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Detection of Small Red Lesions in Retinal Fundus Images Using AC-CLAHE, Gabor Filter and One Class SVM

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Abstract

Presence of long term diabetes affects different body organs, one of the dominant effect it causes on, is retina of human eye ,called Diabetic Retinopathy(DR).DR progresses from mild Non-Proliferative DR too Severe Proliferative DR- leading to loss of vision. The syndromes it causes on retina are treatable if diagnosed in time. Earlier indications occur, due to leakage in retinal capillary, forming red deposits on retina, termed Microaneurysms. The occurrence of microaneurysms counts in diabetic retinopathy and its close correlation to the gravity of the disease is well noted. As a result, identification of Microaneurysms is must; to avoid the further impairments. A novel three stage approach for MA detection is proposed in this paper. Pre-processing is done using advanced - Adaptively Clipped – CLAHE and Directional feature enhancement using Gabor Filter, Candidate region segmentation is performed using Single Optimal Thresholding. Blood vessels are extracted and removed using cascade of morphological operations and line detectors. Further, with feature vector extraction and One Class-SVM, candidate regions are classified as MA's and outliers. The proposed method is tested on images from publicly available DiaretDB1 dataset and accomplished the results compatible to the state-of-the-art methods.

Keywords – AC-CLAHE, Diabetic Retinopathy, Gabor filter, Microaneurysms, OC-SVM, DiaretDB1.

I. Introduction

With an upsurge in the old masses worldwide there is rise in eye disorder, as a result there is a comparative diminution in ophthalmic assistances, particularly in rustic zones and emerging nations. The World Health Organization (WHO) has initiated "Vision 2020," a worldwide lead for stopping the preventable visual loss by the year 2020. Eye fitness includes more than a few methods like magnifying attempts to create alertness regarding eye fitness, identification the syndromes earlier, recognition of the disease, exact analysis, and aimed inhibition to get better results. Current

statistics indicates that worldwide, around 37 million people are blind plus124 million with low eyesight, exclusive of uncorrected refractive faults. The major reasons for worldwide vision loss are glaucoma, cataract corneal scarring, age-related macular degeneration (AMD), hypertensive retinopathy and diabetic retinopathy. The global

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Vision 2020 lead is meant to lessen preventable loss of sight mainly because of ocular disorders, further extra efforts are necessary to deal with glaucoma, cataract, and diabetic retinopathy. Diabetic retinopathy signifies the utmost enduring issue; as a result the majority of the research work has been focused on automatic analysis and grading of DR [1-3].

Diabetes is a metabolic disease, it directs to the problems with circulatory, renal, and eye illness. It is known to be the dominant and rising reason for public health issues worldwide and this fact is supposed to gain a count of 300 million in the year 2025. Creative ideas for recognition, analysis, grading, curing and screening the disease are demanded to deal with this rising problem.[1]

Diabetic Retinopathy originates from rise in blood sugar levels related to diabetes. It is an ongoing worsening disorder related to retina, which has an asymptomatic phase; it may begin very earlier, even before recognition of occurrence of diabetes. Diabetic retinopathy is split into number of phases. The most primitive syndromes of DR are microaneurysms, small red hemorrhages, cotton wool spots, and soft and hard exudates, these syndromes occur due to that result from irregular penetrability and no perfusion of vessels. The presence of initial indicators on retina is defined as non-proliferative DR (NPDR). Indications may occur even before the onset of diabetes. Further growth of disease is pointed out where retinal vessels leaks the fluid on retina, but if the leakage is located in proximity of macula, it may put at risk of vision loss known as Sight Threatening DR (STDR). The utmost common reason for sight loss in diabetes is Diabetic Macular Edema (DME). Growth of new fragile vessels on retina and occlusion of capillaries leads to retinal ischemia, this phase is known as Proliferative DR(PDR).Over the last decades the research in automated DR is continuously on rising edge due to increase in Diabetic patients[3-5].

