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A Retinal Lesion Detection of Diabetic Retinopathy

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Abstract
Diabetic retinopathy (DR) is the most common cause of vision loss among people with diabetes and leading to the cause of blindness. Microaneurysms (MAs) are primary lesion of Diabetic retinopathy, so their detection can give time to prevent further vision loss. Hemorrhages (HMs) and exudates (EXs) are the other type of lesions occurs during Diabetic retinopathy. The Retinal lesion detection consists of retinal image preprocessing, Optic disc detection and removal, Blood vessel segmentation, Candidate Lesion detection, Feature extraction, Classification and post processing. Publicly available DiaretDB1 dataset is used for performance evaluation.

1. Introduction

Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes and remains the leading cause of vision loss in the working-age population. Early diagnosis through regular screening helps prevent vision loss. DR is broadly divided into two stages: non proliferative DR (NPDR) and proliferative DR (PDR). NPDR occurs when the blood vessels get damaged inside the retina and leak fluid on to the retina, causing the retina to become wet and swollen. In NPDR, different signs of retinopathy can exist, such as microaneurysms (MAs), hemorrhages (HMs), exudates (EXs). MAs are the first visible signs of DR and they appear as small circular reddish dots in the retina. so their detection can give time to prevent further vision loss. HEMs are caused due to retinal ischemia and rupture of damaged and abnormally fragile retinal blood vessels. They usually appear as bright red spots/patches with substantial variability in shapes and appearances. EXs, on the other hand, are yellowish intra-retinal fluid deposits that contain protein, lipid, cellular debris etc. They usually appear as yellowish, bright patches of variable shapes and sizes with sharp borders. In proliferative DR Abnormal growth of blood vessels are occurs and leading to the complete vision loss. Microaneurysms (MAs), the first sign of NPDR, can be used as a pre-indicator of DR. However, a manual assessment on fundus images conducted by ophthalmologists is time consuming. Automatic detection of lesions in fundus images is very important to diagnosis and can prevent further vision loss. The objective is to detect Diabetic Retinopathy lesions.

2. Methodologies for detection of retinal lesions

Microaneurysms (MAs), Haemorrhages (HMs), Exudates (EXs) are the retinal lesions. Microaneurysms (MAs), haemorrhages (HMs) are appears as dark lesion. Exudates appears like bright lesion. Figure 1 shows different type lesions in the retina. Many methods are used for the lesion detection. Some detection methods are described below.

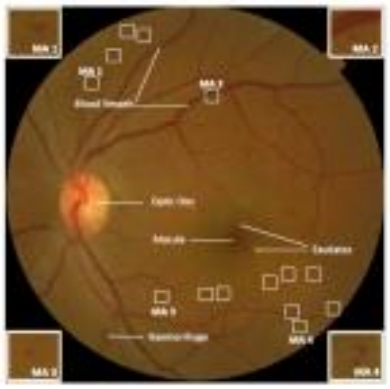

Fig. 1: Instance of digital fundus image containing both anatomic structures and pathological signs of DR [8]

2.1 **Detection using Local convergence index features**

A novel and reliable method for automatic detection of MAs in retinal images. Im age preprocessing, candidate extraction, feature extraction, classifications are the steps in this method. The overall process is taking place in green channel of the retinal images. The input image is preprocessed by using luminosity and contrast normalization method. several pre liminary microaneurysm candidates are extracted using a gradient weighting technique and an iterative thresholding approach. Features extracted using intensity and shape descriptors, local convergence index filters. To discriminate MAs from non-MA candidates RUSBoost classifiers are used. e-ophtha-MA, RC-RGB-MA, RC-SLO-MA, DiaretDB1, Retinopathy Online Challenge (ROC), MESSIDOR datasets are used in the method [1].

2.2 **Detection through singular spectrum analysis**

The method is performed on the green channel of retinal images as MAs and vessels normally present the highest contrast against the surrounding background in this color channel. Preprocessing attenuates the effects of noise and preserves the true information of MAs. A Gaussian filter is applied to the green channel to enhance the small and dark structures. Shade correction algorithm is applied on the Gaussian filtered images to prevent false positives. MA like characteristics are identified in the candidate extraction step. For the dark object detection Multi layered dark object filtering is used and then a confidence map is formed. Candidate object cross-section profiles along multiple directions are processed through singular spectrum analysis. The correlation coefficient between each processed profile and a typical MA profile is measured and used as a scale factor to adjust the shape of the candidate profile. A set of statistical features of those profiles is then extracted for a K-nearest neighbor classifier . Retinopathy online challenge (ROC), DiaretDB1 2.1, and Moorfields Eye Hospital datasets are used in the method [2].

