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AUTOMATIC DETECTION OF EXUDATES USING SVM AND DCNN TECHNIQUES

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ABSTRACT

Diabetic Retinopathy (DR) is the primary cause of vision loss and the early symptoms of this disease are exudates. Prior detection and treatment may prevent the vision loss. Automatic detection of exudate in retinal images is a challenging task. In this paper the two techniques Support Vector Machine (SVM) and Deep Convolution Neutral Network (DCNN) are used for retinal exudate detection and extraction. The SVM technique is applied to enhance and calculate the features of retinal image to recognize exudates. The DCNN technique extracts the blood vessels from the retina images. From these blood vessels the retina image is detected as exudate or non-exudate. Both the techniques are compared for area under the curve, specificity, accuracy and sensitivity. From the simulation results it is evident that DCNN technique is superior compared to SVM technique. The SVM and DCNN techniques are implemented using MATLAB software.

INDEX TERMS: SVM, DCNN, Exudate, Retinal Image, Enhancement

I. INTRODUCTION

Diabetic retinopathy is usually seen in long term diabetic patients, which can lead to vision problems and even eye blindness. Vision impairment is because of DR which is very hard to find and detect at the early stages of this disease. In case of delay in detection of DR, it can be fatal and results in permanent loss of vision. Therefore, efficient follow-up tests are recommended to the diabetic patients, which can help them to delay in progress of blindness and vision loss. It is difficult to address the increasing number of DR patients with available limited number of specialists. The development of automatic detection technique on fundus images to detect the disease at very early stages is quite essential and useful.

A sparse coding technique for retinal image classification to differentiate between retinal images containing either drusen or exudate is presented [1]. Linear SVM is used on the sparse coded features to improve the performance in sensitivity and specificity. Developed an automated diagnosis and detection system for DR [2], by devising appropriate Micro Aneurysm s(MA'S), Hemorrhages (HEM), Bright Lesions (BLs) for images in retinal fundus. In pre-processing it extracts the background pixels and computation takes place on foreground pixels. A study on improved algorithm for a new, larger dataset of 15,000 Area Under the Curve (AUC) exams. Only the small HEM and microaneuryms are detected [3].

A referral system is adopted combining different techniques such as Scale Invariant Feature Transform, Visual dictionaries and K-clustering. Good performance is achieved by improving the sensitivity and specificity parameters but it is a time consuming process [4]. Combination of adaptive and global thresholding to detect the hard exudate images in the retinal fundus for the segmentation in the candidate exudate region is presented [5]. A method of atlas-based exudate segmentation, image registration and retinal atlas building for retinal image analysis is proposed [6]. These methods are used for potential increase in the lesion growth and retinal image grading.

Based on an optimization algorithm for ant colony a new unsupervised approach is employed [7]. The algorithm performance is evaluated with online available dataset. In detecting the exudates it shows better results than the traditional Kirsch Filter. An automated system for screening is adopted to analyze digital retinal colour images for important feature of Non-Proliferative Diabetes Retinopathy (NPDR) to detect the major land marks of the retinal image such as fovea, optic disk and blood vessels [8]. The calculations for specificity and sensitivity are presented. The edge detection and region growing is combined to extraction the main features in retinal colour images. To locate optical disc, principle component analysis is used [9]. Mathematical morphology is used for detecting exudate in the colour fundus images. This method is accurate compared to other available methods to calculate specificity and

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sensitivity but the critical problem is to choose the appropriate size for the detection [10]. Candidate extraction is adopted for precise segmentation of the contour and labelling candidates as true or false exudates [11].

A supervised multi variable classification, optic disc detection technique, and super pixel multi feature classification classifiers are used for the detection of exudates and to differentiate true exudates from the false exudates [12]. It is evident from the above literature survey that sparse coding techniques, binary classifier, referral system for hard exudates, global and adaptive thresholding method, statistical atlas for segmentation of exudates, ant colony optimization, screening system, combined region growing and edge detection, mathematical morphological detection, candidate extraction methods are used for the retinal fundus image classification to extract exudates, but resulted in low accuracy, misclassification in finding the exudate and non-exudate candidates due to non-uniform lighting. To overcome the limitations mentioned SVM and DCNN techniques are proposed in this paper to detect exudate images in the retinal fundus.