One of the crucial steps in DR analysis is detection of MA's. MA's are the first significant indicators of DR. They are tiny, circular and red in color, appears anywhere on retina, may be in a cluster or segregated. Their appearance is not so bright and do not possess well defined borders. A little rise in blood sugar level may have an effect on retina and can lead to development of MA's. The advancement of the disease is indicated by the quantity of Microaneurysms. [4].Laser Therapies available can precisely close the MA leakage and can change the blood flow in retina. So, automated and accurate detection of MA's is must [6]. So, screening systems should be economical, easy and accurate, so automatic analysis of retina pertaining to DR or vasculature diseases are much needed.

The normal fundus image, image containing MA's and enlarged MA's section are as shown in Fig. 1 below.

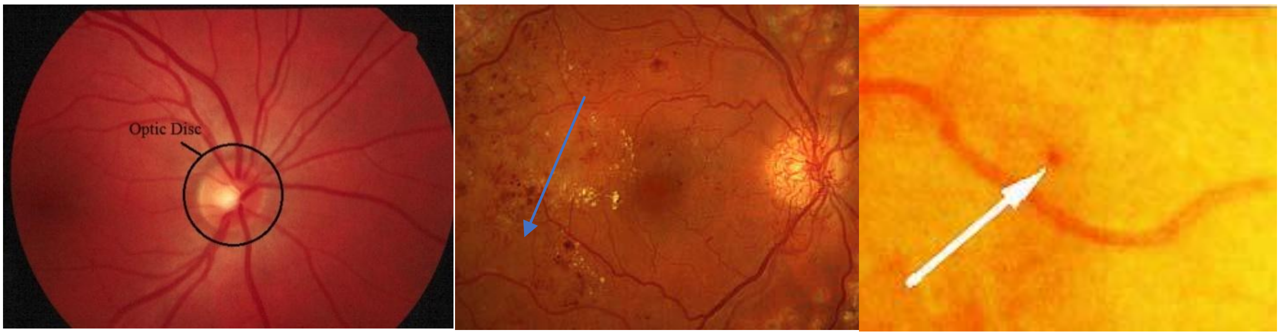

Fig.1-a) Normal Retinal Fundus Image b) Presence of MA's with other lesions c) Retinal Image with Enlarged region

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Problems like lack of contrast, structure is not defined in size, tiny, most of the time gets confused with vessels and present very close to vessels, makes accurate detection of MA still a challenge. Moreover, MA's shows resemblance to intensity and shape to the other lesions of DR, vessel crossovers or bifurcations, dark spots in image and broken vessels, which further complicates the problem.

As they bear a resemblance to vessels, it results into increase in false positive rate along with TPR. We have tried to address few of the issues mentioned earlier, in our proposed algorithm. The uneven illumination of retina image makes it difficult to enhance all tiny and deeply rooted MA's equally and hence remain unsegmented and not detected at the end ,resulting in smaller value of sensitivity .Hence, our first attempt is to visualize all the MA's with advanced enhancement process called Adaptively Clipped Contrast Limited Adaptive Histogram Equalization (AC-CLAHE) . It enhances all regions of images by dynamically choosing the clip limit unlike traditional CLAHE. We have reduced FPR by subduing accurately extracted blood vasculature from extracted candidate regions. Our blood vessel segmentation method [30], extracts all tiny vessels to, thereby reducing FPR by significant amount and increasing overall accuracy. Classifier like SVM is preferred due to its highest accuracy; as well OC-SVM needs very few samples for training, which is easy and fast.

II. RELATED WORK

Automatic detection of microaneurysms on retina of human being is been attempted by many of the researchers in different ways. The research has been concentrated on i) Noise suppression and illumination correction, ii) MA enhancement and segmentation iii) Feature Descriptors iv) Classifiers for MA and Non-MA detection. Pre-processing for contrast enhancement and suppression of noise is must for detection of tiny particles like MA's. It is attempted in terms of noise suppression [7], contrast improvement [7], [8] illumination correction [9] removal of retinal markers viz optic disc and vasculature and additional bright lesions [10], [11].

