A Segment based Technique for detecting Exudate from Retinal Fundus image

(Detecting Exudate from Retinal Fundus Image using technique based on feature Extraction)

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Abstract
Diabetes can cause extensive destruction in both the acquiring and modernized societies. The fast growing effects of it causes serious complications like morbidity and later to diabetic retinopathy which results to blindness. Gibing the feature of the disease at earliest stage takes an interval of time by treatment with Laser.

Initial stage of Diabetes is presented by NPDR, shows their significance by the earliest vessels change in the retina. NPDR has three classes i.e. mild, moderate and severe. Initial changes when the microaneurysms (MA) start appearing followed by haemorrhages, that leads to cotton wool spots & exudates that finally leads to sever NPDR. PDR is occurred due to neo vascularization (NV) [2].

In our work we are identifying the feature of exudates from the image. On basis of their pixels intensity and frequency it classified into moderate stage of NPDR. Accuracy to the extracting feature is then tested with the perception of the ophthalmologist's. Firstly raw dataset (Fundus Retinal Image) is pre-processed by morphological technique as images are of variant size, colour contrast and resolution. Then adaptive threshold and centroid is calculated by Otsu methodology so the Image boundary is traced. Then optic disk is localised by calculating ROI using Hough Transformation and distant from the image as the intensity of exudate and the optic disk is same in the fundus image. The SVM classifier uses features extracted by combined 2DPCA instead of explicit image features as the input vector Combined 2DPCA is proposed and then for acquiring higher accuracy of classification we can use virtual SVM.

Proposed work focusing on a Sensitivity of 97.1% for the classifier and the Specificity is of 98.3%. Thus a segmented based designed tool detects the effective cause of exudate that leads to moderate NPDR at its earliest stage of mild NPDR. By this tool Specialist gets support in screening a detection of early changes causing Diabetic Retinopathy and hence timely intervention leading to reduced DR related blindness.

Key words: Diabetic Retinopathy(DR), Non-proliferative Diabetic Retinopathy(NPDR), Proliferative Diabetic Retinopathy(PD R), Neo-vascularization(NV), Support Vector Machine(SVM), CDPCA.

I. INTRODUCTION

The output of this stage is passed to the Segmentation stage. This stage segments the background pixel from the stage of Diabetic Retinopathy (DR) and the vein networks using class segmentation and class classification with two cluster class centres. The Stage of Non-Proliferative Diabetic Retinopathy (NPDR) and the vein networks class centres also contain some noisy pixels that were over enhanced during the Pre-Processing stage and will be removed during the next stage called Disease Classifier stage. After the whole feature extraction of the entire factor like Microaneurysms (MA), Hemorrhages (HA), Cotton wool spots, Hard Exudates grading is processed and classified them at various Class of NPDR and PDR [3].

- The new blood vessels grow along the retina and along the surface of the clear, vitreous gel that fills the inside of the eye. By themselves, these blood vessels do not cause symptoms or vision loss. However, they have thin, fragile walls. If they leak blood, severe vision loss and even blindness can result.

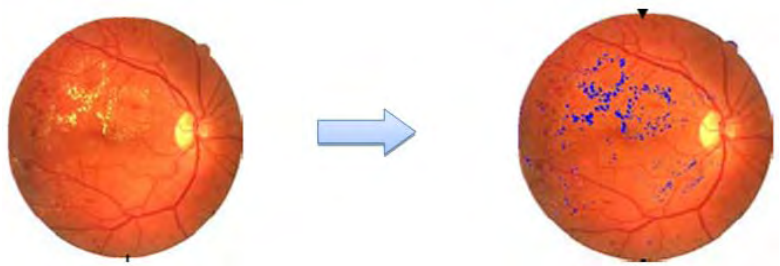

Fig.1. Showing the Retinal image and Exudate image

The national screening committee of UK has proposed the following classification for non-proliferative Diabetic Retinopathy (see figure2).the idea is to develop an automated classification tool for NPDR. With additional research, this computer system could become a useful clinical aid to physicians and a tool for screening, diagnosing, and classifying NPDR [4].