II. PROPOSED SVM TECHNIQUE

In this section, the proposed SVM technique is introduced for exudate detection. The procedure for implementing the SVM technique is presented in Fig. 1.

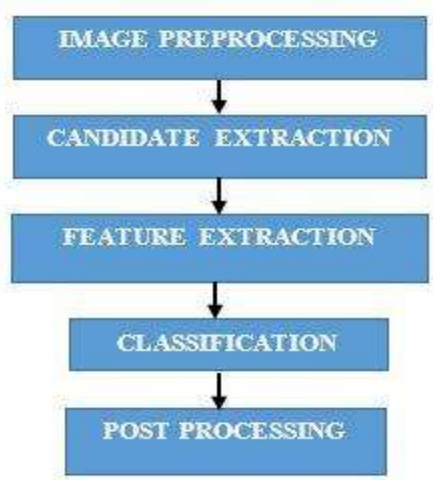

Fig. 1. Flow chart of proposed SVM technique.

In SVM Technique the first step is image pre-processing, The retinal fundus images have non-uniform illumination and display local luminosity. To improve the performance DCT is applied to the pre-processing step. In pre-processing the image is resized to 512x512. The following procedure is followed for improving the image quality. Read the input image and convert the input image in to YCrCb colour space.

The YCrCb represents luma and chroma, the digital components of the video in one of the two primary spaces for colour are red and blue. The difference between RGB and YCrCb is that the RGB stands for colour as red, green and blue, while YCrCb represents Y (luma) as brightness, Cr is red minus luma and Cb is blue minus luma. Increasing the brightness using YCrCb to the input image reduces the non-illumination for detection of exudates. Apply DCT and scaling coefficients for all three colour spaces of YCrCb. The dc coefficients are scaled for brightness, the dc and ac coefficients are scaled for contrast and the Cb and Cr components are scaled for colour. Apply inverse DCT to convert in to RGB colour space, apply bi-cubic interpolation which is used for image resampling and finally comparison using image quality index. The above process is done in image pre-processing to get bright and enhanced image to detect the very small exudates.

The candidate extraction, feature extraction and pre-processing steps is same as in SMFC method. The proposed SVM method is used in the classification step. The SVM primary goal is to find a hyperplane in the N-dimensional space (N – number of characteristics) that emphatically classifies the data points. The data points of two classes can be separated by using many possible hyperplanes that could be chosen. Main aim is to separate the exudates and non-exudate candidates with data points in the plane which has maximum margin. Increasing the marginal distance gives some reference such that upcoming data points could be identified more easily and confidently based on the classified data points.

Hyperplane can be classified as two-dimensional and three-dimensional features. From the placement of data points, hyperplane can be classified in to different planes. These planes classification mainly depends on the number of considered input features. The input features that are given to hyperplane is two then it is just a line. The input features are three then hyperplane is said to be a two-dimensional plane. When number of input features are increased to three then it is difficult to image the hyperplane . Support vectors are the data points that are nearer to the hyperplane and effect the hyperplane's position and orientation. Using these support vectors, margin of the classifier can be maximized. The position of the hyperplane is changed by deleting the support vectors. These are the data points that assist with SVM construction.

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III. SIMULATION RESULTS OF SVM

Exudate or not exudate image with an order of three shown in Fig. 2. is taken as input to SVM. The pre-processing operation is applied to the Fig. 2. In the pre-processing, the output image with greater enhancement is obtained after applying SLIC segmentation and DCT operation. The outcomes are shown in Fig. 3. and Fig. 4 respectively.

Fig. 2. Input Image is an exudate or non-exudate image with an order of three.