After a well-defined pre-processing number of approaches with morphological operations, template matching, classification in terms of pixel and fusion of these are suggested for MA identification in the earlier works mentioned. Morphological Operations -Earlier detection of MA was explored with various types of morphological operations with fluoresce angiography images. Baudoin C [12] identified MA's using various structuring elements with Top-Hat operations followed by extraction of vasculature. [13] Suggested the method using linear top hat operation, matched filter after that threshold and region growing operation, for finding microaneurysms. The use of hit –or- miss transform with feature descriptors using PCA was explored in [14].

The further class for MA identification is template matching methods. Enhancement of MA with the help of Gabor filters bank was discussed in [11]. The application of dynamic threshold and multi scale correlation kernel was proposed by Zhang [15] and achieved a sensitivity of 0.11 on ROC database. In [16] application of Frangi filter along with SVM classifier was explored and obtained a specificity, sensitivity of 50% and 100%.Applicationof Gaussian filters was proposed in [8 ,18-20] for primary candidate recognition process.

In the approaches where classification is done based on pixels, the use of K- k-nearest neighbor classifier for detection of MA was suggested by Niemeijer [8], achieved a specificity value of 87% with sensitivity 100%.Streeter [18] suggested the use of LDA classifier for MA detection and reported a sensitivity of 56%at 5.7 false positives per image. Use of the SVM classifier for DiaretDB1 and MESSIDOR was suggested in [22] and reported a sensitivity of 91% and specificity of 50% on DiaretDB1 database. In [11] the use of classification

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methods like SVM, M-Medoid, and Hybrid classifier were exploited by UsamAkram. Use of deep convolution approach -CNN was proposed in [25], [26], ensemble classifiers [27] are used to discriminate MA from candidate regions. Wen Cao[28] and other three have trained different classifiers using small MA patches, as well applied different feature selection algorithms for detection of MA's.

III. Proposed Methodology

Proposed work is done in 3 major parts i.e.MA enhancement and candidate region segmentation, Segmentation and subtraction of blood vessels, Feature Vector Formation and classification with OC-SVM. The block diagram of the proposed system is as shown in Fig. 2.

a. Candidate Region Enhancement

The input is a retinal fundus image from which is RGB in nature. The pixels from the green plane are extracted or further processing as it shows a better contrast compared to the red or blue plane. The input image is having a resolution of 1152 X 1500 pixels, to reduce the computation complexity and time it is resized by a factor of 0.5 using bicubic interpolation.

Morphological Opening

This morphological opening helps to smooth out bright lesions and optic disc morphological opening operation with SE disk of radius 5 using Eq. 1.

$$\varphi_f^{(sB)} = \max[\min \ f(x+b)] \qquad (1)$$

Here f is pre-processed color image and b∊SB, where SB is structuring element of size s. This gives smooth regions for dark lesions and vessels but it needs contrast enhancement.