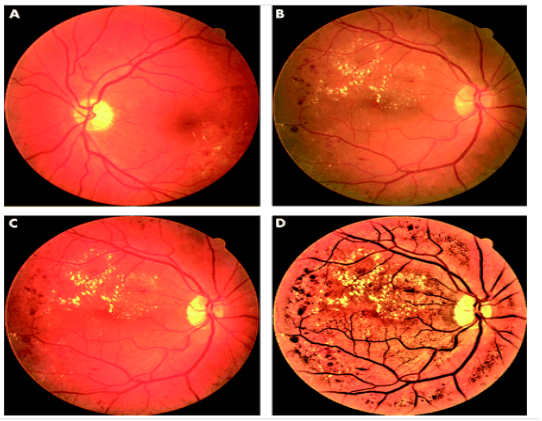

Fig.2. Showing (a) Reference Image, (b) typical retinal image (include exudates), (c) colour normalised version, (d) after colour enhancement.

Table I. Classification of Non-Proliferative Diabetic Retinopathy

NSC	International Term	Symptoms	Features
R0	No DR	None	Normal retina. Grade 0 (US)
RI	Mild non-proliferative (mild pre-proliferative)	None	Haemorrhages & microaneurysms only only Grade 1 (US)
R2	Moderate non-proliferative, moderate pre-proliferative	None	Previously termed mild pre-proliferative. Extensive Microaneurysm, intraretinal haemorrhage, and hard exudates. Grade 2 (US)
R2	Severe non-proliferative severe pre-proliferative	None	Previously termed severe pre-proliferative. Venous abnormalities, large blot haemorrhages, cotton wool spots (small infarcts), venous beading, venous loop, venous reduplication, Grade 3 (US)

II. MATERIAL AND METHODOLOGY

We used 332 retinal fundus images obtained from a Canon CR6-45 non-mydriatic retinal (3CCD) camera with a 45°field of view (FOV) as our initial image dataset. The images were derived from DRIVE and STARE databases [5][6]. The Image resolution was 565 by 584(565×584) at 24bit RGB. The FOV of each images are circular with a diameter of approximate 540pixels.These images sets also contain Fundus photography which was made after pupil dilation with one or more drops of PHENYLEPHRINE HYDROCHOLORIDE (2.5%) and/or TROPICAMIDE (1%) [5].

These 400 images are subdivided into two datasets that is 156 images as training and testing sets which are used for feature extraction from the images and Retinopathy (NPDR) based classification stages. The remaining 176 colour images were employed to investigate the diagnostic accuracy on our system basis for identification of images containing any evidence of retinopathy.

Table II. Grading of diseases according to HRIS

Image #	Formal Grading
1	LEVEL 3=SEVER NON-PROLIFERATIVE RETINOPATHY
2	LEVEL 2=MODERATE NON-PROLIFERATIVE RETINOPATHY
3	LEVEL 3=SEVER NON-PROLIFERATIVE RETINOPATHY
4	LEVEL 1=MINIMAL NON-PROLIFERATIVE RETINOPATHY

A. Material Specification

The images were taken by the CANNON CR6- 45NM (3CCD) camera (see Table 3).

Table III. CANNON CR6-45NM camera Specification

Image Type	*Retinal and Fundus*
Dimension	*565×584 with 24bit RGB*
Diameter	*FOV with 540pixel/image*
Angle of view	*45deg(37 deg when S.P. knop is turned ON)*
Image Magnification	*1.8x on 35mm film*
Examinee's diopter without compensation lens	*-12D to +15D*
Compensation Range with "-" Compensation lens	*-7D to -33D*
Compensation Range With "+" compensation lens	*+11D to +35D*

B. *Software Used*

The Camera which we are using for getting the Fundus Retinal images is CANNON CR6- 45NM (3CCD) and the Platform which we are using for the extraction and classification of feature by utilizing the Fundus Retinal image is Matlab 7.6.0. Here we utilize the initial feature of Matlab as well as implementing our generated algorithm for getting the specified and sufficient result.

C. *Methodology*

Step1: The various steps of image pre-processing (see Figure2).

