

Classification Of Diabetic Retinopathy Diseases By Using SVM(Support Vector Machine)

Puja I. Kumbhalkar, Prof. Nutan Dhande
Department of Computer Science and Engineering
Agnihotri College of Engineering, Nagthana, Wardha, India

ABSTRACT

In this research article, a brief insight into the detection of DR in human eyes using different types of preprocessing & segmentation techniques is being presented. Here we address the detection of Hemorrhages and micro aneurysms in color fundus images. In pre-Processing we separate red, green, blue color channel from the retinal images. The green channel will pass to the further process. The green color plane was used in the analysis since it shows the best contrast between the vessels and the background retina. Then we extract the GLCM (Gray Level Co-Occurrence Matrix) feature. In the GLCMs, several statistics information is derived using the different formulas. These statistics provide information about the texture of an image. Such as Energy, Entropy, Dissimilarity, Contrast, Inverse difference, correlation Homogeneity, Auto correlation, Cluster Shade Cluster Prominence, Maximum probability, Sum of Squares will be calculated for texture image. After feature Extraction, we provide this feature to classifier. Finally it will predict about the retinal whether it is hemorrhages or microaneurysms. After predicting the about the retinal image we will localize the affected place. For segmenting the localized place we will use segmentation. One of the important organ of the human being is the eye. It has to be noted that if the eyes are not there, then the whole world would be dark & the human life even though it is existing will be a waste. Different types of the diseases occurs in the eyes. One of the deadliest disease which occurs in the eyes is the DR. This disease is the second largest disease which is occurring amongst the human beings as per the WHO – United Nations survey. Hence, utmost importance has to be given to the eye care. This disease occurs due the reduction of the nerve area in the retina.. In this paper, a mere introduction is given to the diabetic retinopathy disease.

Keywords: Segmentation, Retina, Artificial Neural Networks, Detection, Diabetic Retinopathy, Data Sets, Enhancement, Feature Extraction, Preprocessing, Simulation, Image Processing

I. INTRODUCTION

Diabetic retinopathy (DR) is a vascular disease of the retina which affects patients with diabetes mellitus. It is the number one cause of blindness in people between the ages of 20-64 in the United States. It is, therefore, a worthwhile topic for all medical students to review. Diabetes mellitus is extremely common, so it is not surprising that DR affects 3.4 percent of the population (4.1 million individuals). Of the millions of people with DR, nearly one-fourth have vision-threatening disease (AAO 2008). The likelihood of developing diabetic retinopathy is related to the duration of the disease. Type 2 diabetes has an insidious onset and can go unnoticed for years. As a result, patients may already have DR at the time of diagnosis. Type 1 diabetics, on the other hand, are diagnosed early in the course of their disease, and they typically do not develop retinopathy until years after the diagnosis is made. The risk of developing retinopathy increases after puberty. Twenty years after the diagnosis of diabetes, 80% of type 2 diabetics and nearly all type 1 diabetics show some signs of retinopathy (Klein 1984a, Klein 1984b). While these numbers are eye-opening, diabetics can decrease their risk of retinopathy and slow the progression of the disease after it has begun with tight glucose control (DCCTRG 1993).



Figure 1: Normal Fundus

Glucose control also has the added benefit of decreasing risk for other end-organ complications of diabetes, so it is important that diabetic patients are educated on the topic. Time since diagnosis and extent of hyperglycemia are the most significant risk factors for the DR, but other risk factors for development and progression include hypertension, dyslipidemia, smoking, nephropathy, and pregnancy (AAO 2008).