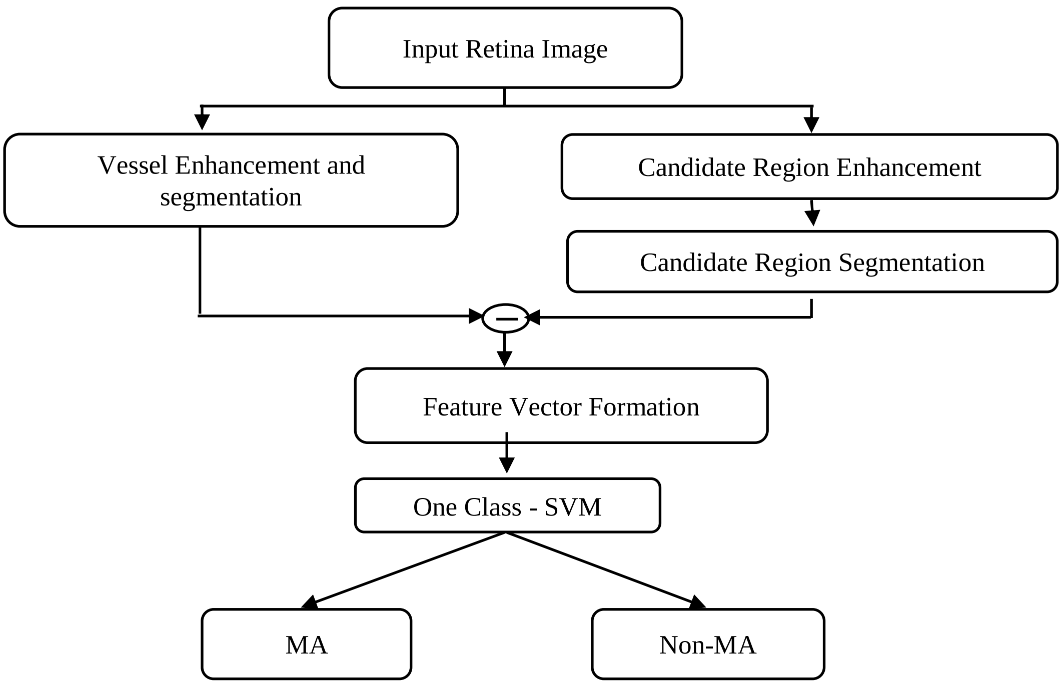

Fig. 1. Block Diagram of Proposed System

AC-CLAHE

In heuristic CLAHE approach, the selection of the value of clip limit and number of sub images are very much crucial to control optimal quality of an image. In CLAHE Size of bins in local histogram of a sub-image decides the value of clip limit in

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CLAHE. In the suggested Auto Clipped CLAHE approach, the number of tiles (M X M sub-images) should be chosen by user as per the objects of interest. The value of clip limit is chosen based on maximum height of bin n local histogram of the sub-image. The pixels above value of clip limit are redistributed equally to all pixels in the sub-image [29]. The AC-CLAHE is algorithmically defined below-

1)Divide the input image into M x M subsections.

2) For each subsection follow the steps given-

_ Find histogram of each tile.

_ Find value of maximum intensity in a tile.

_ Calculate value of Clip limit P using half interval search method.

_ Redistribute the pixels having value more than P uniformly over all the histogram bins in a tile a

and equalize the histogram.

3) For each pixel in given image do the following-

Map the pixel to weighted sum of four neighbor, two neighbors or pixel itself based on location of

Pixel as Internal Region, Border Region or Corner Region respectively to obtain the quality image

Processed by AC-CLAHE.

Gabor Filter

Gabor filters are preferred for directional feature enhancement. It is a product of Gaussian Kernel with a sinusoidal function.The filter response is given with Eq. 2 .

$$G(x, y, \vartheta, s) = e^{-\Pi\left(\frac{(x-x_0)^2+(y-y_0)^2}{s^2}\right)} \times e^{-2\Pi i(\cos\vartheta(x-x_0)+\sin\vartheta(y-y_0))} \quad (2)$$

Here center frequency is (x_0, y_0), s is referred as variance, ϑ angle for sinusoidal wave. $G(x, y, \vartheta, s)$ is the Gbaor filter response , it is convolved with Contrast enhanced image obtained as a result of AC-CLAHE, and maximum of the response is computed with different scales and rotation angles.

b. Candidate Region Segmentation

The output of Gabor filter is thresholded withOtsu's thresholding, which works on reducing intra class variance and raising inter class variance. As MA resembles in properties with blood vessels, the segmented image includes MA's along with blood vessels. So, it is very much required to extract and remove all blood vessels, in order to reduce the False Positive Rate of the classifier. It causes the reduction of spurious regions, as a result accuracy of classifier will be increased significantly.