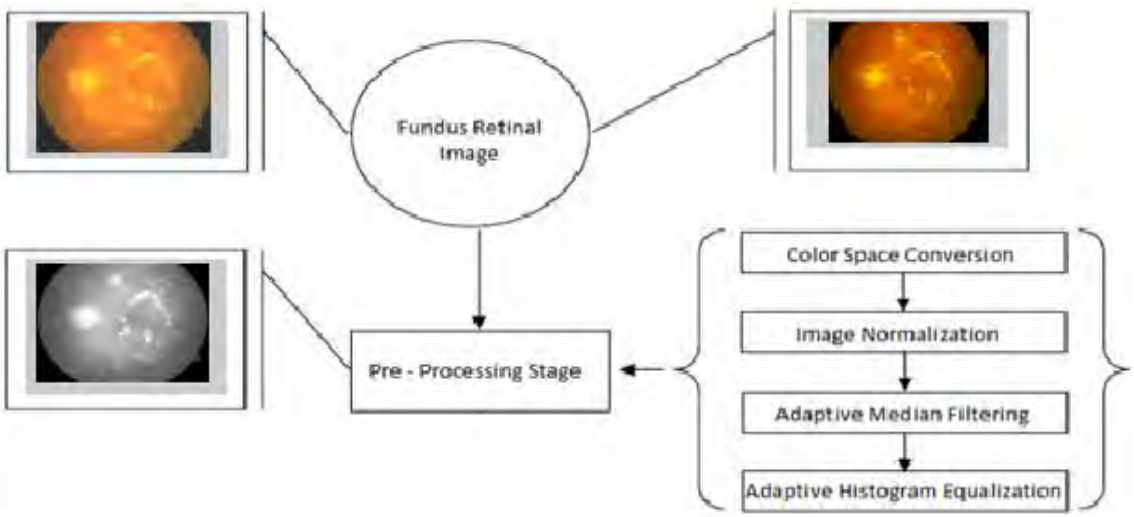

Fig.3. Showing the pre-processing steps

Step2: The various steps for Image boundary tracing (see Figure3).

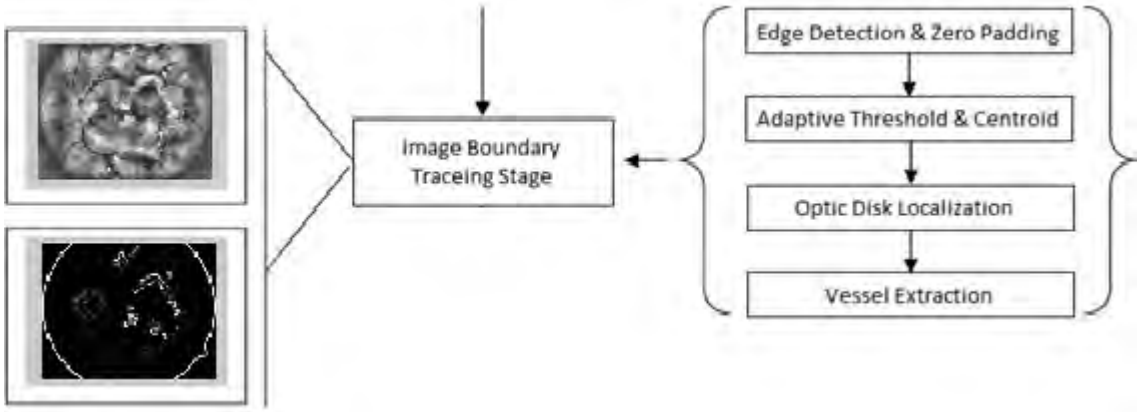

Fig.4. Showing the Image Boundary Tracing steps

Step3: The various steps for Image Segmentation (see Figure4).

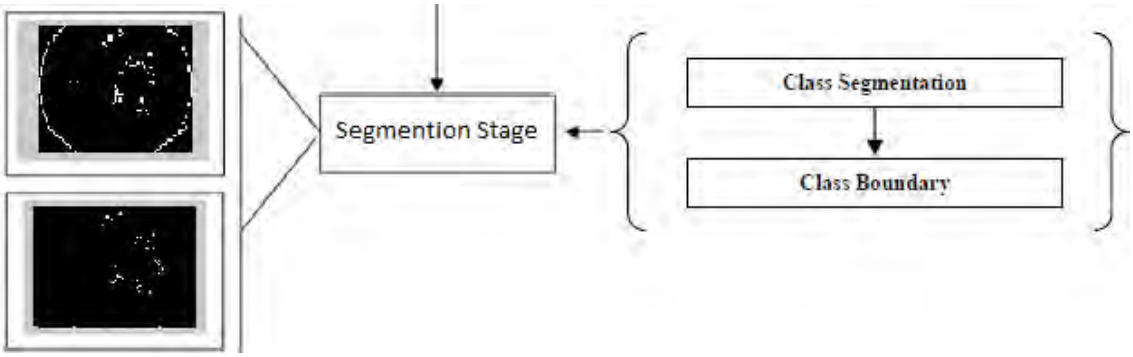

Fig.5. Showing the Image Segmentation steps

Step4: The Final steps for Image Classification (see Figure5).

