].
- [5] Huiqi, L.; Chutatape, O. "A model-based approach for automated feature extraction in fundus images". In *International Conference on Computer Vision (ICCV)*, 2003, pp. 394-399.
- [6] C. Boyce, J.F. Williamson, T.H. Cook. "Automated Detection of Diabetic Retinopathy on Digital Fundus Image". 2002
- [7] Wang; Hsu, H.; Goh, W.; Lee, K.G. An Effective Approach to Detect Lesions in Color Retinal Images. In *Proceedings of "IEEE Conf. on Computer Vision and Pattern Recognition"*, 2000, pp. 181-186.
- [8] Sanchez, C.I. Hornero, R. Lopez, M.I. Poza, J. "Retinal Image Analysis to Detect and Quantify Lesions Associated with Diabetic Retinopathy" In *International Conference on Engineering in Medicine and Biology Society (EMBC)*, 2004, pp. 1624 – 1627.
- [9] Huan Wang, Wynne Hsu, Kheng Guan Goh and Mong Li Lee. 2000. An effective approach to detect lesions in retinal images. *Proc. IEEE Conf. Comput. Vis. Pattern Recogn.*, Hilton Head Island, SC, Vol. 2, pp. 181–187.
- [10] Lili Xu, Shuqian Luo, 2010. A novel method for blood vessel detection from retinal images, *BioMedical Engineering OnLine*, 9:14.
- [11] Rema M. and Pradeepa R., 2007. Diabetic retinopathy: an Indian perspective. *Indian Journal of Medical Research*, Vol. 125, no. 3, pp. 297.
- [12] Sai prasadravikumar et al., 2007. Automated Feature Extraction For Early Detection Of Diabetic Retinopathy In Funds Image. *IEEE international conference on Image Processing*, pp 139-142.
- [13] M. Niemeijer, B. V. Ginneken, S. R. Russell, M. Suttorp, and M. D. Abramoff, 2007. "Automated detection and differentiation of drusen, exudates and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis," *Invest. Ophthalmol. Vis. Sci.*, vol. 48, pp. 2260–2267.
- [14] Sinthanayothin C, Boyce JF, Williamson TH, Cook HL, Mensah E, Lal S, Usher D., 2002. Automated detection of diabetic retinopathy on digital fundus images. *Diabetic Medicine*. 19(2), 105-12.
- [15] Huiqi Li, Opas Chutatape, 2004. Automated Feature Extraction in Color Retinal Images by a Model Based Approach, *IEEE Transactions On Biomedical Engineering*, Vol. 51, no. 2, pp. 246-254.
- [16] Usher, D. Dumskyj, M Himaga, M. Williamson, T.H. Nussey, S. Boyce, "Automated detection of diabetic retinopathy in digital retinal images: a tool for diabetic retinopathy screening". 2004.
- [17] Goh, K.G.; Hsu, W.; Li Lee; Wang, H. adris: "an Automatic Diabetic Retinal Image Screening system". In *Medical data mining and knowledge discovery*; Krzysztof, editor. Physica-Verlag: Heidelberg, Germany, 2001; pp. 181-210.
- [18] Ege, B.M. Hejlese, O.K. Larsen, O.V. Moller, K. Jennings, B. Kerr, D. Cavan, D.A. "Screening for diabetic retinopathy using computer based image analysis and statistical classification". 2000.
- [19] Walter, T. Klein, J.C. Massin, P. Erginay, A. "A Contribution of Image Processing to the Diagnosis of Diabetic Retinopathy-Detection of Exudates in Colour Fundus Images of the Human Retina". *IEEE Transactions on Medical Imaging*, 2002, 21, 1236 - 1243.
- [20] Niemeijer, M. Ginneken, B.V. Russell, S. R. Suttorp-Schulten, M.S.A. Abramoff, M.D. "Automated detection and differentiation of drusen, exudates, and cotton-wool spots in digital color fundus photographs for diabetic retinopathy diagnosis". 2007
- [21] Bezdek, J.C. *Pattern Recognition with Fuzzy Objective Function Algorithms*. Plenum: New York, NY, USA, 1981.
- [22] Osareh, A. Mirmehdi, M. Thomas, B. Mar kham, R. "Automatic recognition of exudative maculopathy using fuzzy c-means clustering and neural networks". In *Medical Image Understanding Analysis*; Claridge, E. Bamber, BMVA Press, UK, 2001
- [23] Osareh, A.; Mirmehdi, M.; Thomas, B.; Markham, R. Comparative Exudate Classification using Support Vector Machines and Neural Networks. In *Internat. Conf. on "Medical Image Computing and Computer-Assisted Intervention"*, 2002

- [24] Xiaohui Zhang; Chutatape, O. Top-down and bottom-up strategies in lesion detection of background diabetic retinopathy. In *IEEE Computer Society Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2005, pp. 422-428.
- [25] Akara Sopharak, Bunyarit Uyyanonvara. (2009). Automatic Exudate Detection from Non-dilated Diabetic Retinopathy Retinal Images Using Fuzzy C-means Clustering. *IEEE Sensors*, 9, 2148-2161
- [26] M. PonniBala, S. Vijayachitra, (September 2012) "Computerised Retinal Image Analysis to Detect and Quantify Exudates Associated with Diabetic Retinopathy," in *International Journal of Computer Applications (0975 - 8887)* Volume 54-No.2.
- [27] S. Kavitha, S. Kavitha, (2011). "Automatic Detection of Hard and Soft Exudates in Fundus Images Using Color Histogram Thresholding" in *European Journal of Scientific Research ISSN 1450-216X Vol.48 No.3* (2011), pp.493-504
- [28] H. Garud, D. Sheet, P. K. Karri, A. Suveer, J. Chatterjee, M. Mahadevappa, A. K. Ray, "Brightness Preserving Contrast Enhancement in Digital Pathology". *Proc. ICIP -2011*, Shimla, India, Dec. 2011.
- [29] Ludo Waltman, Uzay Kaymak, and Jan van den Berg, "Fuzzy Histograms: A Statistical Analysis" The Netherlands, EUSFLAT - LFA 2005.



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