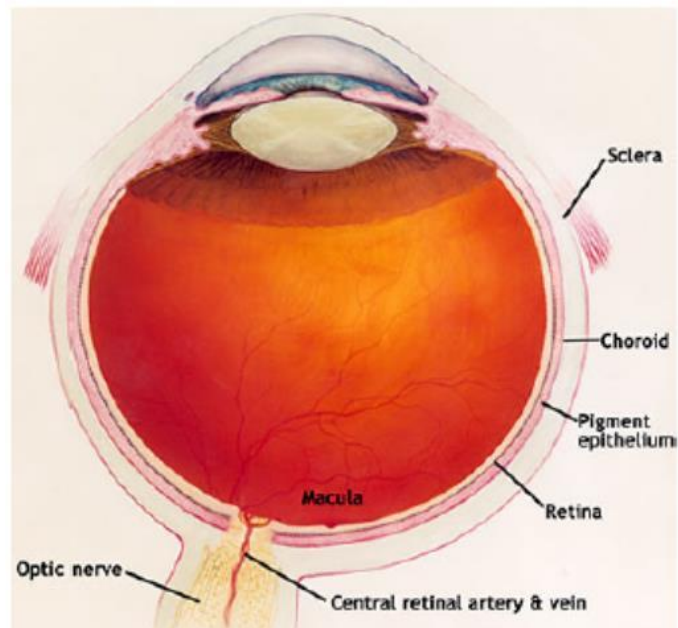


Figure 2: Diagram of Normal Eye

II.RELATED WORK

Automated grading has the potential to improve the efficiency of diabetic retinopathy screening services. While disease/no disease grading can be performed using only micro aneurysm detection and image-quality assessment, automated recognition of other types of lesions may be advantageous. This study investigated whether inclusion of automated recognition of exudates and hemorrhages improves the detection of observable/referable diabetic retinopathy. Automated detection of exudates and hemorrhages improved the detection of observable/referable retinopathy.[1]

To develop a technique to detect micro aneurysms automatically in 50 degrees digital red-free Fundus photographs and evaluates its performance as a tool for screening diabetic patients for retinopathy. Candidate micro aneurysms are extracted, after the image has been modified to remove variations in background intensity, by algorithms that enhance small round features. Each micro aneurysm candidate is then classified according to its intensity and size by the application of a set of rules derived from a training set of 102 images. An automated technique was developed to detect retinopathy in digital red-free Fundus images that can form part of a diabetic retinopathy screening programme. It is believed that it can perform a useful role in this context identifying images worthy of closer inspection or eliminating 50% or more of the screening population who have no retinopathy.[2]

The robust detection of red lesions in digital color Fundus photographs is a critical step in the development of automated screening systems for diabetic retinopathy. In this paper, a novel red lesion detection method is presented based on a hybrid approach, combining prior works by Spencer et al. (1996) and Frame et al. (1998) with two important new contributions. The first contribution is a new red lesion candidate detection system based on pixel classification. Using this technique, vasculature and red lesions are separated from the background of the image. After removal of the connected vasculature the remaining objects are considered possible red lesions. Second, an extensive number of new features are added to those proposed by Spencer-Frame.

The detected candidate objects are classified using all features and a k-nearest neighbor classifier. An extensive evaluation was performed on a test set composed of images representative of those normally found in a screening set. When determining whether an image contains red lesions the system achieves a sensitivity of 100% at a specificity of 87%. The method is compared with several different automatic systems and is shown to outperform them all. Performance is close to that of a human expert examining the images for the presence of red lesions.[3]

This paper addresses the automatic detection of micro aneurysms in color Fundus images, which plays a key role in computer assisted diagnosis of diabetic retinopathy, a serious and frequent eye disease. The algorithm can be divided into four steps. The first step consists in image enhancement, shade correction and image normalization of the green channel. The second step aims at detecting candidates, i.e. all patterns possibly corresponding to MA, which is achieved by diameter closing and an automatic threshold scheme. Then, features are extracted, which are used in the last step to automatically classify candidates into real MA and other objects; the classification relies on kernel density estimation with variable bandwidth.

A fully automated, fast method to detect the fovea and the optic disc in digital color photographs of the retina is presented. The method makes few assumptions about the location of both structures in the image. We define the problem of localizing structures in a retinal image as a regression problem. A KNN regressor is utilized to predict the distance in pixels in the image to the object of interest at any given location in the image based on a set of features measured at that location. The method combines cues measured directly in the image with cues derived from a segmentation of the retinal vasculature. A distance prediction is made for a limited number of image locations and the point with the lowest predicted distance to the optic disc is selected as the optic disc center. Based on this location the search area for the fovea is defined. The location with the lowest predicted distance to the fovea within the fovea search area is selected as the fovea location. The method is trained with 500 images for which the optic disc and fovea locations are known. An extensive evaluation was done on 500 images from a diabetic retinopathy screening program and 100 specially selected images containing gross abnormalities. The method found the optic disc in 99.4% and the fovea in 96.8% of regular screening images and for the images with abnormalities these numbers were 93.0% and 89.0% respectively.[5]