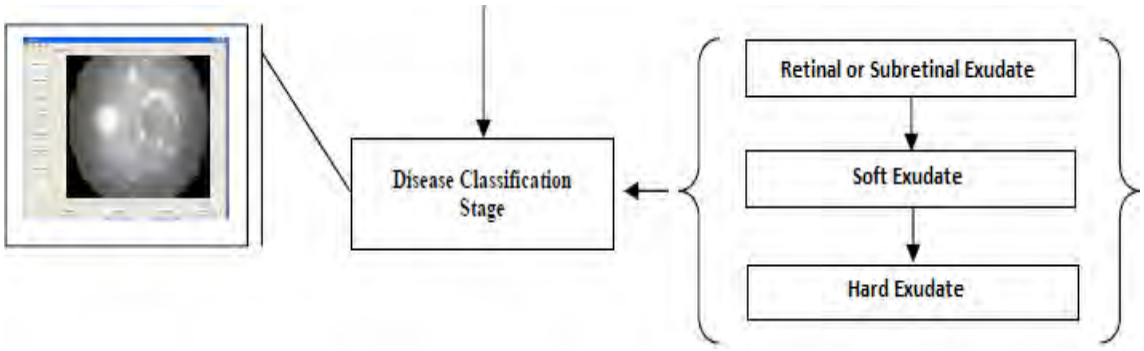

Fig.6. Showing the GUI for Image Classification steps

D. *Pre- processing Stage*

In input images are Pre-Processed before extracting the abnormalities from Fundus image. By Pre-processing image noise, colour normalization, image resizing, image brightness, is processed.

D.1. Image Processing and Image Normalization:

The first step is therefore to normalize these images across the set. It leads to removing of differences in brightness correction, contrast enhancement, color modification from the Original images. After that modification of the pixels value of each Image in the database is performed by Histogram Specification. Then by converting the RGB image to Grayscaled image intensity is adjust by applying contrast enhancement technique. 2-D filter is used which returns the central part of the correlation that is the same size as X (matrix).

D.2. Morphological structuring of Images:

In our approach, resultant image form the previous step are utilize for creating and manipulating the structuring element by implementing morphological operation.

First structuring element is enumerated and ellipsoid structure during the operation is implemented. A closing operation is performed on the green channel image using two different sizes of a structuring element (filter). Closing operation is defined as dilation (Max filter) followed by erosion (Min filter). The formulations of dilation and erosion for gray scale images are as follows.

Dilation:

$$A \oplus B = A1(x, y) = \max_{i,j \in B} (A(x - i, y - j) + B(i, j)) \quad (1)$$

Erosion:

$$A \ominus B = A2(x, y) = \max_{i, j \in B_1} (A(x - i, y - j)\, B1(i, j)) \quad (2)$$

where, A is the input image, B and B1 are the structuring elements or masks used for dilation and erosion respectively.

After Image Filtering, Adaptive Histogram Equalization is implemented. The main problem attached with Fundus image is uneven illumination. When the distance from the center of the image is increases, the uneven illumination is decreases. To resolve this problem AHEM is implemented. In this methodology a point transformation is defined within a local fairly large window. This method also assumes that there is a local distribution of intensity value over the whole image. During this process the gradual intensity variation between centre of the image and edges doesn't affects the local window. The Mean of the intensity value is calculated and there is a localisation of point transformation distribution over the window takes place and by this range of intensities value of image is covered.

Let there is a running sub image W, whose size N X N pixel. Here it is centre on pixel P (i, j). This running sub image is filtered according to the range of mean intensity value so that another sub image P of same size is obtained. Mathematical equation is given as:

$$p_n = 255.\left(\frac{[\phi_w(p) - \phi_w(Min)]}{[\phi_w(Max) - \phi_w(Min)]} \right)$$

And

$$\phi_w(p) = \left[1 + \exp\left(\frac{\mu_w - p}{\sigma_w}\right)\right]^{-1} \quad (3)$$

Here, Max and Min are the intensity value of the image and σ_w and μ_w is the standard deviation and mean of local window.