c. Enhancement and Extraction of Blood Vessels

Here we have used our earlier proposed method for blood vessel segmentation. In this method blood vessels are enhanced using cascade of morphological operations and line detectors and finally segmented using single optimal threshold. Experimental results have shown that proposed methodology achieved a high value of sensitivity even in presence of lesions and it is free from the problems of scale and orientation. A dominant cause of increased FPR is tiny vessels, this method proved successful in segmenting tiny blood vessels too as a result, False positive rate is reduced to a greater extent as compared to other methods. The method is described in more detailed manner in [30] and has proved one of the major contributions of proposed work.

d. Feature Vector Formation

To differentiate the candidate regions as MA or Non- MA, total 8 different features are extracted here. It has been proved in previous literature [11] that the shape, color, gray level intensity and statistical features plays a measure role to describe the MA objects. Here SVM is directly trained by choosing the actual MA objects in input image and in addition the following features are used as an input for one class-SVM-

1) Area- Total number of pixels in MA region.

2) Eccentricity – Eccentricity is used to characterize the shape of an object, as eccentricity of a circle

is zero. Ratio of the distance between foci of ellipse and major axis length defines it.

3) Perimeter- It defines the boundary of candidate region.

4) Aspect Ratio-Ratio of major axis length to minor axis length of the candidate region.

5) Mean and Standard Deviation- The mean and standard deviation of all declared candidate region

from the extracted green channel image are obtained.

6) Mean and Standard Deviation- The mean and standard deviation of all declared candidate region

from the contrast enhanced green channel image are obtained but here the green channel image is

enhanced using AC-CHAHE as described in sections above.

7) Entropy- It is the measure of average amount of information contained in MA's. Entropy of given

M x N section of an image is given by Eq.3

$$\text{Entropy} = \sum_{\substack{0\leq i \leq M \\ 0\leq j<N}} C_{i,j} \ \log(C_{i,j}) \quad (3)$$

8) Energy- Energy of all pixels including candidate region pixels and its neighboring pixels. Energy of a given region is given by

$$\text{Energy} = \sum_{u=1,v=1}^{M,N} (P_i)^2 \quad (4)$$

e. One Class SVM

In earlier methods where SVM is used for classification of MA's, it has been observed that gray level intensity, color and shape of object are the most significant features keeping higher contribution to increase the accuracy of SVM.

A special category of Support Vector Machines is One-Class Support Vector Machine (OC-SVM). A binary class SVM returns an optimum hyperplane to maximize the margin for two class separation whereas OC SVM forms a hyper circle that encompasses the sections of data distribution. Accordingly, OC-SVM encloses the minimum sphere having maximum samples. The sample which lies outside the hypersphere is called as outlier [31]. The advantage of using OC-SVM is, it needs very small data for training[29]. SVM is trained for a smaller number of samples rather it is trained with MA's from only one image. For SVM learning we need to apply data from only target class with labels, then SVM returns an optimum hypersphere which separates samples from outliers.

Thus, the output of trained SVM is classification of given object as MA or not. Here SVM is trained only for one class i.e.MA. Here Gaussian kernel is used for training SVM. Used SVM is trained with only one image having maximum microaneurysms.