2.3 Detection using dynamic shape features

Illumination equalization, Denoising, Adaptive contrast equalization, Color normaliza tion are applied on the preprocessing stage. Then the optic disc is removed which is the significant source of false positive for the red lesion detection. Intensity lower than the mean intensity is taken as the candidate region. Shape information are used for classification of false positives and true lesions. Random Forest classifiers are used for the feature classification. The method is validated on the Retinopathy online challenge (ROC), Messidor, Erlagen, CARA1006, CARA143 datasets [3].

2.4 Detection through local rotating cross section profile

In preprocessing stage input image is convolved with the Gaussian mask. This smooth ing process suppresses noise sufficiently while preserving true MAs. Local maximum region is extracted at the next step which is considered as the possible candidate region. Analysis of directional cross-section profiles centered on the local maximum pixels and Peak detection is applied on each profile, and a set of attributes regarding the size, height, and shape of the peak are calculated subsequently. The statistical measures of these attribute values as the orientation of the cross-section changes constitute the feature set which is used in a na¨ıve Bayes classi fication to exclude non-MA candidates. The method is validated on the Retinopathy online challenge (ROC) dataset [4].

2.5 Detection using sparse principal component

The process takes place on the green channel of the image. At the preprocessing stage Contrast limited adaptive histogram is applied in order to enhance the contrast of the retinal image. To remove the effect of the noise, smoothing process is applied. Multi-scale Gaussian Correlation Coefficients is applied to extract MA candidates. MA candidates are detected by computing the correlation coefficient between Gaussian function distributions of its grayscale image. Then shape, intensity, Gaussian filtering-based features are extracted. sparse PCA based classification method is used for MA and Non-MA classification. The method is validated on the Retinopathy online challenge (ROC) dataset [5].

2.6 Region growing based segmentation

The preprocessing of retinal images uses non local means (NLM) filter and contrast limited adaptive histogram equalization (CLAHE) for noise removal and enhancement image quality. In segmentation, region growing algorithm in which the seeds for the grower are selected and positioned by means of Forstner Corner Detection theory is used. Unwanted regions are removed by using morphological operations such as dilation, erosion, Niblack Adaptive Thresholding etc. Then segmented regions are passed through linear binary pattern for feature extractions. Geometrical features/parameters like size, area and length of minor and major axes are used to eliminate the abundant segmented regions. Predator prey algorithm (PPA) is used for optimizing the features for MA detection and minimizing the execution time. The method is validated on the DiaretDB0 dataset [6].

2.7 Morphology based detection

The process takes place on the green channel of the image. Median filter is used to remove pepper noise from the image. Contrast of the image is improved by using contrast adaptive histogram equalization. Illumination correction applied on the preprocessed image. Extended minima transform is applied for extracting preliminary candidate regions. Vessels and bright features are removed by using morphological closing operation. Candidate MAs are selected by extracting the connected components from image 6 with 15 pixels in range. The method is validated on the DiaretDB1 dataset [7].

2.8 Detection using matched filter

Having been converted into grey-scale, fundus images are filtered using Gaussian filter and enhanced by Contrast Limited Adaptive Histogram Equalisation (CLAHE) to isolate the microaneurysms, while blood vessels are isolated using Gaussian filter only. Gaussian filter is performed by convolving Gaussian

window. To extract the microaneurysms candidates, a modified matched filter is used. Twelve rotated matched filter windows are convolved on the isolated images and the intersection of each convolution results are taken. The detected mi croaneurysms candidate image is then multiplied with its each masking images to eliminate the border. Blood vessel removal operation is performed by subtracting the detected vessels from the microaneurysms candidate images. The method is validated on the Retinopathy onlinechallenge (ROC) dataset [8].

2.9 Ensemble based detection

An ensemble-based framework to improve microaneurysm detection. Unlike the well known approach of considering the output of multiple classifiers, a combination of internal components of microaneurysm detectors, namely preprocessing methods and candidate extractors are used. Grey level transformation, Contrast Limited Adaptive Histogram Equalization Vessel Removal and Extrapolation, Illumination Equalization are the preprocessing methods. Diameter closing, Top hat transformation, Circular Hough transform, Matching multiple Gaussian mask, Cross sectional profile analysis are the candidate extractors. The framework relies on a set of < preprocessing method, candidate extractor > pairs, from which a search algorithm selects an optimal combination. The method is validated on the Retinopathy onlinechallenge (ROC), Messidor, Diaretdb1 dataset [9] . Flow chart of ensemble-based framework is given below in Fig.2

