

# Automatic Detection of Micro aneurysm in Retinal Images

E.Dhiravidachelvi<sup>1</sup>, E.Jayanthi<sup>2</sup>, I.S.Suganthi<sup>3</sup>, S.Priyadharshni<sup>4</sup>

<sup>1</sup>Electronics and communication engineering department, Mohamed Sathak A.J college of Engineering, Chennai, TamilNadu, India, selvi.sathi@gmail.com

**Abstract:** One of the early detectable red lesions in Diabetic Retinopathy fundus Images is Microaneurysms (MA). Detecting MA automatically is a tough job since the size of the MA is very small. The colour, size and shape features of MA are merely similar to Haemorrhages and exudates. MA is a reddish, circled spot on the surface where its size is bigger than Haemorrhages and smaller than the hard exudates. The main objective of this paper is to detect MA automatically and help ophthalmologist for pre-screening process. Various techniques and methodologies were discussed for detecting and analysing MA in the earlier researches. In the existing system the author proposed Bi-Linear-Top-Hat method for detecting MA in DRF images. In this paper an ACHT – [Automatic Circular Hugh Transform] method is applied to detect the circular shape of MA in a DRFI. The detect MA originality is investigated and evaluated using the feature extraction, classification by GLCM combined SVM, which compares shape model with the colour features. The experiment result shows that the performance of the proposed approach is better than the existing approaches.

**Keywords:** Micro aneurysm; Diabetic Retinopathy; Image Processing; Pre-Processing; Image Classification.

## 1. Introduction

Vision loss is a main disease occurs nowadays among all age group of human being due to the food habit and color visions. Various CAD systems are developed for analyzing the eye images on various components like OD, BV, MA and so on. But vision loss happens very fast due to MA in the eye image especially for diabetic retinopathy people. The risk of the vision loss can be avoided by earlier treatment which prevents Diabetic retinopathy.

## 2. Related Works

The literature survey says there are various methods and techniques are available for detecting the red lesions. Abhir et al introduced a shape profile, and by automatically identify the normal images the manual workload and cost could be reduced while increasing the effectiveness of the screening [6]. Fleming et al, Spencer et al. and [8, 17] introduced top-hat morphological transform method to eliminate the blood vessels from the diabetic retinopathy fundus images which will helps to easily identify the micro aneurysms. The candidate MA is the residual regions from the detection operation. Watershed region growing

method is used for detecting the MA which is distinguished from other tiny dots in the retina. Avinash K. Ikhara et al.[5] proposed candidate extractor method to detect the MA effectively from the diabetic retinopathy images. The features of the DR are recognized and MA in the images are detected using gradient values using a CAD-DR screening method, which highly depends on the MA availability [9, 1]. Reliable MA detection method combined with ensemble-based framework was proposed to detect and improve the MA efficiently and the sensitivity and specificity are great in score [3, 15]. K. Adal et al. [2] proposed a novel approach which enhance the image in contrast value using SVD. Automatic grading of these images is being considered by health boards so that the human grading task is reduced. Also the candidate selection is obtained by the Hessian-based algorithm which extracts the MA region. The object, region detection can be obtained by finding the dissimilar values among the pixels and are classified into foreground, background for the adjacent pixels, then subtract the background which gives only the foreground object to do image processing successfully [21], the edges of the blood vessels and other features can be detected [19] and are analyzed. The central point of the micro aneurysms are detected by circular Hough

Transform [4]. The candidate regions for MAs were detected double ring method [12] any false positive located regions nearby the blood vessels are removed. The statistical texture features of the images are extracted [10] and applied to the classifier for better performance. A visual inspection of the optic disc, macula and the blood vessels of the eye requires to be done routinely. Diabetic patients run the risk of damage to retinal vessels, which are referred to as diabetic retinopathy [20].

### 3. Materials

The input images used in this paper are DIARETDB1; benchmark dataset images totally 100 colour fundus images in which 50 images are MA affected images. The image size is 1500 x 1152 at 32 bit, true colour images.