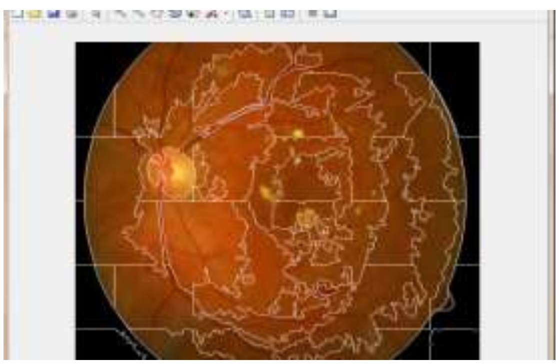

Fig. 3. Output image after the SLIC segmentation with region size and regularizer.

In feature extraction non-exudates candidates have different set of features compared with exudate candidates. Exudate candidates will have distinct colour contrast channels. So, extraction of a set of features for exudate candidates in each channel is important. The enhanced image given in Fig. 4. is provided as saturation input.

Fig. 4. Enhanced output image after DCT operation.

(a) Gray image

(b) Red image

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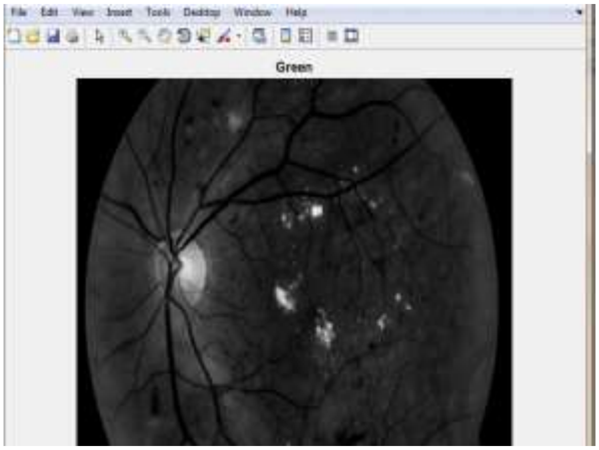
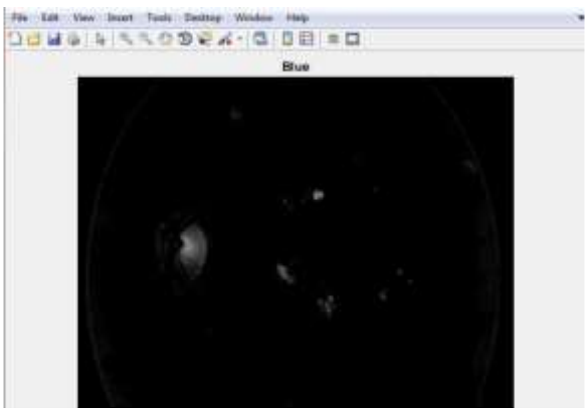
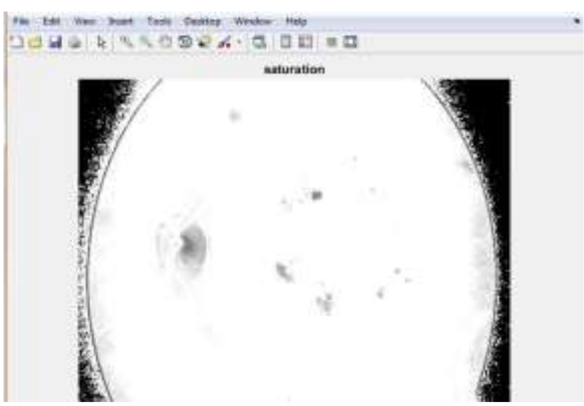


(c) Green image



(d) Blue image



(e) Saturation image

Fig. 5. (a)-(e) Saturation results from different colour channels.

The Figs. 5 (a) – (e) are for different colour channels for the saturation after the feature extraction step. Finally the exudate is extracted for the input image using the SVM network , shown in Fig. 6.

The optic disc is a non-exudate that is regarded and identified as an exudate in the classification outcomes. So to remove the non-exudate candidate and to improve the performance post processing pace is used. The results are displayed in Fig. 6-7. The proposed optic disc detection is largely based on two assumptions. Firstly view the optic disc as bright region, second the optic disc displays shape as a gaussian. The optic disc is extracted from the Fig. 6. to differentiate the optic disc from the exudates which is a non- exudate. The output result is shown in Fig. 7.