E. Image Boundary Tracing Stage

In the binary image form the Boundaries tracing block traces object (RGB Images) boundaries, where objects are represented by nonzero pixels while other by 0 pixels i.e. the background. In our approach, initialize image is divide into blocks and the Grayscaled image is converted into floating point real values which are initialize for generating threshold by implementing Otsu's function.

Columnwise neighborhood operation is implementing which provide a way of speeding up neighborhood or block operations by rearranging blocks into matrix columns that stored into a temporary matrix that has a separate column for each pixel in the original image. The column corresponding to a given pixel contains the values of that pixel's neighborhood from the original image. The temporary matrix is passed to a function, which must return a single value for each column. This function

1. Reshapes each sliding or distinct block of an image matrix into a column in a temporary matrix
2. Passes the temporary matrix to a function you specify
3. Rearranges the resulting matrix back into the original shape

E.1. Edge Detection:

It is the technique which is used to implement that function which detects the edge of the object. In this approach, by using the local maxima gradient of an input image block of edge is determined. Also with the help of Gaussian filter gradient of the image is calculated.

The edges which are strong and weak are extracted by using *canny edge detection* methodology, which take two threshold value of an input image.

Canny Method: (1) Define low and high threshold value using User-defined threshold value.
(2) Set Threshold value by using the source threshold parameter.
(3) Determine the gradient value using gaussian filter.
(4) Implement edge detection block which compute automated threshold value.
(5) Implement Standard deviation of gaussian filter.

The Edge Detection block computes the automatic threshold using the mean of the gradient magnitude squared image. In our methodology, we select Canny, the Edge Detection block finds edges by looking for the local maxima of the gradient of the input image. It calculates the gradient using the derivative of the Gaussian filter. The Canny method uses two thresholds to detect strong and weak edges. It includes the weak edges in the output only if they are connected to strong edges. As a result, the method is more robust to noise, and more likely to detect true weak edges. Global threshold values is applied with canny function , If a pixel's magnitude in the gradient image, which is formed by convolving the input image with the derivative of the Gaussian filter, exceeds the high threshold, then the pixel corresponds to a strong edge. Any pixel connected to a strong edge and having a magnitude greater than the low threshold corresponds to a weak edge. If, for the Threshold source parameter, you choose Input port, use input port Th to specify a two-element vector of threshold values. These values must have the same data type as the input data.

E.2. Zero Padding:

In this approach, Discrete wavelet transform extension function is implemented which decompose intensity values into subbands with smaller bandwidths and slower sample rates. In the DWT approach, Zero padding mode is used from which zero values of Fundus Image is calculated that determine minimum and maximum intensity value. Original coordinator from the image is originated and then zero matrix of image size is created. Exterior of the mask is filled with zero and minimum and maximum intensity within the mask is calculated that returns a new zero matrixes.

E.3. Optic Disk Localization:

Before optic disk identification, maximum pixel information from the gray scaled image is calculated which is then stored in the array. After that localization of non-zero pixels values is performed. Then standard deviation is calculated. Here, median wrt. row and column is calculated which were round off towards negative intensity

values. Then initial boundary location point is extracted which is utilize to trace the boundary of the image to fit the circle to the boundary. Backslash operation is implemented in the least- square values that calculate the location of the centre and the radius after tracing boundary.

After that Vessel Convergence in which the thicker blood vessel skeletons are modelled as lines. We transform the vessel image into Hough space through Hough transformation is implemented to detect the connecting vessels in the image and then ROI is extracted by creating the binary mask, which is a binary image that is the same size as the image we want to process with pixels that define the ROI set to 1 and all other pixels set to 0. The Hough Transform block implements the Standard Hough Transform (SHT). The SHT uses the parametric representation of a line:

rho = x*cos (theta) + y*sin (theta) (4)