### 4. Existing Method

In this existing system, the author proposed a computerized scheme to Microaneurysm detection. Image pre-processing is followed by the detection of Microaneurysm regions using Bi-Linear-Top-Hat Method. Since detecting circular region using this method is little hard the accuracy of the MA detection should be improved.

### 4. Proposed method

The overall functionality of the proposed approach is carry out in step by step manner and it is shown in Figure-1.

#### 4.1 Image Enhancement

It is necessary to enhance the image before image processing which improve the image data by suppressing the unwanted distortions on the image. In this paper using PT-[Pixel Transformation] method the image is enhanced. This method will adjust the pixel value by adjusting the  $\alpha, \beta$  [bias and gain]. The mathematical representation for PT method is

$$g(x) = \alpha.f(x) + \beta$$

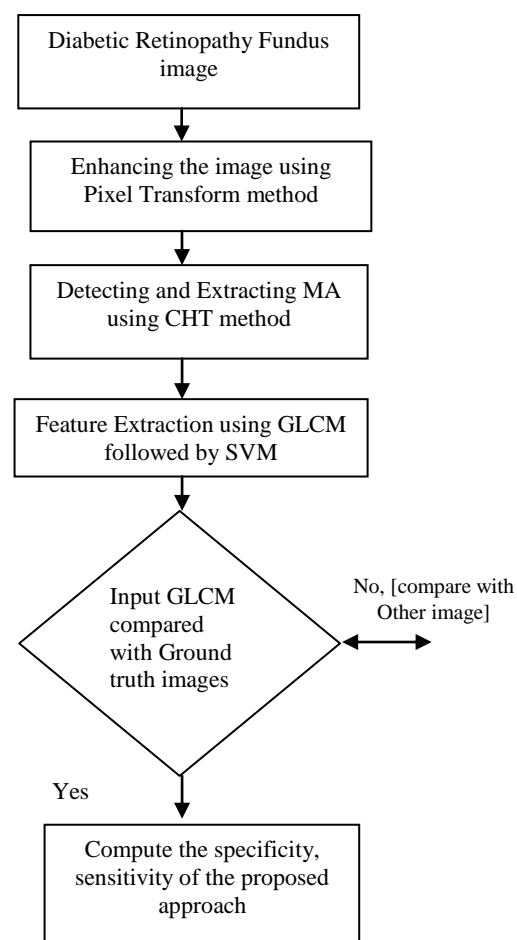
This follows two point processes as addition and multiplication. In this form, the value of  $\alpha > 0, \beta$  are called as controlling the contrast and brightness respectively. The output pixel value is always depends on the input pixel value. Since the resultant image provides more brightness, contrast enhanced image and it can written as

$g(i, j) = \alpha.f(i, j) + \beta$ , where i, j indicates the pixel location, g is the resultant image, f is the input image,  $\alpha$  is the bias parameter and  $\beta$  is the gain parameter assumed by the user.

#### 4.2 Micro Aneurysm Detection using CHT

Microaneurysms (MA) appear as small, roughly circular lesions on the retinal photograph. The

retinal MA's are discrete, and it appear as small round dark red dots on the surface of the retinal images.



**Figure 1.** Flow diagram of the proposed method for Detection of MA

From [11], [7] the colour of the MA is reddish in circular form of diameter  $\lambda < 125 \mu\text{m}$ . According to the diameter size and red colour pixels with fixed intensity values, are detected as a micro aneurysms.

Shape based object detection is a challenging task in computer vision. There is various feature extraction methods are openly available for circle detection but one of the most common method used to detect circular objects in an image can be obtained CHT – [Circular Hough Transform] method. CHT can do accurate circular edge detection even in a noisy image. It is accepted by most of the research people since it is understandable easily. CHT has its own preprocessing method with Hough transformation method. CHT converts the input image into binary images and utilizes the sobel, canny edge detection methods. CHT can understand irregular shapes of an object which is predefined set of shapes by electing procedure.