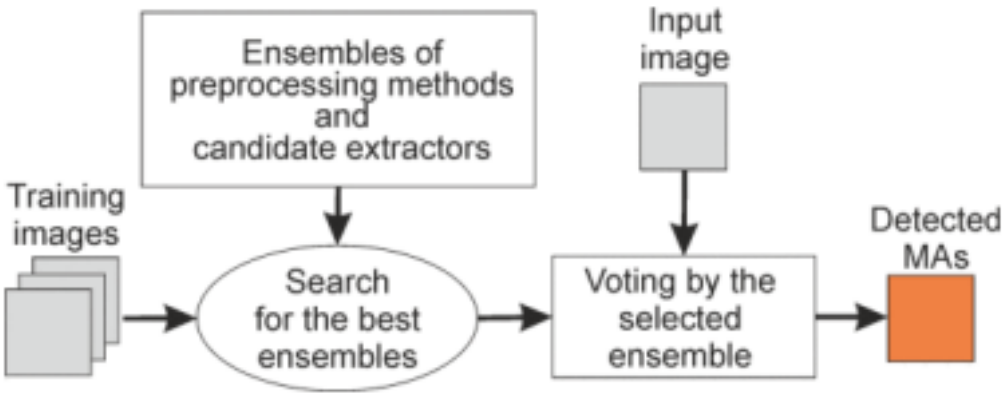

Fig. 2: Flow chart of ensemble-based framework [9]

2.10 Automatic detection of microaneurysms

Image enhancement, shade correction and image filtering of the green channel is per formed on the preprocessing step. The preliminary candidates are extracted by diameter closing and an automatic threshold method. 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 [10].

2.11 Automatic detection of retinal lesions

Novel and automated lesion detection scheme, which consists of the four main steps: vessel extraction and optic disc removal, preprocessing, candidate lesion detection, and post processing. The optic disc and the blood vessels are suppressed first to facilitate further processing. Curvelet-based edge enhancement is done to separate out the dark lesions from the poorly illuminated retinal background, while the contrast between the bright lesions and the background is enhanced through an optimally designed wide band

bandpass filter. The mutual information of the maximum matched filter response and the maximum Laplacian of Gaussian response are then jointly maximized. Differential evolution algorithm is used to determine the optimal values for the parameters of the fuzzy functions that determine the thresholds of segmenting the candidate regions. Morphology-based post processing is finally applied to exclude the falsely detected candidate pixels. The method is validated on the Retinopathy online challenge (ROC), DRIVE , STARE, DIARETDB1 and MESSIDOR dataset [11].

2.12 Detection & classification of retinal lesions

The system consists of preprocessing, extraction of candidate lesions, feature set formulation, and classification. In preprocessing, the system eliminates background pixels and extracts the blood vessels and optic disc from the digital retinal image. The candidate lesion detection phase extracts, using filter banks, all regions which may possibly have any type of lesion. A feature set based on different descriptors, such as shape, intensity, and statistics, is formulated for each possible candidate region: this further helps in classifying that region. This method presents an extension of the m-Mediods based modeling approach, and combines it with a Gaussian Mixture Model in an ensemble to form a hybrid classifier to improve the accuracy of the classification. The method is validated on the DRIVE , STARE, DIARETDB1 and MESSIDOR dataset [12].

3. Proposed Methodology

The block diagram of proposed methodology is given below in figure 3. The proposed methodology detects red lesions and dark lesions. microaneurysms, hemorrhages are the red lesions and exudates are the bright lesion. The system consists of Preprocessing, Blood vessel and Optic disc segmentation, Candidate Extraction, Feature extraction, Classification and Post processing etc.

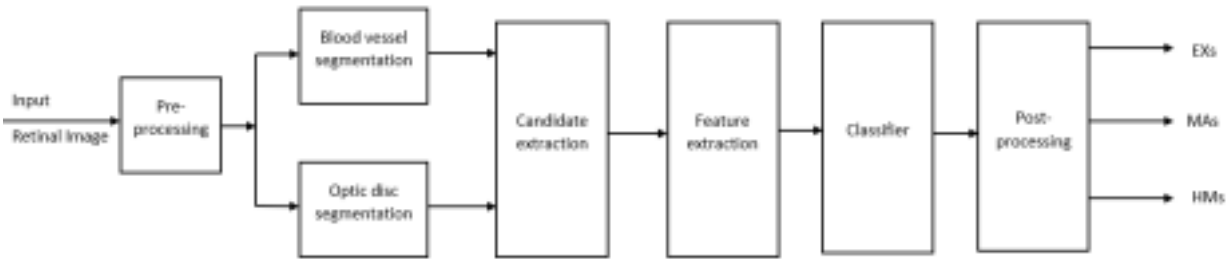

Fig. 3 : Block Diagram of proposed methodology

3.1 Preprocessing

The pre-processing work helps to improve the quality of image and reduce the noise, bad contrast and uneven illumination. The fundus image is taken as an input of preprocessing step. Pre-processing involves conversion of original image into a resized 750 * 576 pixel image. Since the green channel of retinal images in RGB provides a better contrast between Lesions and background, so green channel is extracted for lesion detection. An image mask is created by applying threshold on the green channel image. As a result of the acquisition process, most of the retinal lesions are nonuniformly illuminated. In order to make the lesion detection more robust, each image is normalized. Polynomial contrast enhancement is used to image normalization. The polynomial contrast enhancement operator is a simple gray level transformation: it assigns to each pixel a new gray level independently of the neighbor gray level