III. PROPOSED SYSTEM

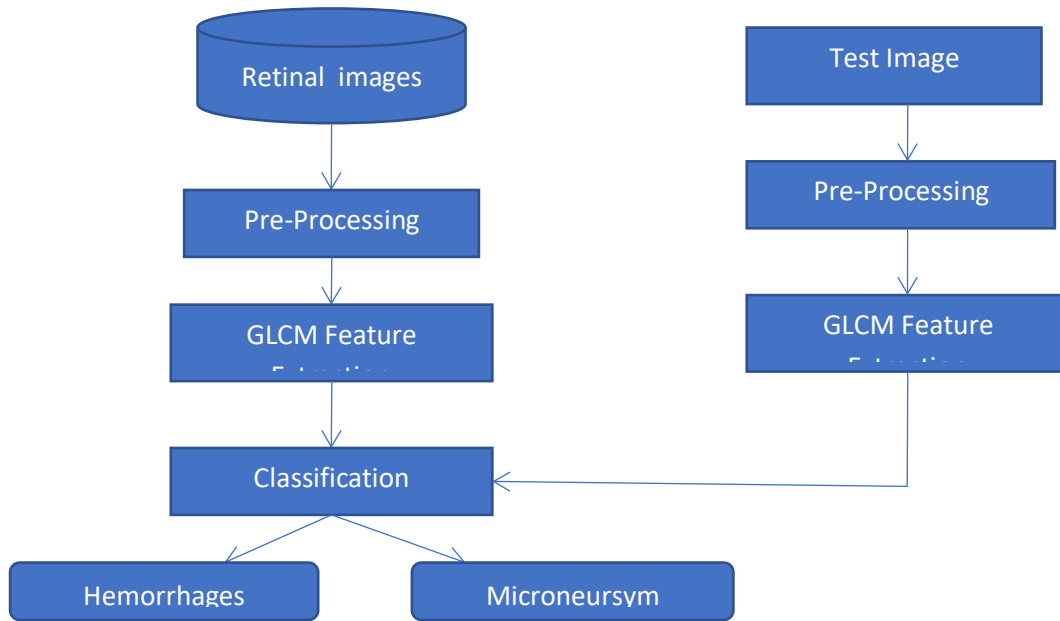


Fig 1: Working model of proposed system

Phase 1

1.1 Image Pre-processing

Images are enhanced by sharpening and removing unwanted outliers.

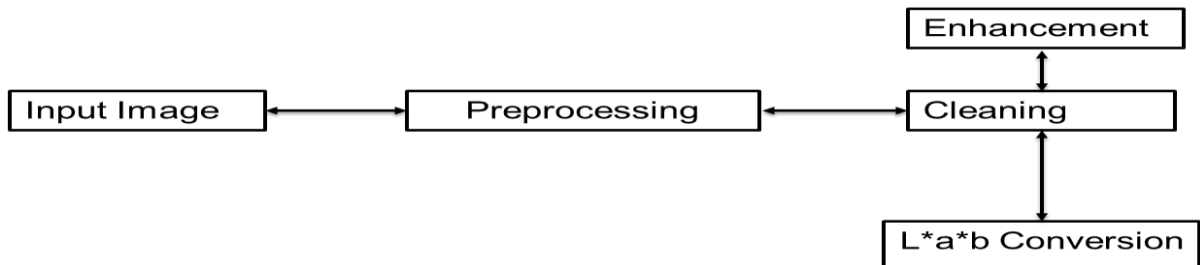


Fig 2: Image processing

Phase 2

2.1 Segmentation

Image will be segmented to fetch out the image edges and then detected all required parameters