Than the LHT the CHT utilizes circular based equations. The circle can be represented in the form of

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

Where  $a, b$  are the center co-ordinates of the circle,  $r$  is the radius of the circle. The parametric representation for the circle can be written as:

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

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

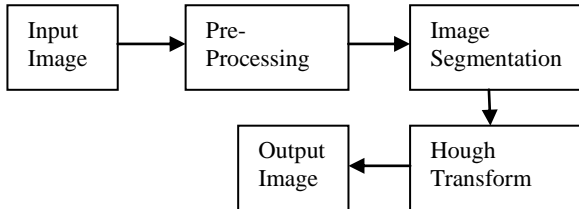


Figure-2: Circular Hough Transform Method

CHT utilizes memory storage, complexity feature extraction and computation time efficiently than other methods. In CHT the radius of the circular objects are fixed as constants in the hard code, where the programmer can change the value due to the size of the object. This has a minimum and a maximum value for setting the user necessity values. It uses 2D as well as 3D coordinates of the circle. The circle is drawn by changing the radius repeatedly on the image until get the accurate circular object by calling the edge detection method. The procedure of the CHT is shown in figure-2.

Once the circular shape object detection is obtained then it will be classified for finding the accuracy of the CHT. The methodology of the CHT is written in the form algorithm, where it can be programmed using any computing languages and tested.

*Algorithm\_CHT* ( )

```

{
➤ Input the RGB image into Gray scale image
➤ Construct a 3D Hough array with the first two
  ○ dimensions representing
  ○ The coordinates of the circle
    ▪ origin and the third dimension
  ○ Represents the radius
➤ Detect the edges using canny edge detector.
  ○ For each pixel, increment the
  ○ Corresponding elements in the Hough array
➤ Collect candidate circles, and then delete similar circles.
➤ Draw circles around MA
}
  
```

The detected MA objects which are mainly smaller in shape and the number of pixels with the boundary are having more or less 10 pixels within the boundary are classified as MA. There are many red colour dots in circular shapes will be detected in by the

extended minima method. But the exact MA can be classified by extracting the second order texture features of the image using Gray Level co-occurrences Matrix (GLCM).

### 4.3 Feature Extraction using GLCM

In gray level co occurrences matrices, the number of rows and columns are equal to the number of gray levels.

Indexing and retrieving the visual contents in an image can be obtained by Feature Extraction method.

The GLCM is a  $L \times L$  square matrix of the gray scale image  $I$  of spatial dimension  $M \times N$  with gray level in the range  $T = [t_{i,j}]L \times L$ . It can be represented by  $T = [t_{i,j}]L \times L$  matrix. Every element in the matrix specifies the number of transitions among all pair of gray values in a specific manner. Every pixel in the image at spatial co-ordinate  $(m, n)$  including its gray value specified by  $f(m, n)$ , it deliberates all its nearest adjacent pixels in the locations of

$(m + 1, n), (m - 1, n), (m, n + 1)$  and  $(m, n - 1)$

The co-occurrence matrix is formed by comparing gray level changes of  $f(m, n)$  to its corresponding gray levels,

$f(m + 1, n), f(m - 1, n), f(m, n + 1)$  and  $f(m, n - 1)$ .

There are various co-occurrence matrix are possible and it duly depends on the gray level  $I$  follows the gray level  $j$ . The co-occurrence matrix by considering horizontally right and vertically lower transitions can be given as

$$t_{i,j} = \sum_{m=1}^M \sum_{n=1}^N \delta$$

where

$$\delta = 1 \text{ if } \begin{cases} f(m, n) = i \text{ and } f(m, n + 1) = j \\ f(m, n) = i \text{ and } f(m + 1, n) = j \end{cases}$$

$\delta = 0$  otherwise

Normalizing the entire number of transitions in the co-occurrence matrix, a desired transition probability  $p_{ij}$  from gray level  $I$  to gray level  $j$  is obtained as follows.

$$P_{i,j} = \frac{t_{i,j}}{\sum_{i=1}^L \sum_{j=1}^L t_{i,j}}$$

Using the feature extraction method the texture properties of the DRFI are extracted. These feature values are used by the classifier after some times to categorize the images accurately.