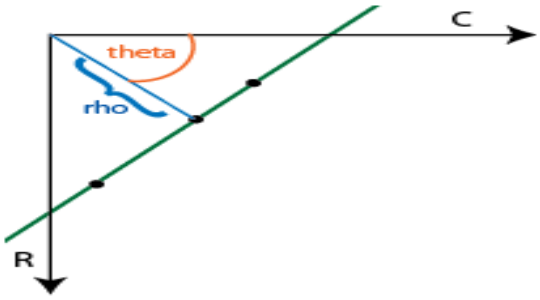

Fig.7. Showing the Hough space matrix vector

Meshgrid function is utilize which then transforms the domain specified by vectors x and y into arrays X and Y, which can be used to evaluate functions of two variables and three-dimensional mesh/surface plots. The rows of the output array X are copies of the vector x; columns of the output array Y are copies of the vector y. Optic disk boundary from the fundus image is determined by implementing binary mask over the extracted Region of Interest (ROI) which contain optic disk.

F. Image Segmentation Stage

Image segmentation is a process of partitioning image pixels based on one or more selected image features and in this case the selected segmentation feature are Vessels[11]. This proposed algorithm implemented on the green-channel of a Fundus Image. Morphological operations are performed to modify the sampled image.

After that we applying Matched filter (basically simple Gaussian filter).

- The size of filter is 16×15(since resolution is not known, size of image is 605×700**).**
- Since Direction of Vessels is not known, filter is rotated 12times (each 15 degree) [12].

$$G_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-x^2/\sigma^2) \quad (5)$$

(Gaussian Function for Vessels of a certain width)

By Optimizing coefficients of Gaussian Convolution kernels there is a selection of choice parameter. These parameters are further used to extract the reasonable reason for extraction.

$$G(w) = \sum_{i=1}^{M} | G_m(w) \exp[-j G_m(w)] | \quad (6)$$

Where,

G_m = Gaussian function

$_m$ = phase function (i.e. G_m is rotated).

After that the resultant pixels intensity values of a resultant image are converted into binary image then image transformation is performed and then resultant image is inverted. Region props technique is used where properties of the image region is extracted. Here area covered by the maximum pixel intensity feature from each neighborhood pixel. It is the area occupied by the featured vector is extracted. Finally optic disk is removed from the original image.

G. Disease Classification Stage

Input pathological Retinal Images (RGB), from which I (Intensity) of the green channel is extracted as feature vector. Then, from each step artifacts are removed, which is done by taking the measurement of skeleton length (in pixels) of each connected region (Four-connected region). Skeletonization is performed using the

morphological operation (Threshold is User define). Then, by using Normalized Gradient Vectors Centrelines are located. Two different Phases are implemented in this procedure:-

(a) High-contrast centerlines from the vessels in the region are determined.
(b) From the vessels in region, Low-contrast centerlines are determined.

Finally, by summation of both high-contrast centerlines and low-contrast centerlines of the specific region the Retinal Centerlines image are generated. Then, Blood vessel-like objects is detected by using Gradient Vector Field. Finally Pruning Operation is performed according to detected centerlines so that around the Fundus retinal image the false detected vessels are removed. For classification SVM is implemented, before that 2DPCA is implemented for feature vector calculations.

A support **vector machine** (**SVM**) is a supervised type of learning methodology that classifying input date by analyze them and also by recognize there patterns. The standard SVM predicts the set of given input data and on the basis of prediction it determines which input data belongs to which class. It makes a concept of non-probabilistic binary linear classifier to SVM.

Step1: Training Data is used to Estimate Function

$$f : R^N \rightarrow \{\pm 1\} \quad (x_1, y_1),\ldots, (x_l, y_l) \in R^N \times \{\pm 1\} \tag{7}$$

Step2: Evaluate Risk of estimation

$$R_{emp}[f] = \frac{1}{l}\sum_{i=1}^{l} \frac{1}{2}\left| f(x_i) - y_i \right| \tag{8}$$

Step3: Find Risk

$$R[f] = \int \frac{1}{2}\left| f(x) - y \right| dP(x, y) \tag{9}$$

Step4: Minimization of Structural Risk.
Step5: Hyperplanes Class is generated.

$$(w.x) + b = 0, w \in R^N, b \in R \tag{10}$$

Step6: Determine Decision functions for decision making.

$$f(x) = sign\ ((w.x) + b) \tag{11}$$

Step7: Separation of margin is maximizing.