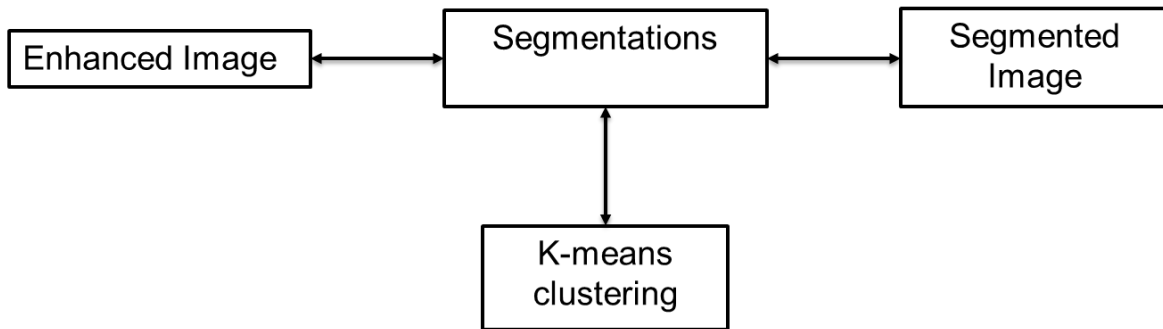


Fig 3: Segmentation

Phase 3

3.1 Recognition and Classification

Once the image is segmented it can be tested to recognize it first and then classify it into original or fraud image using SVM algorithm.

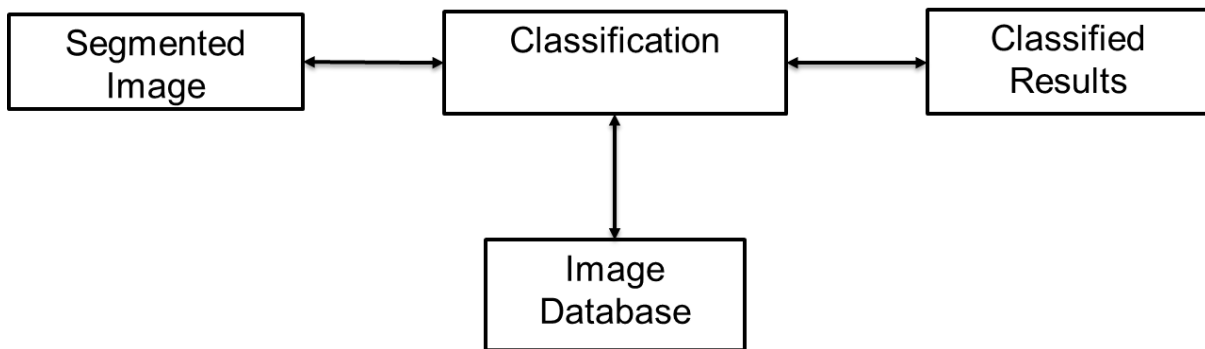


Fig. 4 SVM Algorithm

Clustering will be done using k-means algorithm. Recognition and classification will be done using SVM algorithm.

3.2 K-means Algorithm

k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster.

The algorithm has a loose relationship to the k-nearest neighbor classifier, a popular machine learning technique for classification that is often confused with k-means because of the k in the name. One can apply the 1-nearest neighbor classifier on the cluster centers obtained by k-means to classify new data into the existing clusters. This is known as nearest centroid classifier or Rocchio algorithm.

3.3 SVM Algorithm

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling

exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

IV. Methodologies

Automated microaneurysm, hemmorrhages detection is very useful in diagnosing the diabetic retinopathy for the prevention of blindness. With the help of automated system, the work of optahlmologists can be reduced and the cost of detection of diabetic retinopathy can also be reduced. Most of the existing methods of microaneurysms detection work in two stages: microaneurysm candidate extraction and classification.