Textural features are the characteristics of the surface of DRFI and the relationship among the nearest neighbor pixels on the surface. There are

several textural features available a DRFI, but in this scenario the mean, standard deviation, entropy and homogeneity of the pixels are calculated and compared for evaluating the performance of the CHT. The spatial distribution of the gray level features can be obtained from Co-Occurrence matrix of the image.

#### 1. Area of MA

The area of the MA is calculated and computed by counting the pixels in an iterative manner by row wise or by column wise.

$$\text{Area} = \sum_{i=0, j=0}^{m, n} p(i, j)$$

#### 2. Mean

$$\text{Mean}[\mu] = \left[ \frac{\sum_{i=0}^m \sum_{j=0}^n p(i, j)}{m * n} \right]$$

#### 3. Standard Deviation

$$\text{Standard Deviation} [\sigma] = \sqrt{\sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [P(i, j) - \mu]^2}$$

#### 4. Third moment

$$\text{Third moment} [\mu_i] = \sum_{i=0}^{L-1} (Z_i - m)^3 p(Z_i)$$

#### 5. Entropy

$$\text{Entropy} = - \sum p \log_2 p$$

#### 6. Homogeneity

Closeness of the distribution of the image GLCM diagonal can be mathematically written as

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P_{ij}}{(1 + |i - j|)}$$

For our proposed work 50 normal images and 50 Microaneurysm affected images (totally 100 images) are taken as input images and their features are extracted and the classification results are shown below.

### 4.4 SVM classification

Several features are extracted using GLCM methodology. In this scenario only 6 features are taken to classify the MA. One is area and 5 textural features. The SVM classifier is employed to infected or infected MA in the diabetic retinal Microaneurysms images. The selected features feed as input to SVM classification parameters and it classifies the normal and abnormal categories.

### 4.6 Experiment results

To investigate the efficiency of the CHT, the algorithm is programmed in MATLAB 2012a software and run on entire datasets. MA detection was gathered from the result set.

### 4.7 Performance Evaluation

To run a normal image in MATLAB software takes a minimum of 14 second using PC with core i5 processor and 4 GB RAM. All the database images are individually called for training and testing the detection as well as classification processes. The sample of each data set is divided into 50% of training and 50% of testing categories. Finally SVM classifier is trained with the training data set. Then the each testing image is compared with the trained images and classify. To evaluate the performance of the CHT using evaluation metrics such as sensitivity, specificity and accuracy which are computed using the following equations given below:

$$\text{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100\%$$

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100\%$$

$$\text{Accuracy}(\%) = \frac{TP + TN}{N} \times 100\%$$

Where  $TP \rightarrow$  True Positive;  $TN \rightarrow$  True Negative;  $FP \rightarrow$  False Positive;  $FN \rightarrow$  False Negative;  $N \rightarrow$  is the total Number of images

The input image and the gray scale based enhanced image used in the experiment is shown in the following Fig-3a, Fig-3b.