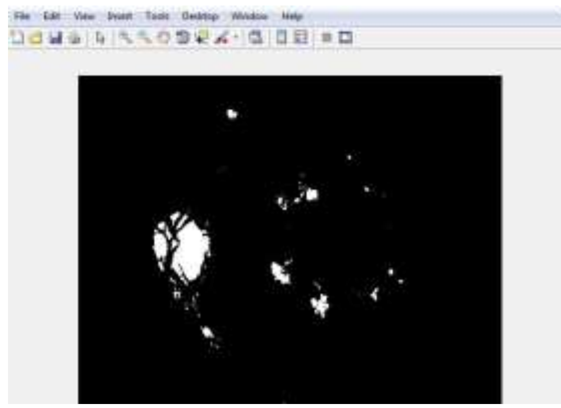


Fig. 6. Exudate extraction from input image .

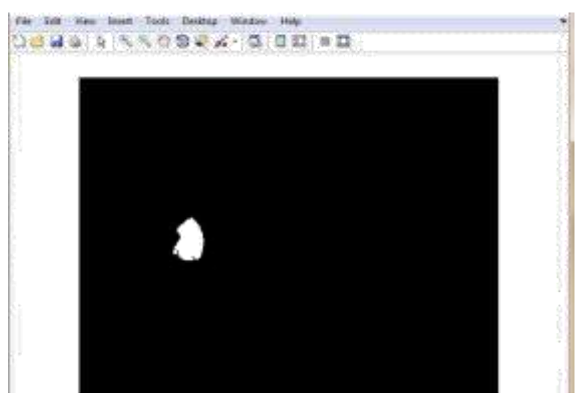


Fig. 7. Post processing output for input image

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Using SVM technique for the input image, specificity of 0.85, sensitivity of 0.98, area under the curve of 0.92 and accuracy of 0.87 are achieved respectively.

There is a misclassification, i.e. the proposed model makes a mistake in predicting the data point class, including the regularization parameter loss to perform gradient update. To reduce this misclassification the Deep Convolution Neural Network (DCNN) technique is implemented.

IV. PROPOSED DCNN TECHNIQUE

The DCNN consists of many neural networks. The main two networks are convolution network and pooling network. In this network the depth of each filter increases from left to right. The last stage is typically made of one or more fully connected layers.

The DCNN is used to obtain the features for retinal fundus images, audio files and text recognition. The DCNN is used for recognition and image classification because of its high performance in accuracy. The block diagram for DCNN based classification is displayed in Fig. 8.

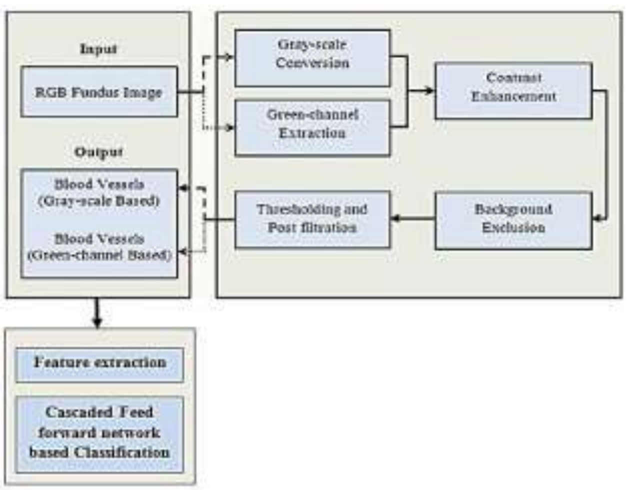

Fig. 8. Block diagram of DCNN technique.

For conversion RGB to gray/green format the retinal colour fundus image firstly converted to a gray/green channel image for easier segmentation of the blood vessels and it reduces the time of computation. Gray-scale eliminates the hue and saturation from the colour image and only the luminance information from the colour image, whereas the green-channel image offers maximum local contrast between images background and fore- ground images. The results of segmentation achieved using gray and green-channel images are then compared with the results obtained using other established algorithms. The output of RGB to gray/green channel is given as input to the contrast enhancement in order to increase the contrast.