distribution. f: E → T be a gray level image with T = {t_{min}, ...t_{max}} ⊂ R a set of rational numbers. Let u= {u_{min}, ...u_{max}} ⊂ R be a second set of rational numbers. Gray level transformation τ is a mapping T → u, u =τ (t) . It can be expressed in equation (1)

$$u = \Gamma(t) = \begin{cases} \frac{1}{2}(u_{max} - u_{min}) \cdot (t - t_{min})^r + u_{min} & \text{if } t \leqslant \mu_f, \\ \frac{1}{2}(u_{max} - u_{min}) \cdot (t - t_{max})^r + u_{max} & \text{if } t > \mu_f. \end{cases} \quad \text{.....(1)}$$

μ_{f-} - Global grey level mean of image f

With parameter r, which can be chosen freely, we can control how much the contrast is enhanced. Suppose that $\mu_f = 1/2(t_{min} + t_{max})$. After having normalized the image, apply a small Gaussian filter in order to attenuate the noise [10].

3.2 Optic Disc & Blood Vessel Segmentation

After the preprocessing , the system extracts the main components, such as the optic disc and the blood vessels, from the retina, something which will help eliminate any spurious and false regions caused by their similarities with bright and dark lesions, respectively. The optic disc is localized by using circular Hough transform. The blood vessels are segmented by using Fuzzy C means clustering algorithm.

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3.2.1 Optic Disc Segmentation

The Normalized image is converted to the grey scale image and perform morphological closing operation on the gray scale image by using disk shaped structuring element. The center and boundary of the optic disc are found by applying the Hough transform to the gradient image. The gradient image is obtained by using canny edge detector. The Hough transform is used to isolate features of a particular shape within an image. The Hough transform is to transform the image into a parameter space that is constructed specifically to describe the desired shape analytically. Maxima in the parameter space corresponds to the presence of the desired shape in image space. The circular Hough transform is almost similar to the Hough transform for lines, but uses the parametric form for a circle as denoted in equation (2),

$$(X - a)^2 + (Y - b)^2 + r^2 = 0 \text{..... (3.2)}$$

where (a, b) is the center of the circle of radius r that passes through (x, y). The Hough space is three dimensional (3D). The gradient image is transformed to a set of three parameters, namely the accumulator, its center and its radius etc. For each feature point, votes are accumulated in an accumulator array for all parameter combinations. The accumulator will have set of edge points. Each edge points contribute a circle of radius r in the accumulation space. The accumulation space has a maximum where these contributory circles overlap at the center of the original circle. The center is an N×2 matrix with each row containing the (x, y) positions of the circles detected in the image. The estimated radius of the circles detected is stored in an N×1 column vector with a one-to-one correspondence to the center array [22] [23].

3.2.2 Blood Vessel Segmentation

Perform inversion of optic disc detected image and apply contrast limited adaptive histogram equalization on the inverted image in order to equalize the contrast of the image. Perform morphological opening process by using ball shaped structuring element. Subtract CLAHE image from morphological opened image to remove optic disc. Apply median filter on the optic disc removed image. Obtain background

image by performing morphological opening by using disk shaped structuring element. To remove background subtract median filtered image from background image. Adjust the intensity of background removed image. Perform Fuzzy C Means Algorithm to extract vessel map [11] [19] [21].

3.2.3 Fuzzy C-Means Segmentation Algorithm

It is the Iterative clustering method. Performs an optimal c partition by minimizing the weighted within group sum of squared error objective function J_{FCM} . It can be expressed in equation (3).

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q d^2 (x_k, v_i)$$

’’’’’’’’’’’’’’’’’’(3) • xk – Datasets • n - number of data items • c - number of clusters • u^i_k - degree of membership of xk in the i th cluster • q - Weighting exponent on each fuzzy membership • $d^2(xK, v_i)$- Distance measured between object xK and cluster centre v_i

In fuzzy c means clustering, find out centroid of the data points and then calculate the distance of each data points from the given centroid until the clusters formed becomes constant. The flowchart of Fuzzy C-Means segmentation Algorithm is shown in Fig 4.