Figure-3a: Original Image



Figure-3b: Gray Scale Image

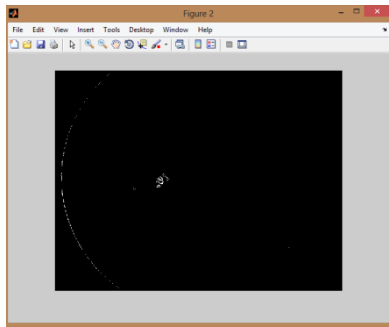


Figure-4: MA Detection by CHT

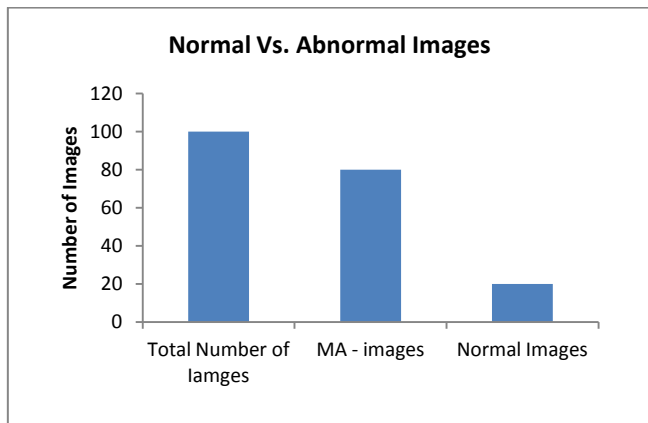


Figure-5: Obtained Normal Vs Abnormal Detection by CHT

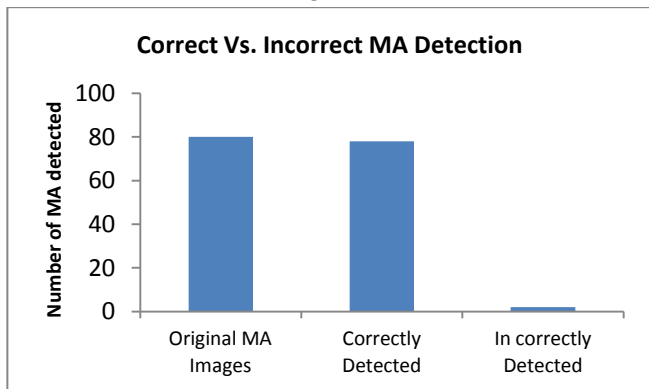


Figure-5: Obtained Correctly Rejected Vs in correctly rejected by CHT

The following table shows the GLCM matrix obtained from the DR image where all these values in matrix represent the features of the image.

$$\begin{bmatrix} 82279 & 5262 & 8 & 1 & 0 & 0 & 0 & 0 \\ 5266 & 18825 & 541 & 746 & 33 & 0 & 0 & 0 \\ 5 & 649 & 441 & 674 & 35 & 1 & 0 & 0 \\ 0 & 618 & 710 & 158369 & 9871 & 2 & 0 & 0 \\ 0 & 57 & 104 & 9774 & 120898 & 999 & 0 & 0 \\ 0 & 0 & 1 & 6 & 995 & 3881 & 180 & 0 \\ 0 & 0 & 0 & 0 & 0 & 180 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Co-Occurrence Matrix

The textural features such as gray level, contrast, homogeneity, correlation and energy are also calculated from the GLCM.

The micro aneurysms segmentation results for sample images of DIARETDB1.

Total Number of Images	TP	FP	Sensitivity
80	78	2	97.50 %

Table 1. Classification Sensitivity Results

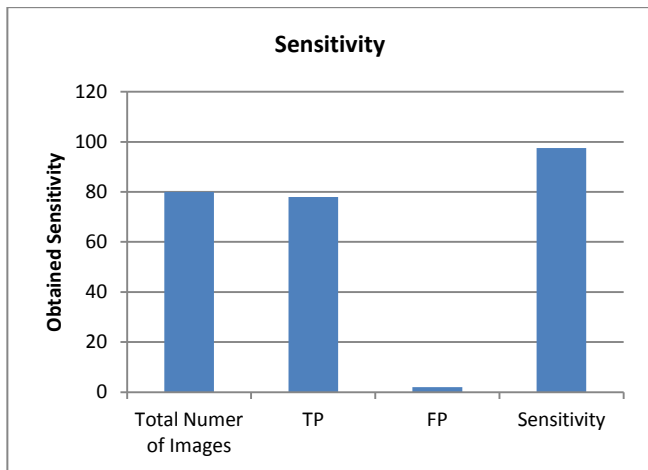
$$\text{Sensitivity} = \frac{TP}{TP+FN} = \frac{78}{(78+2)} = 97.5\%$$

