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Automated Detection Of Exudates Using DBSCAN Clustering And Fuzzy Classifier

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Abstract: Diabetic Retinopathy is a major cause of vision loss for diabetic patients, but early detection of its symptoms and treatment can prevent blindness. Exudates are the key indicators of diabetic retinopathy that can potentially be automatically quantified. In this paper the authors have attempted to detect exudates by a combination of DBSCAN clustering algorithm and Fuzzy classifiers. The DBSCAN algorithm produces many clusters that human cannot make out. In order to correctly identify exudates, Post processing is performed using fuzzy classifier to classify clusters as exudates or non-exudates. Exudates in training retinal images are marked by expert ophthalmologists. Various histogram based features are calculated for the regions marked. These features are used for training the Fuzzy classifiers. Optic disc is localized by the Circular Hough Transform. The publicly available diabetic retinopathy data set DIARETDB0 is used for evaluation .In addition to the above set; images from VASAN Eye Care Hospital (Reputed local Eye care centre) have been used. Our proposed algorithm achieved image based classification accuracy above 90%.

Keywords: Optic disc, Exudates, Diabetic Retinopathy, DBSCAN clustering, Fuzzy classifiers

I. INTRODUCTION

According to World Health Organization (WHO) report around 135 million people have diabetes mellitus worldwide and that the number of people will increase to 300 million by the year 2025. WHO estimates that more than 75% of patients, who have had diabetes for more than 20 years are likely to develop some form of Diabetic Retinopathy. There are different kinds of abnormal lesions caused by diabetic retinopathy, alterations in blood vessel diameter, micro aneurysms, lipid, protein deposits also known as hard exudates, cotton wool spots, hemorrhages and new vessel growth are all characteristics of Diabetic Retinopathy.

The only visible symptoms of DR in several patients are Exudates. Hard exudates occurring in the macula can cause significant visual impairment .The main obstacle in Exudates detection is extreme variability of color in retinal images that depends on the degree of pigmentation, size of the pupil and illumination. These factors affect the appearance of exudates in the retinal images. Many techniques have been employed for the exudates detection

Periodic screening and automated early detection can prevent the blindness. The screening program produces an enormous amount of retinal images since diabetic patients typically have both their eyes examined at least once in a year. The manual screening methods have both high financial cost and human resource needs. Nowadays, several approaches have been considered to build automatic computer-based screening programmes. Automated detection can reduce the workload and increase the follow-up management of diabetic patients.

Sinthunayothin [1] et.al used recursive region growing which yielded hard exudates as well as optic disc. Optic disc was removed by identifying the area with highest variation in intensity of adjacent pixels. Sensitivity of 88.5% and a specificity of 80.7% were obtained on a image based validation.

Akara [2] et.al used Fuzzy C-means and morphological based segmentation for diagnosing the exudates from low-contrast images of non-dilated pupils Sensitivity of 80% and specificity of 99.55 were obtained. Author performed a series of experiments [3] and did a comparative analysis between mathematical morphology, fuzzy c-means clustering, Naive Bayesian classifier, Support Vector Machine, Nearest Neighbor Classifier and detected exudates were validated with ophthalmologists hand drawn ground-truths. Highest sensitivity 97.29% was obtained with FCM.Highest specificity of 99.46% was obtained with mathematical morphology.

Hussain F.Jaafar [4] et.al proposed a method based on top-down image segmentation and local thresholding by a combination of edge detection and region growing. Grading of hard exudates was performed and overall sensitivity of 93.2% was obtained.

Maria Garcia [5] .et.al used a combination of global and local thresholding for segmentation of candidate exudates regions. Group of features like mean RGB values around the region , mean RGB values inside the region standard deviation values around the region , region size were extracted from the candidate regions which are used for the training of RBF networks. The trained network performed the pixel wise classification.

R.Vijayamadheswaran[6].et.al used contextual clustering(CC) for feature extraction and extracted features were used as input to RBF network.

Neera Singh [7] et.al used fuzzy C-means clustering. Features like color, size, edge and texture are extracted from the resulting clusters. A 3 layer perceptron neural network with 18 input nodes corresponding to 18 features is used to classify pixels into exudates and non-exudates.

Nathan Silberman[8] et.al extracted SIFT features from a limited ROI region which is a horizontal conic area spanning from the location of optic disc outward toward center of the retina. These features were used to train the Gaussian Support Vector Machine to label individual patches of image.