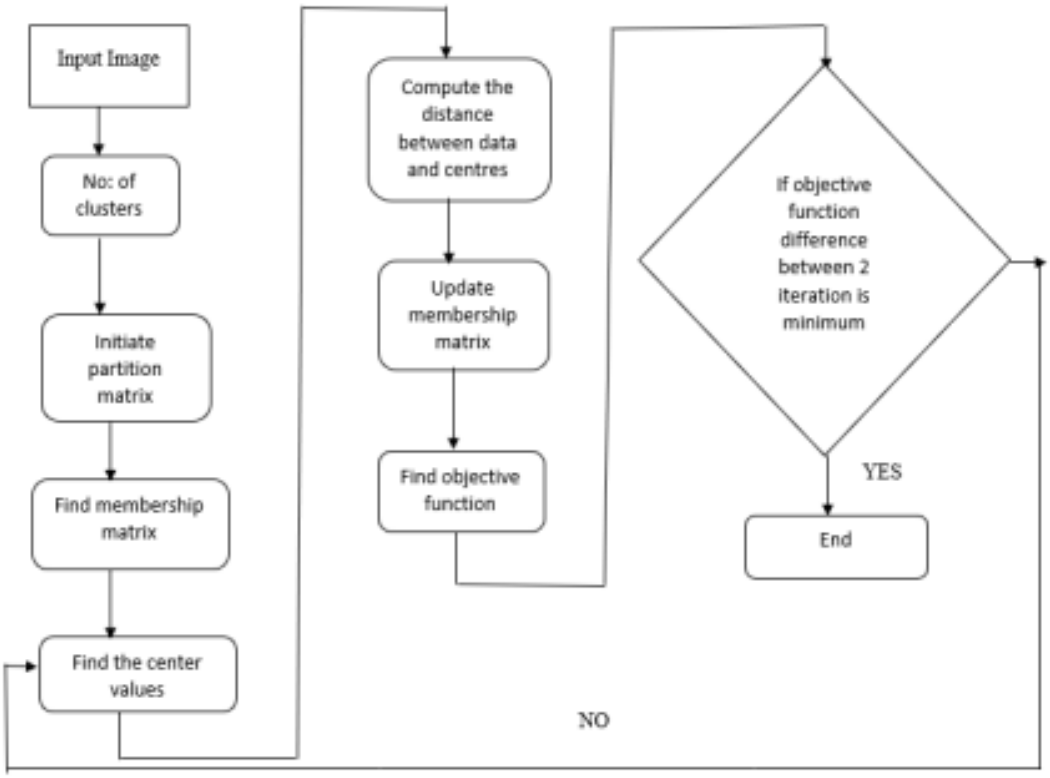

Fig 4. Lesion Candidate Extraction & Detection

3.3 Lesion Candidate Extraction & Detection

The objective of this step is to find “candidates”, i.e. regions possibly corresponding to lesions. For that compute the morphological closing operation for each angle 0 to 180 degree at the step of 15 degree by using line shape structuring element. Compute top hat and remove elements outside the mask and inside the optic disc. Experimentally select the lower and upper threshold values. For each threshold, check how

many connected components are present in the image [10]. Perform Gradient weighting at the different scales [1]. Then Select the candidate which has maximum gradient value and removes all connected components (objects) that have fewer than 5 pixels from the binary image. The pixel fewer than 5 pixels are considered as false positive for lesion detection. For Exudates, separate candidate extraction process is performed. The dilation followed 15 by thresholding is take place on the vessel and optic disc suppressed image [26]. Extract region properties of candidate image such as Bounding Box, Area, Eccentricity, Euler Number, Extent, Centroid & Mark lesions on the Green channel image.

3.4 Feature Extraction

• **Intensity based features** : These features are descriptors indicating the darkness of Le sions compared to their neighborhood background. The following features are extracted Intensity based features

– Average green intensity values obtained for candidate region
– Minimum green intensity values obtained for candidate region
– Maximum green intensity values obtained for candidate region

• **Shape-Based Features** : Since Lesions are small and they appear as different size & shape, the following shape-based features are extracted for each candidate region :

– Area : Area of candidate region specified by the actual number of pixels.
– Convex area : Area of candidate convex region specified by the actual number of pixels.
– Solidity : Ratio of the area of candidate over the convex area.
– Extent : Ratio of Area to the pixels in the bounding box.
– Perimeter : Distance around the boundary of the region by calculating the distance between each adjoining pair of pixels.
– Circularity : Diameter of a circle with the same area as the region which is equal to $^{p}(4 * \text{Area})/\pi$.
– Ellipticity : Lengths of the major and minor axes of the ellipse that has the same normalized second central moments as the candidate region.
– Eccentricity : Ratio of distance between the foci and the major axis length of the ellipse with a same 2th moment as the region.