$$\text{Specificity} = \frac{TN}{FP+TN} = \frac{20}{(0+20)} = 100\%$$

$$\text{Accuracy} = \frac{Tp+TN}{P+N} = \frac{(78+20)}{(50+50)} = 98\%$$

Where P = TP+FN

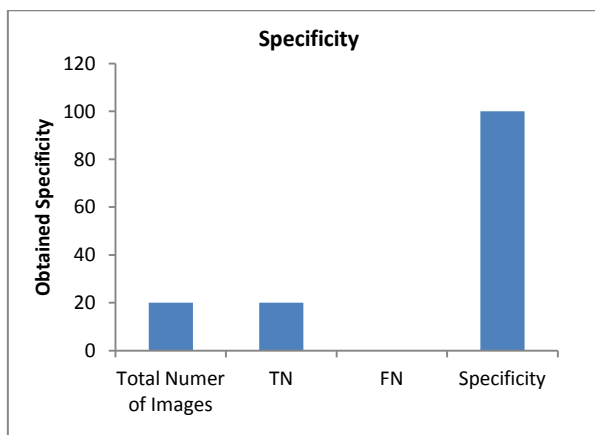
N =FP+TN



**Figure-5:** Sensitivity obtained from SVM

Total Number of Images	TN	FN	Specificity
20	20	0	100.00%

**Table 2.** Classification Specificity Results



**Figure-6:** Specificity obtained from SVM

#### 4.7. Conclusion

Automatic MA detection using CHT with SVM classification proved its performance via performance metrics such as Sensitivity is 97.5%, Specificity is 100% and its Accuracy in classification is 98%. Our system gives the better performance, so it is very helpful to the ophthalmologists in detecting MA. Also this proposed approach can help rural people to find out the MA occurrence in DRFI in case of emergency situations [Absence of Ophthalmologists].

In future, it is concentrated on automatic detection of Haemorrhages in Diabetic Retinopathy Fundus Images.

#### References

- [1] Abramoff.M, Reinhardt.J, Russell.S, folk.J, Mahajan.V, Niemeijer.M “Automated early detection of diabetic retinopathy”, *Ophthalmology*, vol. 117, no. 6, pp.1147-1154, 2010.
- [2] Adal. Ali. S, Sidibe .D, “Automated Detection of Microaneurysm Using Robust Blob Descriptors”, *SPIE Medical Imaging - Computer-Aided Diagnosis*, Orlando - FL: United States (2013).
- [3] Antal.B, Hajdu.A, “An Ensemble-Based System for Microaneurysm Detection and Diabetic Retinopathy Grading”, *IEEE Transactions On Biomedical Engineering*, vol.59, no.6, June 2012.
- [4] Asadi S, Hassan. H, ‘Detection of Micro aneurysms in Retinal Angiography Image using the circular Hough Transform’, *Journal of Advances in computer Research* ,vol 3,No 1,2012,pages 1-12
- [5] Avinash K. Ikhar, N. Ambatkar .S, “Enhancement of Blood Vessel for Microaneurysm Detection and Diabetic Retinopathy using an Ensemble Based System”, *IJAIST, ISSN: 2319:2682, Vol.15, No.15, and July 2013.*
- [6] Bhalerao.A,Patanaik.A,Anand.S,Saravanan.P, ‘Robust detection of Microaneurysm for sight threatening Retinopathy Screening’, *Journal of computer Vision, Graphics & Image processing*, 2008, pages 520-527.
- [7] Dupas.B, Walter T., Erginay. A, “Evaluation of automated fundus photograph analysis algorithms for detecting Micro aneurysms, Hemorrhages and exudates, and of a computer-assisted diagnosticsystem for grading diabetic retinopathy,” *Diabetes & Metabolism*36 (3), 2010, pp. 213-220.
- [8] Fleming .A, Philip S, Goatman K, Oslon J, Sharp P. “Automated micro aneurysms detection using local contrast normalization and local vessel detection”. *IEEE Trans Med Image* 2006; 25:1223–1232.doi:10.1109/TMI.2006.87995 3.
- [9] Jelinek.H.J, Cree. M.J, Worsley. D, Luckie. A, andNixon.P, “An Automated Microaneurysm Detector as a tool for identification of diabetic retinopathy in rural optometric practice, *Clin.Exp.Optom*” vol.89, no. 5, pp. 299-305, 2006.
- [10] Malik. F and Baharudin.B “The Statistical Quantized Histogram Texture Features Analysis for Image Retrieval Based on Median and Laplacian Filters in the DCT Domain” *The*