V.Vijayakumari[9] et al used template matching for optic disc detection. Authors used sobel edge detector to find objects with sharp edges and used enhanced MDD classifier to find yellowish objects. Later images obtained from both methods are ANDed to get objects with sharp edges and yellowish color

Asha gowda[10] et.al attempted a method in which Back propagation Neural Networks are used for exudates detection. Features like Hue, Intensity, Standard deviation of intensity, distance between mean of optic disc pixels and pixels of exudates and non-exudates and mean intensity have been used as inputs to train the neural network . Decision trees and GA-CFS are used for identification of significant features. They obtained sentivity of 99.97% and specificity of 100%.

Ivo soares[11] et.al used a method which is based on the use of morphological operators and adaptive threholding. This method reveals a good resilience to contrast changes, non-uniform illumination and variable background resulting in correct detection of exudates. They obtained a sensitivity of 97.49% and specificity of 99.95% and an accuracy of 99.91% for exudates detection.

II. PROPOSED METHOD

Fig.1. shows a sample retinal image having exudates. There are three types of objects in such retinal images. Bright objects, dark objects and retinal background. Optic disc, exudates, cotton wool spots form the bright objects, blood vessels, fovea, haemorrhages form the dark objects. Retinal background is in-between the above two.

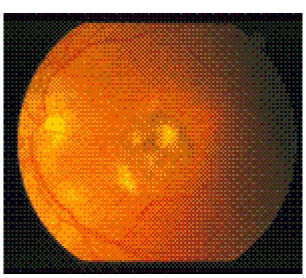


Figure.1. Retinal image having exudates

In this paper authors have attempted a novel approach for automated detection of exudates. The methodology is shown in Fig.2. It involves the following steps.

a. Contrast enhancement is done using CLAHE and median filter of size 3X3 is used to remove noise.
b. Hough transform is used for the detection of the optic disc
c. DBSCAN clustering algorithm for the detection of exudates. This segmentation segments all possible bright lesions as well as false positives due to non-uniformity of color distribution and noise.
d. Fuzzy classifier is used to distinguish between exudates and non-exudates from the segmentation done by DBSCAN algorithm

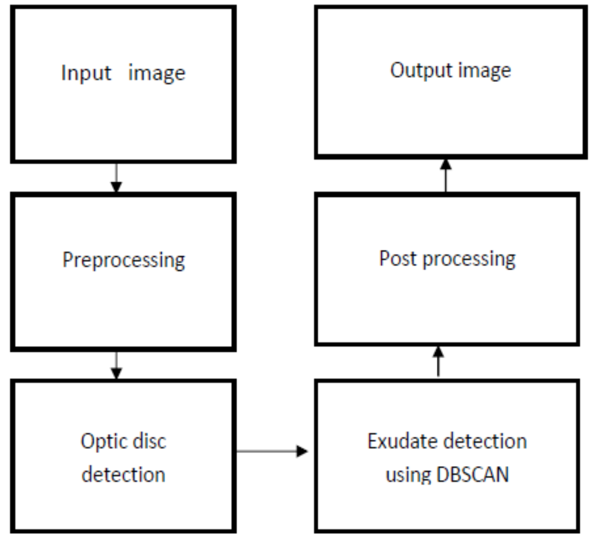


Figure 2: Proposed system of exudates detection

A. *Image acquisition:*

Twenty five images from Standard Diabetic Retinopathy dataset DIARETDB0 [13] are used for training and evaluation of the proposed algorithm. Twenty five images from the local hospital VASAN EYE CARE are also used for training and testing.

B. *Image Pre-processing:*

The input images are in RGB format which are converted to L*a*b* color space and Contrast Enhancement is done using Contrast-limited Adaptive Histogram Equalization (CLAHE). L*a*b* color space has image intensity as one of its components. CLAHE enhances the contrast of images by transforming the values in the Luminosity layer 'L*' of the image. Manipulating luminosity affects the intensity of the pixels, while preserving the original colors.

a) ***Noise removal****:* The image was filtered using median filter of size 3X3 which removes the noise effectively while preserving edges.

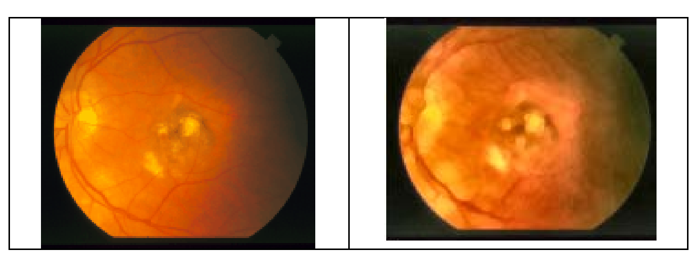


Figure.3.a Original Retinal image b. Enhanced and median filtered image

C. Optic Disc Detection:

The Optic Disc (OD) is the brightest part in normal fundus retinal images. It is the entrance region of blood vessels and optic nerves to the retina and it works as landmark to other features in the retinal fundus image. Locating and segmenting OD is an important prerequisite in automatic detection of exudates since it has characteristics similar to exudates in terms of color, shape, brightness and contrast. It has been detected using edge detection followed by circular Hough transform. The result of optic disc detection by Hough transform is shown in fig.4.Optic disc thus obtained is superimposed on the result obtained by DBSCAN algorithm.