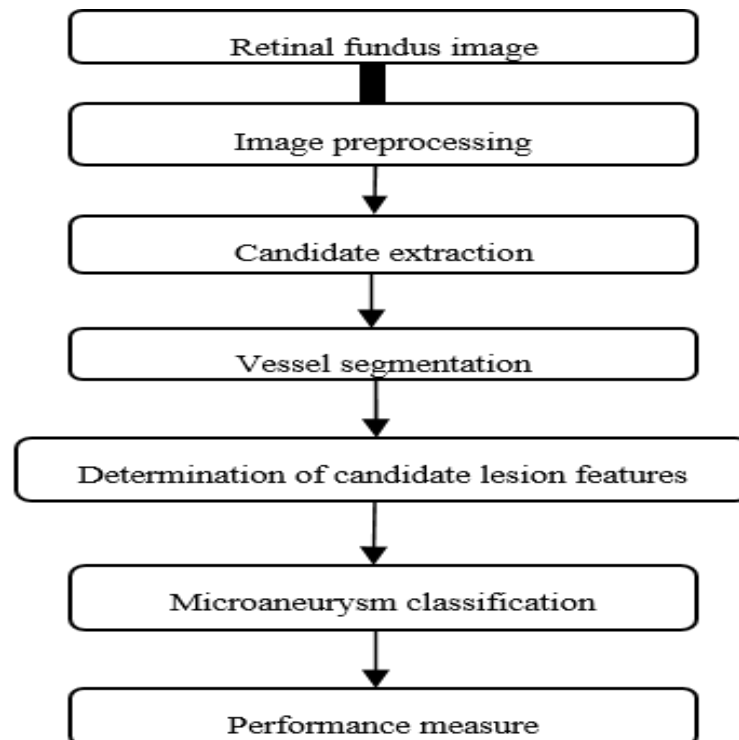


Figure 7: Steps for detection

A.Morphological Processing

Morphological processing is the most common method used for detection of microaneurysm & hemorhages. Morphological processing is a collection of techniques that can be used for image component extraction. In 1996, Spencer et al. [11] used morphological processing which detects microaneurysms present in fluorescein angiograms. After preprocessing stage, a bilinear top-hat transformation and matched filtering are used to provide an initial segmentation of the images. Then Thresholding is used to produce a binary image that contains candidate microaneurysms. Then a novel region-growing algorithm results in the final segmentation of microaneurysms.

B.Neural Network Approach

In this Paper, we propose a CNN approach to diagnosing Dr from digital fundus images and accurately classifying its severity. We develop a network with CNN architecture which can identify the intricate feature involve in the classification task , such as micro-aneurysm, exaudate, haemorrhages on the retina.

C.Classification

Here proposed a method to detect the microaneurysms using SVM (Support Vector Machine) in retinal fundus images. In this method, first of all a generalize histogram algorithms are used to enhance the images. Then blood vessels and any object which is too large to be a red lesion are removed. Then finally, extraction of microaneurysm is performed and its result is given as the input to the SVM to classify the microaneurysms, Hemorrhages.

V. ALGORITHM

Algorithm DiseaseDetect()

Step 1: Read Image from local directory in var img

Step 2: Extract RGB Panels in three different variables

```
rimage = img(:,:,1)
```

```
gimage = img(:,:,2)
```

```
bimage = img(:,:,3)
```

Step 3: Convert gimage into gray scale

```
gray = rgb2gray(gimage)
```

Step 4: Extract Feature from gray image in GLCM Matrix

```
GLCM[]=extract(gray)
```

Step 5: call svmclassify(GLCM,train.mat) and store result in class_var class.

Step 6: if class==0

```
call hem_detect()
```

```
if class==1
```

```
call micro_detect()
```

Step 7: Exit

Algorithm svmclassify(GLCM[],train.mat)

Step 1: Read train.mat in temp array

```
temp[] = read(train.mat)
```

Step 2: Read GLCM[] array

Step 3: FOR I = 1 TO LENGTH(temp)

```
compare GLCM[i] with temp[i] and store max_compare[]
```

```
END FOR
```

Step 4: Sort Descending max_compare[]

Step 5: Read max_compare[0]

Step 6: return class(compare[0])

Step 7: Exit

Algorithm hem_detect()

Step 1: Read image from temp

Step 2: Perform k_means algorithm with $k = 3$

Step 3: Perform segmentation on disease area

Step 4: Show segmented area in axis

Step 5: Exit

Algorithm micro_detect()