TABLE I. FOUR SITUATIONS OF ONE CLASS CLASSIFIER FOR CLASSIFYING OBJECT

	MA–Object from Target Class	NonMA-Object from outlier Class
Classified as MA	True Positive f_{T+}	False Positive f_{O+}
Classified as Outlier	False Negative f_{T-}	True Negative f_{O-}

TABLE II. EVALUATION PARAMETERS USED TO EVALUATE PERFORMANCE OF PROPOSED METHOD

Parameters	Description
Sensitivity/TPR	TP/ Total Count of MA pixels

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IV. Results

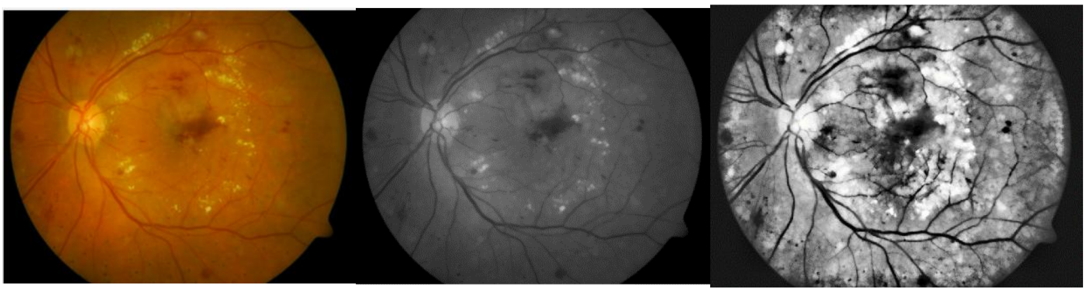
A. Material

IMAGERET – The performance of proposed system is analyzed using images from DIARETDB1 dataset. It is a dataset of total 89 patients, images were annotated by many experts manually, at Kuopio hospital. In the dataset there are 5 images of healthy persons, where there are no signs of Diabetic Retinopathy. Remaining 84 images were found with the indications of mild NPDR. The reason to choose this database is, it is rich in lesions and provided with ground truths of many other lesions like exudates and hemorrhages along with Microaneurysms. The digital fundus camera with FOV of 50 degree was used to take images [32].

B.Evaluation Parameters

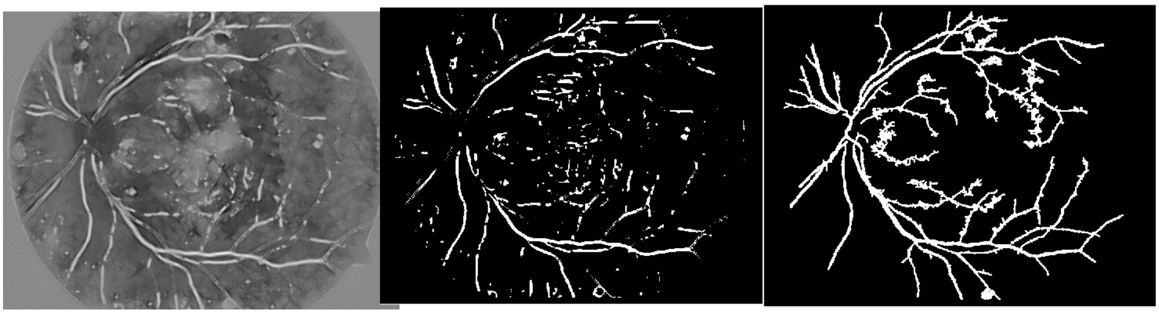
Performance of one class SVM is tested with four conditions. The MA's and Non – MA's, which are correctly classified by the classifier are termed as True Positives and True Negatives respectively. The faulty conditions are termed as false negatives and false positives.

Correctly classified MA's i.e. target class are defined as True Positives (f_T+)and correctly recognized Non-MA's i.e. outliers are termed as, true Negatives (f_O+). TP and TN contribute to increase the accuracy of classifier. The objects recognized by classifier as MA's, but they are outliers in input image are termed as False Positives(f_O+)and MA's classified as outliers are defined as false Negatives f_T-. FP and FN add to error.