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– Euler number : Number of objects in the region minus the number of holes in those objects.

• **HOG (Histogram of oriented gradient) Features** : Histogram of oriented gradients (HOG) is a feature descriptor used to detect objects in the images. HOG counts occurrences of gradient orientation in localized portions of an image.

3.5 Classification

SVM (support-vector machines) classifier is used to lesion identification. Support Vector Machine can be used for both regression and classification tasks. But, it is widely used in classification objectives. The objective of the support vector machine algorithm is to find a hyper plane in an N-dimensional space (N — the number of features) that distinctly classifies the data points. To separate the two classes of data points, there are many possible hyper planes that could be chosen. The objective is to find a plane that has the maximum margin, i.e the maximum distance between data points (support vectors) of both classes.

Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence. Lesion and non-lesion classification can be done by using SVM classifier [26]. The Fig 5 shows SVM classifier with hyper plane.

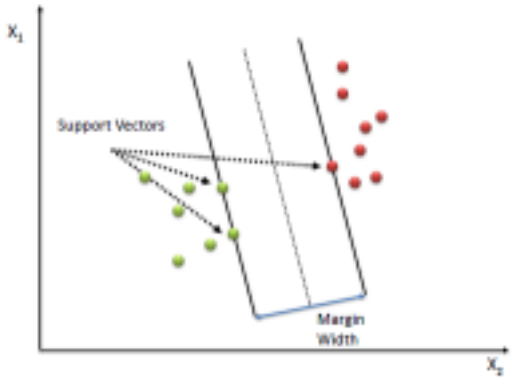

Fig. 5: SVM classifier

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3.6 Post Processing

The proper post processing operation is necessary for each lesion type. The area of microaneurysms are considered as less than 20 pixels in range and area of hemorrhages are considered as greater than 20 pixels . The circularity and area of the Exudates are considered as greater than 0.1 and greater than 25 respectively.

4. Results and Discussions

4.1 Dataset Description

DiaretDB1: The database consists of 89 color fundus images of which 84 contain at least mild non-proliferative signs (Microaneurysms) of the diabetic retinopathy, and 5 are considered as normal which do not contain any signs of the diabetic retinopathy. Images were captured using the same 50-degree field-of-view digital fundus camera with varying imaging settings. Independent markings from 4 medical experts were collected by using a software tool provided for image annotation. The ground truth confidence levels, less than 50 %, greater than 50%, 100%, represented the certainty of the decision that a marked finding is correct. Images are in PNG format with Resolution of 1500 x 1152 [24].

4.2 Results & Analysis

The original image is resized to 750 * 576 pixel image . The Fig 6 shows the resized image. The green channel is extracted from the resized image. The Fig 7 shows the green channel image. A mask image is created by applying a threshold on the green channel image. The value selected for the thresholding is 10. The Fig 8 shows the mask image. The green channel image is normalized by using Polynomial contrast enhancement. The value of r is taken as 2. The Fig 9 shows the normalized image.

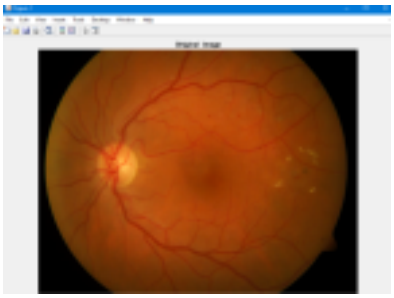

Fig 6. Resized image

Fig 7. Green channel image

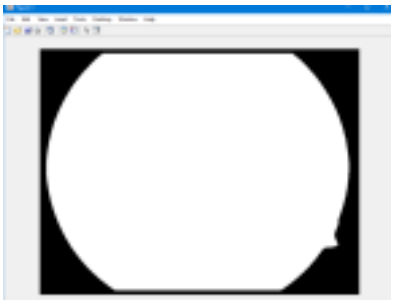

Fig 8. Mask image

Fig 9. Normalized image

Morphological closing operation is performed on normalized image by using disk shaped structuring element . The size of structuring element is taken as 15. Edge is detected by using canny edge detector and hough transform is applied on the edge detected image. The Fig 10 shows the optic disc detected image by using hough transform . The Fig 11 shows the optic disc removed image.