Step 1: Read image from temp

Step 2: Perform iteration method to find micro_segments in image

Step 3: Perform image mapping for finding holes

Step 4: Perform erosion to find position to place boxes

Step 5: FOR I=1 TO NUM_MICRO

 Place square boundaries in READ_LOCATION_MICRO

 END FOR I

STEP 6: EXIT

VI. CONCLUSION

Prolonged diabetes leads to DR, where the retina is damaged due to fluid leaking from the blood vessels. Usually, the stage of DR is judged based on blood vessels, exudes, hemorrhages, microaneurysms and texture. In this paper, we have discussed different methods for features extraction and automatic DR stage detection. An ophthalmologist uses an ophthalmoscope to visualize the blood vessels and his or her brain to detect the DR stages. Recently digital imaging became available as a tool for DR screening. It provides high quality permanent records of the retinal appearance, which can be used for monitoring of progression or response to treatment, and which can be reviewed by an ophthalmologist, digital images have the potential to be processed by automatic analysis systems. A combination of both accurate and early diagnosis as well as correct application of treatment can prevent blindness caused by DR in more than 50% of all cases. Automatic detection of microaneurysm presents many of the challenges. The size and color of microaneurysm is very similar to the blood vessels. Its size is variable and often very small so it can be easily confused with noise present in the image. In human retina, there is a pigmentation variation, texture, size and location of human features from person to person. The more false positives occur when the blood vessels are overlapping or adjacent with microaneurysms. So there is a need of an effective automated microaneurysm detection method so that diabetic retinopathy can be treated at an early stage and the blindness due to diabetic retinopathy can be prevented. We performed the classification in the detection of the diabetic retinopathy. The features specific to this disease were used in making the codebook and with this codebook we performed the features matching and analysis of the images using the vector. The size of the codebook depends on the number of feature points we are taking in the image and also on the number of segments we are dividing the fundus images. The results obtained were satisfactory as the method detected the pathology with

quite good percentage accuracy. For images of better resolution, the technique is expected to give better result than the results obtained with images of 130x150 pixels. The reason being that the image will contain more information and the codebook will be stronger, with the values being more accurate.

REFERENCES

- [1] S. Wild, G. Roglic, A Green, “Global prevalence of diabetes: estimates for the year 2000 and projections for 2030,” *Diabetes Care*, 27, pp.1047- 1053, 2004.
- [2] S. R. Nirmala, M. K. Nath, and S. Dandapat, “Retinal Image Analysis: A Review,” *International Journal of Computer & Communication Technology (IJCCT)*, vol-2, pp. 11-15, 2011.
- [3] National Eye Institute, National Institutes of Health, “Diabetic Retinopathy: What you should know,” Booklet, NIH Publication, no: 06-2171, 2003.
- [4] A. D. Fleming, K. A. Goatman, and J. A. Olson, “The role of haemorrhage and exudate detection in automated grading of diabetic retinopathy,” *British Journal of Ophthalmology*, vol 94, no. 6, pp. 706- 711, 2010.
- [5] A. D. Fleming, S. Philip, K. A. Goatman, J. A. Olson, and P. F. Sharp, “Automated microaneurysm detection using local contrast normalization and local vessel detection,” *IEEE Trans. Med. Imag.*, vol. 25, no. 9, pp. 1223–1232, Sep. 2006.
- [6] M.Niemeijer, B. V. Ginneken, J. Staal, M. S. A. Suttorp-Schulten, and M. D. Abramoff, “Automatic detection of red lesions in digital color fundus photographs,” *IEEE Trans. Med. Imag.*, vol. 24, no. 5, pp. 584– 592, May 2005.
- [7] M. J. Cree, J. A. Olson, K. C. McHardyt, J. V. Forrester and P. F. Sharp, “Automated microaneurysms detection,” *IEEE conference*, pp. 699-702, 1996
- [8] A. Mizutani, C. Muramatsu, Y. Hatanaka, S. Suemori, T. Hara, and H. Fujita, “Automated microaneurysm detection method based on double ring filter in retinal fundus images,” in *Proc. SPIE, Med. Imag, Computer-Aided Diagnosis*, vol. 7260, 2009.
- [9] K. Ram, G. D. Joshi and J. Sivaswamy, “A successive clutter rejection based-approach for early detection of diabetic retinopathy,” *IEEE Transaction on Biomedical Engineering*, vol. 58, no. 3, pp. 664-673, Mar. 2011
- [10] M. Esmaili, H. Rabbani, A. M. Dehnavi, and A. Dehghani, “A new curvlet transform based method for extraction of red lesions in digital color retinal images,” in *Proc. ICIP*, pp.4093-4096, 2010.
- [11] T. Spencer, J. Olson, K. McHardy, P. Sharp, and J. Forrester, “An image processing strategy for the segmentation and quantification in fluorescein angiograms of the ocular fundus,” *Comput. Biomed. Res.*, vol. 29, pp. 284–302, 1996.
- [12] A. Frame, P. Undrill, M. Cree, J. Olson and K. McHardy, P. Sharp, and J. Forrester, “A comparison of computer based classification methods applied to the detection of microaneurysms in ophthalmic fluorescein angiograms,” *Comput. Biol. Med.*, vol. 28, pp. 225–238, 1998.
- [13] X. Zhang and G. Fan, “Retinal Spot Lesion Detection Using Adaptive Multiscale Morphological Processing,” in *Proc. ISVC (2)*, pp.490-501, 2006.
- [14] T. P. Karnowski, V. P. Govindasamy, K. W. Tobin, E. Chaum, M. D. Abramoff, “Retina Lesion and Microaneurysm Segmentation using Morphological Reconstruction Methods with Ground-Truth Data,” *Conf Proc IEEE Eng Med Biol Soc 1*, pp. 5433-5436, 2008.
- [15] G.B. Kande, S.S. Tirumala, P.V. Subbaiah, and M.R. Tagore, “Detection of Red Lesions in Digital Fundus Images,” in *Proc. ISBI*, pp.558-561, 2009.
- [16] G.B. Kande, S.S. Tirumala, and P.V. Subbaiah, “Automatic Detection of Microaneurysms and Hemorrhages in Digital Fundus Images,” presented at *J. Digital Imaging*, pp.430-437, 2010.
- [17] STARE: Structured Analysis of the Retina, [Online]. Available: <http://www.ces.clemson.edu/ahoover/stare/>
- [18] DIARETDB: Diabetic Retinopathy Database and Evaluation Protocol, [Online]. Available: <http://www2.it.ut.fi/projectlimageret/>
- [19] Matei, Daniela, and R. Matei., “Detection of diabetic symptoms in retina images using analog algorithms,” *International Journal of Biological and Life Sciences*, pp. 224-227, 2010.