III. RESULT AND DISCUSION

In this section, results of applying the proposed approach are presented. We used a dataset of 332 images for evaluating the algorithm. The images were obtained diverse source hence has sufficient variations in color, illumination and quality. The dataset images were classified by ophthalmologists based on the lesion type (exudates/MAHMs) into those with the lesion and those without it. An image having no lesions is considered normal whereas one that has lesions like exudates, microaneurysms and hemorrhages is considered abnormal. The sources of images are as follows: 211 images from local Hospitals, 81 images from STARE database and 40 images from DRIVE database.

Table IV. Results of optic disk localization for specific databases & for the overall normal, abnormal cases.

Source or Type	No. of Images	No. Correct	% Success
Hospitals	211	209	99.1
STARE	81	76	93.8
DRIVE	40	39	97.7
Overall Normal	112	111	99.1
Overall Abnormal	320	308	96.5

To measure the segmentation accuracy, the true positive rate *P*true and the false positive rate *P*false are introduced as

$$Ptrue = TrueNum/Num_{vp} \quad (12)$$

$$Pfalse = FalseNum/Num_{uvp} \quad (13)$$

Where,

Num_{vp} is the sum of the pixels that are marked as a vessel in a ground actual image, Num_{uvp} is the sum of the pixels that are marked as non-vessel in the ground actual image, TrueNum is the sum of the pixels that are segmented as vessel truly, and FalseNum is the sum of the pixels that are segmented as vessel falsely.The classifier uses features extracted by combined 2DPCA instead of explicit image features as the input vector Combined 2DPCA is proposed and virtual SVM is applied to achieve the higher accuracy of classification. We demonstrate a Sensitivity of 97.1% for the classifier with the Specificity of 98.3%.