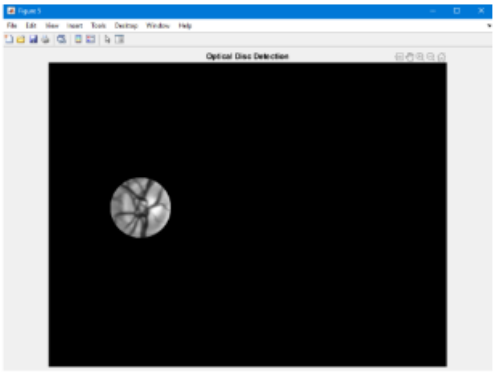

Fig 10 Optic disc detected image

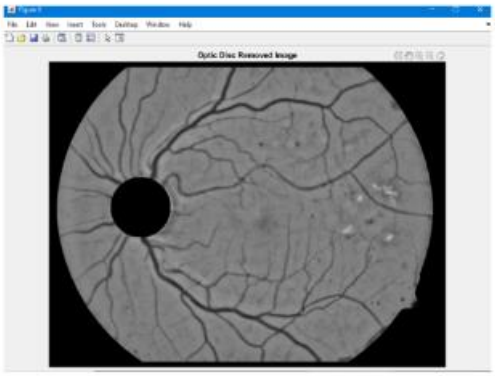

Fig 11 Optic disc removed image

Vessel segmentation is done by using Fuzzy C means clustering method. The fig 12 shows the vessel segmented image and fig 13 shows vessel and disc removed image.

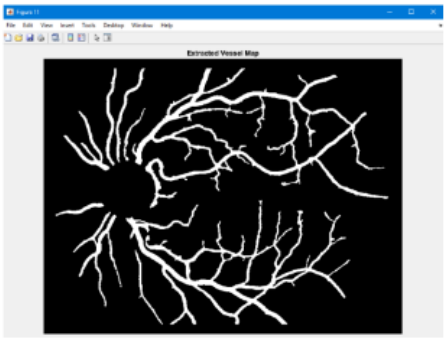

Fig 12. Vessel segmwented image

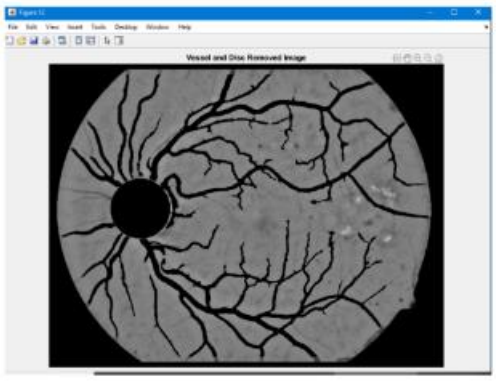

Fig 13. Vessel and disc removed image

The lesion candidates (objects) are obtained by gradient weighting and thresholding. The upper and lower threshold values are 0.5 and 0.05 respectively. The connected component value is taken as 120. The Fig 14 shows the lesion candidate extracted image. The Fig 15 shows the lesion candidate detected image.

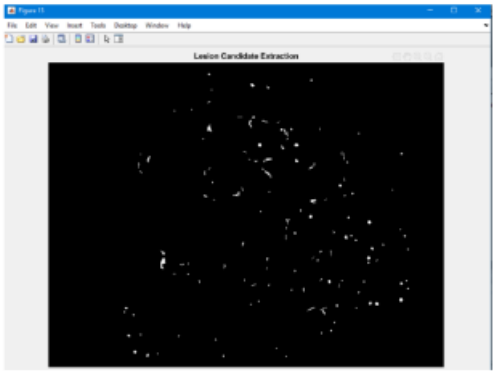

Fig 14. Lesion candidate extracted image

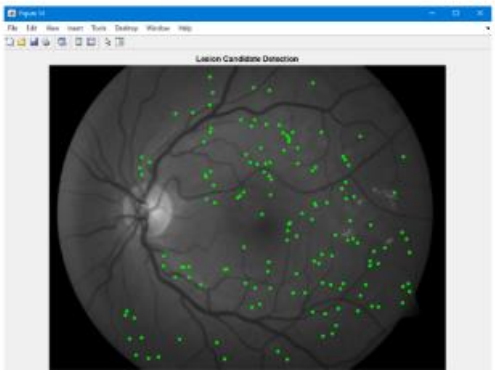

Fig.15 Lesion candidate detected image

Identification is done by using SVM classifier. Classifier is trained based on the extracted features. The input image is tested based on the trained features . Algorithm outputs an optimal hyperplane which dividing a plane in two parts where in each class lay in either side . If the trained and tested features are matched then it output the detected lesion area. The Fig 16 shows lesion identified image. The Fig 17 shows red lesion detected image.