(a) (b) (c)

Fig. 2. Results of Preprocessing (Image 005 DiaretDB 1 Database) - a) Input Retinal Image b)Image after Morphological Opening c) Results of AC-CLAHE



(a) (b) (c)

Fig. 3. Results of Segmentation - a) Gabor Filter Response b) Segmentation of MA along with vessels c) Blood Vessels Extraction

The proposed work is evaluated with images from DiaretDB1 database as its rich with the patterns of diabetic retinopathy. The work here is experimented in three parts, as accuracy of stage is going to affect the others. The use of single clip limit for complete image causes either the loss of minor red points or increase in noise at the other end. So, most of the minor red dots were not visible

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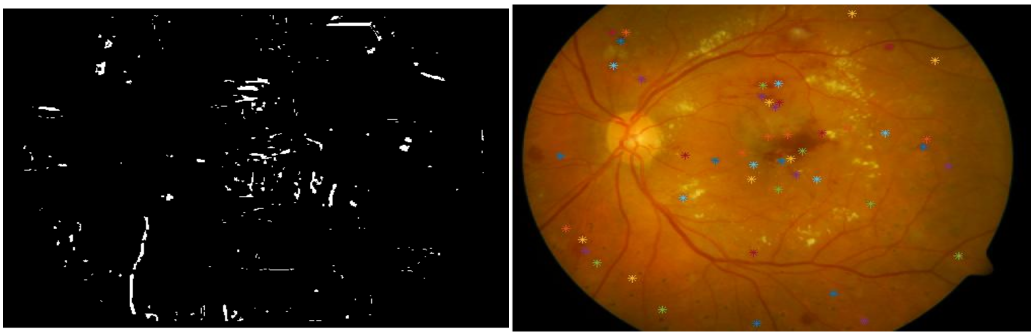
with CLAHE but use of AC-CLAHE has significantly improved the results of enhancement showing all the smallest possible MA's. The results for pre-processing are shown in Fig. 4 below.

The enhancement of image by AC-CLAHE proved much noteworthy, as it is showing all theMA's even those which are not visible with necked eyes. The resultant image is applied to Gabor filter, for enhancement of directional features and then segmented using Otsu's thresholding. The segmented image includes MA's along with blood vessel, further blood vesselsare extracted separatelyusing a cascade of morphological operations and line detectors using method described in [30] andsubtracted from candidate region image in order to reduce the FPR of the classifier. The proposed blood vessel segmentation method has extracted all tiny vessels connected to major vessel regions, further Blood vessels are subtracted from Gabor filter segmented image, if the answer of subtraction is -1 , it is equated to zero, so the rate of FPR has improved as compared to the methods described by Junior et al.[23] and UsamAkram et al.[11].The results ofthe discussion are as shown in Fig. 5.

The One Class SVM is trained only for MA's i.e. Target class. The OC-SVM is easily trainedwith very few MA samples. The results for classification in terms of MA's are marked on inputimage as shown in Fig. 6 below.



(a) (b)

Fig. 4. SVM Classification - a) Candidate Lesion after subduing vessels b) MA's marked at the output of Classifier.

TABLE III. PERFORMANCE EVALUATION FOR MA DETECTION FOR IMAGES FROM DIARETDB 1 DATASET CONSIDERING ON AN AVERAGE 3 TO 4 FALSE POSITIVES PER IMAGE.

Factors	One Class SVM
True MA lesions found	TP = 242
MA lesions not found	FN=101
Percentage of true MA's found out of Total	Sensitivity=0.70

The comparison of proposed method with the state-of-the-art techniques is shown in Table IV. Results are observed very good on all images from DiaretDB1 dataset. We have done the evaluation of proposed method by comparing the results with ground truth MA's at lesion level. The performance evaluation is done with 343 chosen Microaneurysms from DiaretDB1 dataset. Since, training of OC-SVM is done only for target class, True negatives cannot be marked with it. One class SVM gives the counts of only true positives and false negatives as well false positives can be calculated by comparing ground truth and classified results.