Figure.4. Optic disc detection by Hough transform

D. Detection of Exudates using DBSCAN Clustering:

a. DBSCAN Clustering:

In this study we apply a density based clustering method, DBSCAN to image segmentation problem. DBSCAN is a density based clustering algorithm that is designed to discover areas of high density that are separated from each other by area of low density [12]. It can identify clusters in large spatial data set. It has two parameters eps and MinPts minimum number of points to form a cluster. It starts with an arbitrary starting point that has not been visited. This point's epsilon neighborhood is retrieved. If it has sufficiently many points, a cluster is started. Otherwise this point is labeled as noise. This point might later be found in a sufficiently sized epsilon environment of a different and hence is made part of a cluster.

If a point is found to be a dense part of a cluster, its ε-neighborhood is also part of that cluster. Hence, all points that are found within the ε-neighborhood are added, as is their own ε-neighborhood when they are also dense. This process continues until the density-connected cluster is completely found. Then, a new unvisited point is retrieved and processed, leading to the discovery of a further cluster or noise. Figure 5 shows classification of certain points. DBSCAN has the advantage that it does not require you to know the number of clusters in the data a prior.

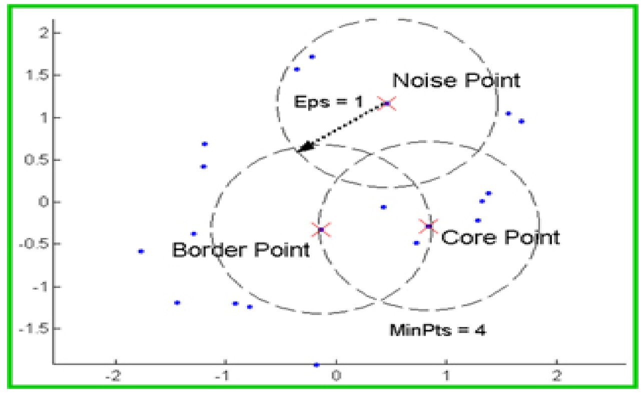


Figure.5.Classification of points using DBSCAN algorithm

Pseudocode

```
DBSCAN(D, eps, MinPts)
  C = 0
  for each unvisited point P in dataset D
    mark P as visited
    NeighborPts = regionQuery(P, eps)
    if sizeof(NeighborPts) < MinPts
      mark P as NOISE
    else
      C = next cluster
      expandCluster(P, NeighborPts, C, eps, MinPts)
expandCluster(P, NeighborPts, C, eps, MinPts)
  add P to cluster C
  for each point P' in NeighborPts
    if P' is not visited
      mark P' as visited
      NeighborPts' = regionQuery(P', eps)
      if sizeof(NeighborPts') >= MinPts
        NeighborPts = NeighborPts joined with NeighborPts'
    if P' is not yet member of any cluster
      add P' to cluster C
regionQuery(P, eps)
  return all points within P's eps-neighborhood
```

b. Feature selection for DBSCAN:

We have chosen L*a*b color space for clustering. We used 3 features and used them as input to DBSCAN clustering algorithm.

a) The Pixels chromaticity value *a after preprocessing
b) The Pixels chromaticity value *b after preprocessing.
c) The standard deviation of preprocessed *a value in a window around the pixel. The window size is chosen 3X3. We are using standard deviation because exudates are more textured than non-exudates.

Two parameters are very important for DBSCAN clustering EPS and MinPts. In order to fine tune algorithm parameters 15 representative images were selected from the set. After parameters were fine-tuned, algorithm is applied on the remaining images. Eps was set to 1.3 and MinPts was set to 50.

DBSCAN is designed to discover noise as well as clusters in the spatial data set. The number of clusters obtained from the algorithm is much more than number of color regions that can be identified by humans. Fig.5a. There were nine clusters in this. Thresholding the 9th cluster gave the result shown in Fig.5.b. Along with exudates, there are some bright regions that have been segmented as exudates. Therefore some post processing is necessary to classify these segments as Ex and non-Ex.