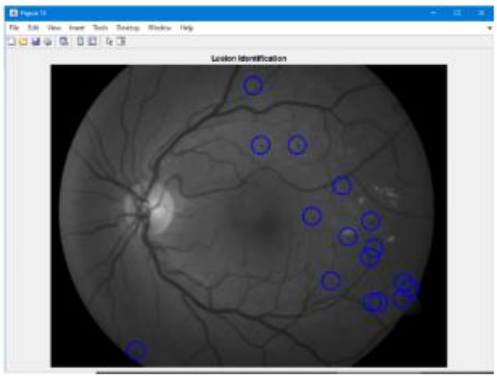

Fig 16. Lesion identified image

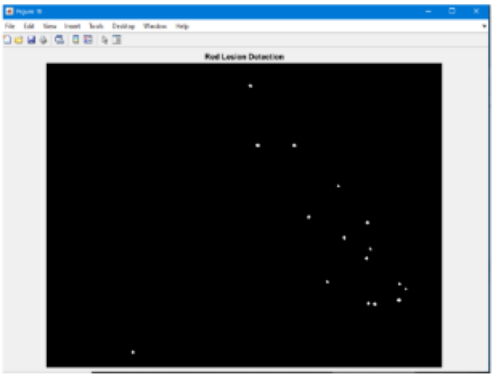

Fig 17. Red lesion detected image

The Fig 18, Fig 19 and Fig 20 show detected hemorrhages, microaneurysms and exudates respectively.

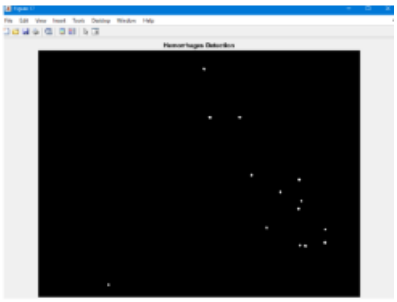

Fig 18 Hemorrhages detected images

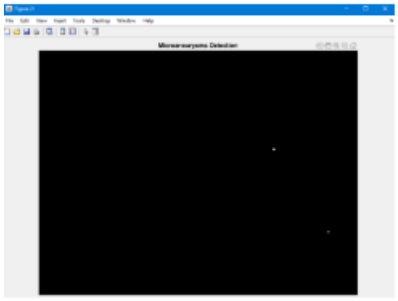

Fig. 19 Microaneurysms detected image

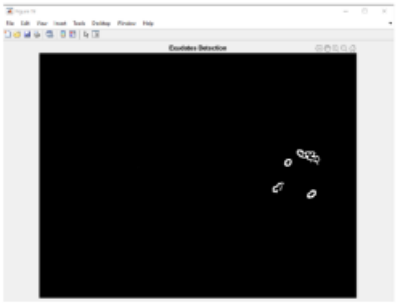

Fig 20. Exudates detected image

4.3 Performance Evaluation

To evaluate the performance of the system; performance measures such as sensitivity, specificity and accuracy are calculated. The terms used to measure the test performance are true positive (TP), true negative (TN), false positive (FP) and false negative (FN). TP is the number of successfully identified lesions and FP is the number of non lesions detected wrongly as lesions. FN gives the information about the number of undetected lesions while TN is the number of non lesions detected as non lesions.

• Sensitivity : TP/(TP+FN)

• Specificity : TN/(TN+FP)

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• Accuracy : (TP+TN)/(TP+TN+FP+FN)

sensitivity defines how well the algorithm detects true positives in given set of images as compared to true negative images in ground truth images set. Specificity defines how well the algorithm detects true negatives in given set of images as compared to true negative images in ground truth image set. Accuracy defines how well the algorithm separate images with lesion and images with without lesion in given set of images.

A total of 89 images from DIARETDB1 database used. Out 89, almost 84 images have at least mild grade severity microaneurysms and 5 images are normal. The proposed algorithm is able to achieve 97.619%, 80% and 96.629% of sensitivity, specificity and accuracy when evaluation is done on total 89 images DIARETDB1 dataset. In evaluation 82 images are found to be containing lesions as compared to 84 as proposed by experts of dataset. The proposed method is also able to detect 4 images without any lesions. The performance evaluation of method is shown in Table I.

Database	DIARETDBI
TP	82
FP	2
TN	4
Sensitivity (%)	97.618
Specificity (%)	80
Accuracy (%)	96.62

Table 1. Performance evaluation of Retinal lesion detection

5. Conclusion

Diabetic retinopathy (DR) is the most common microvascular complication of diabetes and remains leading cause of vision loss in the working-age population. Microaneurysms are the first visible sign of diabetic retinopathy. So their detection provide time to prevent further vision loss. Hemorrhages are another type of lesion occurs during Diabetic retinopathy. The proposed method detects retinal lesions that includes microaneurysms, hemorrhages, Exudates and achieves 97.619% of sensitivity, 80% of specificity and 96.629% of accuracy. Future work will involve exploiting the Local Convergence filter-based features for the detection of hemorrhages and bright lesions namely exudates.

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