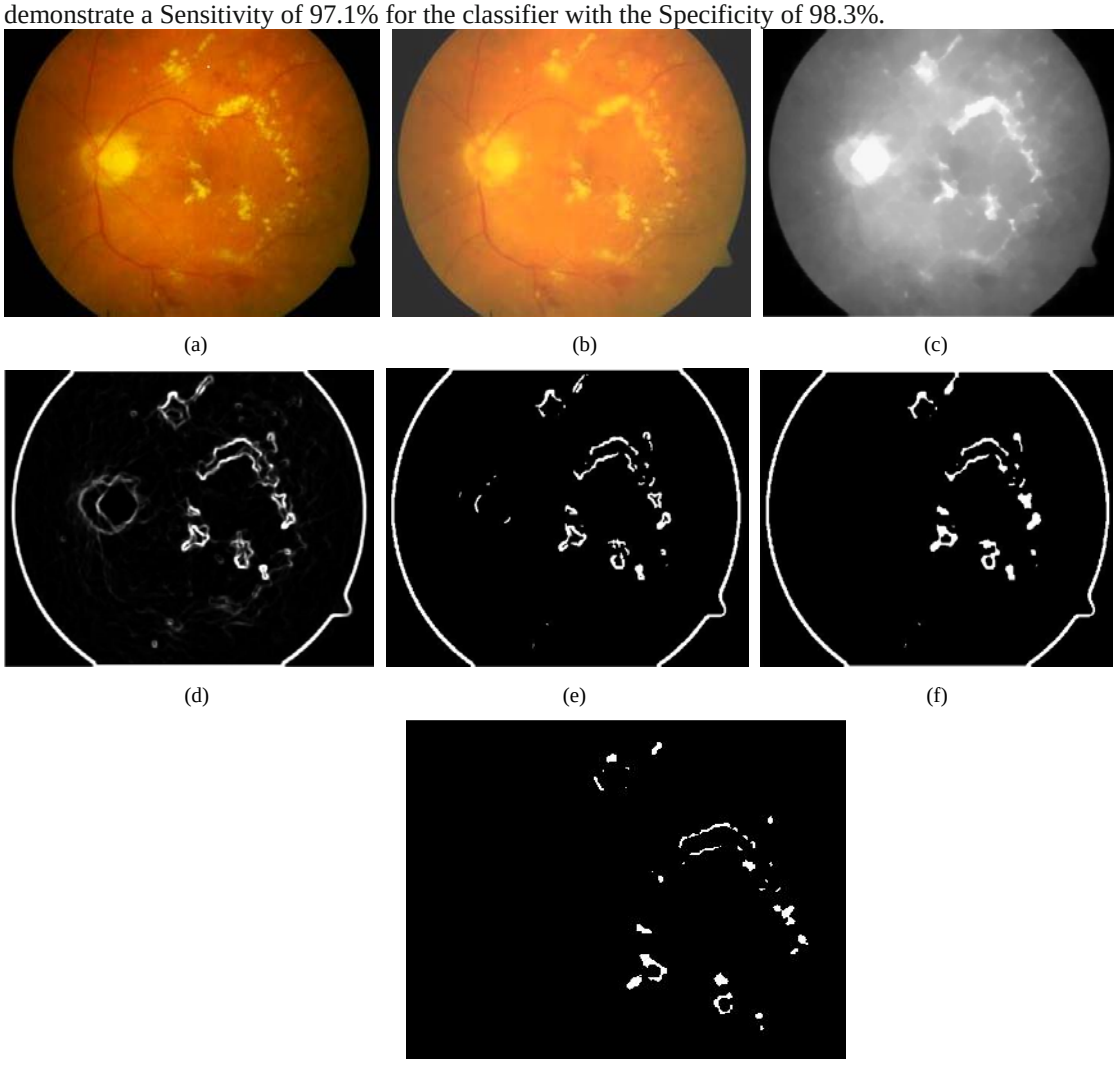

Fig.8. Results of an abnormal retinal image: (a) original image, (b) preprocessed image, (c) grayscaled filtered image, (d) Morphological closing, (e) optic disk localized image, (f) filling image, (h) exudate image.

IV. CONCLUSION

In this paper, a segment based technique for detecting the exudate from the retinal image is presented. The methodology is composed of morphological operation with the SVM algorithm. Image pre-processing is first implemented for getting the skeletonized dataset from row dataset. Then morphological operation is implemented to localize the optic disk from the retinal fundus image. Then feature is extracted for classification by using support vector machine which is a supervised learning technique. Both qualitative and quantitative experiments on normal and abnormal retinal images indicate that the proposed approach is effective and can produce identical results as NPDR also known as pre-proliferative stage of Diabetic Retinopathy if diagnosed early can go a long way in reducing DR associated blindness. An automated process for the early diagnoses and intervention can hence be of great help to the patient and Specialist alike in the timely management of this widespread disease.

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VII. APPENDIX

A.1. List of Function used with description

Function Name	**Description/ Usage**	**Section Applicable**
BackgroundSpotProcess_ver1.m	Detect and Diagnose DR background related diseases	Classifier Stage for Bleeding detection
BleedingProcess_ver1.m	Detect and remove bleeding points	Classifier Stage for Bleeding detection
Check4ProcessingPartialProcessing.m	Search for processing data, if not available then call all processing data	Main Processing
cnp5×5.m	Modify Crossover detection Algorithm	Classifier Stage for Crossover detection
CVision.m	A GUI for DR Diagnosis	Main Processing
MyFinalImage.m	Show Final image without all the diseases	Image Output Stage
MyZeroPaddingRemoval.m	Remove add zero at the edges of image	Pre-processing Stage
RemoveFovea_ver1.m	Detect Fovea like material and remove it	Classifier Stage for Bleeding detection
MyMainProcessing.m	Extract feature from data	Main Processing
MyRgb2Hsi.m	Convert an Image from RGB to HSI	Pre-processing Stage
MyMean.m	Calculate the mean of processed data	Pre-processing Stage
ZeroPadding.m	Add zeros to the edges of an Image	Pre-processing Stage
MyWinAdaptiveEq.m	Perform Window and Adaptive Histogram Equalisation	Pre-processing Stage

B.1. List of Function with implementation

Function Name	**Description/ Usage**	**Section Applicable**
imgprep.m	Exudate image resizing, brightness correction, colour conversion	Pre-processing stage
imgprepAh.m	Noise removing, Adaptive Histogram equalization	Image Normalization
exudate1.m	Dilation, erosion, image subtraction is performed	Image Boundary Traceing
exudatehist.m	histeq function is performed	Histogram Plotting
dubmin.m	Mean Calculation using mean taking from intensity value	Mean Calculation
adaptive_threshold.m	Otsu's Method Implementation	Adaptive Thresholding
Function_Ex	vessel Extraction, segmentation	Main Function

C.1. List of Tables

C.2. List of Figures