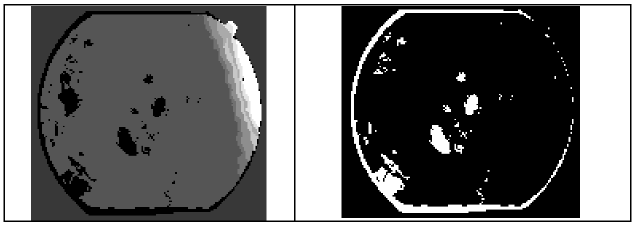


Fig.5. (a) (b)

(a) Result of DBSCAN (b) After threholding and Optic disc removal

E . Post processing:

We performed connected component analysis. Post processing is done in two steps

a. Components having size of less than 20 pixels is regarded as noise and they are removed by morphological operations

b) Remaining components are classified as exudates or non-exudates using Fuzzy classifiers. Fuzzy system was trained to label individual patches of image

a. Training Fuzzy Classifiers:

In a training set, each exudates location marked by opthalamalagist is extracted. For these regions, histogram based features like mean, variance and energy are calculated for chromaticity a plane, chromaticity b plane, and green plane and Intensity plane. These features are used for training the fuzzy classifier. Fifteen images were considered for training the classifiers. The number of training samples obtained from these images is 100, 50 samples contained exudates, 50 samples contained retinal background together with blood vessels. Each row consists of 16 variables. The features and their values for sample regions are shown in the table 1.

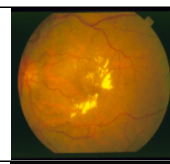
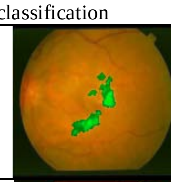
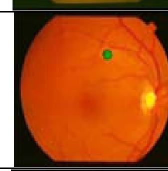
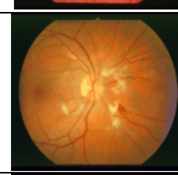
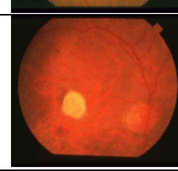
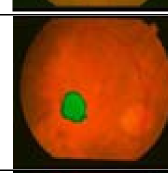
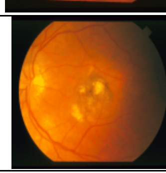
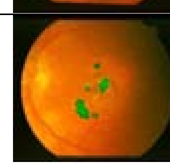
For each test image, for each region given by DBSCAN clustering algorithm, the same set of features are computed. These region features are given as input to the fuzzy classifier which classifies segmented information as exudates or non-exudates.

III. EXPERIMENTAL RESULTS

Fig.6 shows the regions that are classified as exudates by fuzzy classifier and the total area of the regions in terms pixels. We have chosen images from the DIARETDB0 database in which optic disc is nearly circular for our study. We have tested our system on 35 images. On an image based validation criterion we have obtained an accuracy of above 90%. The results obtained from DBSCAN algorithm combined with Fuzzy classifier are quite good.

Table I. Histogram based features and their values for sample regions

Plane	Features	R1	R2	R3
Green	Mean	2.332296	3.540984	3.25
	Variance	0.312148	0.24832	0.1875
	Energy	0.501397	0.503359	0.625
Intensity	Mean	3.09572	7.221311	6.125
	Variance	2.530137	0.172333	0.109375
	Energy	0.401346	0.655335	0.78125
a plane	Mean	4.498833	6	6
	Variance	0.427431	0	0
	Energy	0.459131	1	1
b plane	Mean	5.320623	6	6
	Variance	0.247396	0	0
	Energy	0.534965	1	1
A	Max	177	182	177
B	Max	189	199	190
Green	Max	96	124	97
intensity	Max	220	251	205

Original retinal image	Result after segmentation and classification	Area of Exudates in pixels
		574
		175
		518
		479
		272

(a) (b) (c)

Fig.6.a.Retinal image b.Regions classified as exudates c.Area of regions identified as exudates.

IV. CONCLUSION

The use of clustering algorithm combined with fuzzy classifier reduces the amount of training data as well as time. DBSCAN algorithm does not need any assumptions about the number of clusters. There are some non-Ex regions that are classified as Ex. The quality of retinal images plays a vital role .In our future work we will try to improve lesion based accuracy. This system can be used as a preliminary diagnosis tool to help the ophthalmologists in the initial screening process. Development of a screening system, which provides a simple yes-no answer, may be enough to reduce diabetic screening requirement by a trained personnel by up to 70%.

V. ACKNOWLEDGMENTS

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