- International Arab Journal of Information Technology*, Vol. 10, No. 6, November 2013
- [11] Martins.C.I.O,Veras.R.M.S.,Ramalho.G.L.B,'Automatic Microaneurysm Detection and Characterization through Digital Color Fundus images', *International Joint Conference-Brazilian Symposium on Artificial Intelligence and Brazilian symposium on Neural Networks*,2010
- [12] Mizutani.A,Muramatsu.C,'Automated Microaneurysms Detection Method based on Double Ring Filter in Retinal Fundus Images', *medical Imaging 2009 proceedings of SPIE* vol 7260, IN-1
- [13] Murugan.R,Dr. Reeba Koreh, Microaneurysm 'Detection Methods in Retinal Images Mathematical Morphology ', *International journal of Advances in Engineering science and technology*, 2003
- [14] Prakash.J,Sumathi.K,' Detection and Classification of Microaneurysm for Diabetic retinopathy', *International journal of Engineering research and Applications*, 2013,page 31-36
- [15] SharvariPatil, Dr. Gaikwad . M.S., "Automated Microaneurysm Detection and Diabetic Retinopathy Grading", EEC 2013, ISBN: 978-981-07-6935-2 doi: 10.3850/ 978-981-07-6935-2\_77.
- [16] Sopharak. A, Uyyanonvara. B. and Baraman. S,'Automatic micro aneurysm Quantification for Diabetic Retinopathy Screening', *world Academy of Science, engineering and Technology* 2013, page 1735-1738
- [17] Spencer T, Olson J, Mc Hardy K, Sharp P, Forrester J. "An image processing strategy for the segmentation and quantification in fluoresce in angiograms of the ocular fundus". *Comput. Biomed Res.* 1996; 29:284–302. doi: 10.1006/cbmr.1996.0021.
- [18] Streeter Le and, Cree M. J.'Microaneurysm detection in color fundus images', *Image and vision computing NZ*, Palmerston North, Nov 2003, page 280-285.
- [19] Sujith Kumar S, Vipula Singh B., 'Automatic Detection of Diabetic Retinopathy in Dilated RGB Retinal Fundus Images', *international journal of computer Applications*, volume 47, No.9, 2012.
- [20] Tom S.F. Haines and Xiang. T, "Background Subtraction with Dirichlet Processes", *Springer-Verlag Berlin Heidelberg* 2012.
- [21] C.Aravind, M.PonniBalaS.Vijayachitra" Automatic Detection of Microaneurysms and Classification of Diabetic Retinopathy Images using SVM Technique'', *International Journal of Computer Applications* page no .0975 – 8887
- [19]. E. Dhiravidachelvi and Dr V. Rajamani ,'Analysis of retinopathy images by examining blood vessels , *International journal of Applied engineering Research* ,ISSN 0973-4562, Volume 9,number 22 (2014)pp. 13465-13474
- [20]. E. Dhiravidachelvi and Dr V. Rajamani,'A novel approach for diagnosing diabetic retinopathy in fundus images,' *Journal of Computer science*, 11(1): 262-268,2015, ISSN 1549-3636
- [21]. E. Dhiravidachelvi and Dr.V. Rajamani, " Computerized detection of optic disc in diabetic retinal images using background subtraction model, *IEEE International Conference on Circuits, Power and Computing Technologies (ICCPCT 2014)*, Noorul Islam University, Nagerkovil ,978-1-4799-2395-3/14/\$31.00,2014 IEEE