The comparison of results is done with different methods in literature, as shown in Table IV. Note that the comparison is done just to get a rough idea of evaluation parameters, as different authors have

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done comparison on different basis like image based, pixel based and lesion-based evaluation. Junior et al[] reported a sensitivity of 0.87 , where he has not taken care of the false positives due to tiny blood vessels. Akram et al. [11] reported a specificity of 0.99, though it is not possible to find out TN's in lesion-based evaluation. Srivastava et al. [23] reported a sensitivity of 100% but the specificity is dropped to 50%.According to the literature [2], the value of sensitivity can be lowered, as finding one MA per image is sufficient to detect image with MA's. We have tried to lower false positives per image i.e 1-2 per image with a reasonably good value of sensitivity.

TABLE IV.COMPARISON OF THE PROPOSED METHOD WITH STATE OF THE ART METHODS

Dataset	Method	Method	Sensitivity
Local Dataset	Hipwell et al. 2000 [15]	Simple Thresholding	0.60
	Streeter et al. 2003 [16]	Gaussian filter and LDA	0.30
DIARETDB1v1	Ram et al. 2011[19]	MorphologicalOperations and KNN	0.73
	Junior et al. 2013 [21]	Cascade of Morphological operations	0.87
	Inoue T. et al. 2013 [22]	Principle Component Analysis and Artificial Neural Network	0.73
	Akram et al.2013[11]	Gabor Filter and Hybrid Classifier	0.99
	Srivastavaet al. 2015 [23]	Frangi Filter and SVM	1.00
	NoushinEftekhari et al. 2019[24]	Two step CNN	0.80
	Proposed Method	AC-CLAHE, One Class – SVM	0.70

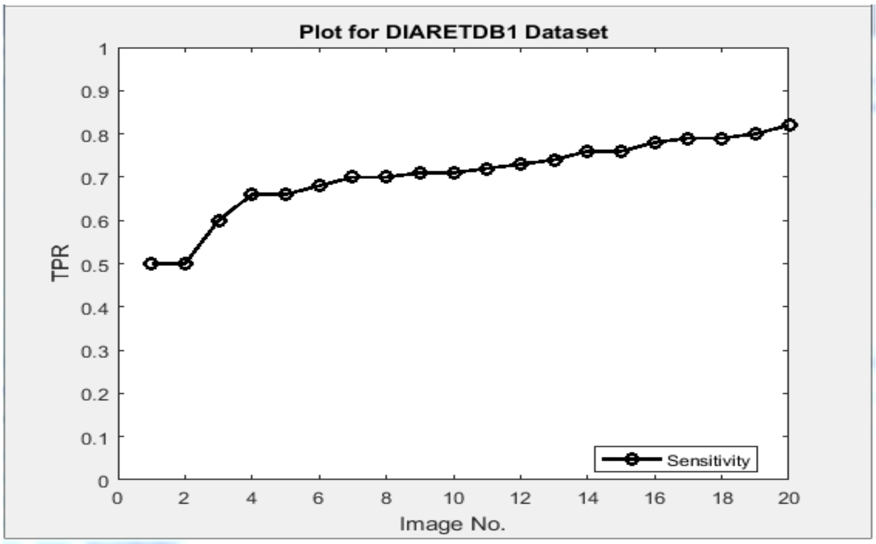

Fig. 5. Receiver Operating Curve for all MA's for20 images from DiaretDB 1 Dataset, Considering on an average 1-2 false positives per image.

V. CONCLUSIONS

The proposed method for provides a tool for automatic detection of MA's. The method is simple and rotation invariant. We have proposed three major contributions here. Compared to the available CLAHE method, a significant improvement is

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achieved due to the use of the contrast enhancement using AC-CLAHE enhancing all the minute MA's. Prominent reduction in spurious regions and significant achievement in reduction of FPR is observed due to accurately detected and extracted complex blood vessel structure. Use of One Class SVM has made the training part very easy as training is done only for MA's and with very few samples. Further the work should be done on feature extraction and selection in order to increase the accuracy of Classifier.

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