- [20] M. N. Langroudi, H. Sadjedi, “A New Method for Automatic Detection and Diagnosis of Retinopathy Diseases in Colour Fundus Images Based on Morphology,” *Bioinformatics and Biomedical Technology (ICBBT)*, pp. 134 - 138, 2010.
- [21] A. Purwita, K. Adityowibowo, A. Dameitry, M. Widhi and S. Atman, “Automated Microaneurysm Detection Using Mathematical Morphology,” *IEEE, International Conference on Instrumentation, Communication, Information Technology and Biomedical Engineering*, , nov. 2011.
- [22] M. Kamel, S. Belkassim, A. M. Mendonca, A. Campilho, “A Neural Network Approach for the Automatic Detection of Microaneurysms in retinal Angiograms,” *IEEE Conference*, pp. 2695-2699, 2001.
- [23] D. Usher, M. Dumskyj, M. Himaga, T. H. Williamson, S. Nussey , J. Boyce, “Automated detection of diabetic retinopathy in digital retinal images: a tool for diabetic retinopathy screening,” *Diabet Med.*, vol. 21, pp. 84- 90, 2004.
- [24] M. Garcia, C. I. Sanchez, M. I. Lopez, A. Diez, R. Hornero, “Automatic Detection of Red Lesions in Retinal Images Using a Multilayer Perceptron Neural Network,” *Conf Proc IEEE Eng Med Biol Soc.*, pp. 5425-5428, 2008.
- [25] M. Garcia M. I. Lopez, D. Alvarez and R. Hornero, “Assessment of four neural network based classifiers to automatically detect red lesions in retinal images,” *Med Eng Phys.* , pp. 1085-1093., 2010.
- [26] S. Balasubramanian, S. Pradhan, V. Chandrasekaran, “Red Lesions Detection in Digital Fundus Images,” *IEEE Conference, ICIP*, pp. 2932-2935, 2008