Due to non-linearity or small dynamic range of the image, sensor image has low contrast i.e. illumination within the image is allocated non-uniformly, poor or non-uniform lighting condition. Hence it is important to deepen the contrast of the images to provide a better transform characterization for following image analysis steps.

The contrast enhanced image is applied for background extraction. It is used for tracking targets and motion detection. The primary aim of this step is to remove background lighting differences from an image so that the foreground objects can be analysed easily. In the proposed algorithm, by removing initial intensity image from the average filtered image the background exclusion is performed. The thresholding and post-filtering operation is done for the background extraction image.

The purpose of this module is to create a binary image with either 1 (blood vessel) or 0 (background) value for each pixel. Unfortunately, no thresholding technique exists to determine a unique threshold value that will deliver perfect results in all cases. To extract the blood vessels for exudate detection is done. An initial set of MA candidates can be identified after the shade correction noise removal. The above used method is proposed by Fleming. The circular dark regions in the image are enhanced by using a Gaussian matched filter. The intensity profiles of blood vessel cross-sections are similar to MicroAneuryms (MA's), they need to be removed before applying the Gaussian matched filter.

Finally, the output image after detection undergoes DCNN operation. A CNN consists of different layers, such as input layer, output layer, and multiple hidden layers. A DCNN'S multiple hidden layers are generally convolution layers and Rectified Linear Unit (RELU). In RELU layer the pooling layers, activation function, fully connected layers and normalization layers are present. When convolutional layer is programmed, each neural network in a convolution layer should be given the following attributes:

- A tensor shaped input (image width) x (number of images) x (image height) x (image depth).
- Number of convolutional kernels.
- The hyper-parameters are kernel Width and height
- The image depth must be the same as Density of kernels. After processing the operation convolution operation, convolution layers sends

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output results to the next layer. Individual neuron emulates the response to visual stimuli.

Max Pooling acts as a noise suppressant. The noisy activations are discarded all together and it performs de-noising and dimensionality reduction. On the other hand, the dimensionality reduction is simply performed by average pooling as a noise suppressing mechanism. Every neuron from each layer are connected to every other neuron of corresponding layer is said to be fully connected layer which is same as traditional Multi-Layer Perceptron neural network (MLP). To classify the images the flattened matrix goes through a fully connected layer. The softmax layer extends into a multi-class world i.e, each class in a multi-class problem is assigned as a decimal probabilities by softmax. Those decimal probabilities must add up to 1.0. The training converge helps this additional constraint to read more quickly. The softmax is implemented through a neural network layer just before the output layer. The softmax layer must have the same number of nodes as the output layer.

IV. SIMULATION RESULTS OF DCNN

The simulation results for DCNN based classification are presented from Fig. 9. – Fig. 13. The results of gray component of an image is shown in Fig. 9. and average filtered image is removed from the input and displayed in Fig. 10.

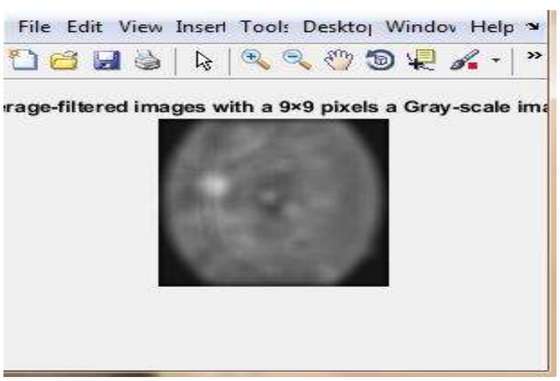

Fig. 9. Gray component of an input image.

The detection of exudate for the input is shown in Fig. 11. The obtained exudates are combined with the extracted vessels for the better visualization as shown in Fig. 12. The final detected image for exudate detection is shown in Fig. 13.

Fig. 10. Average filtered image for green scale image shown in Fig. 9.

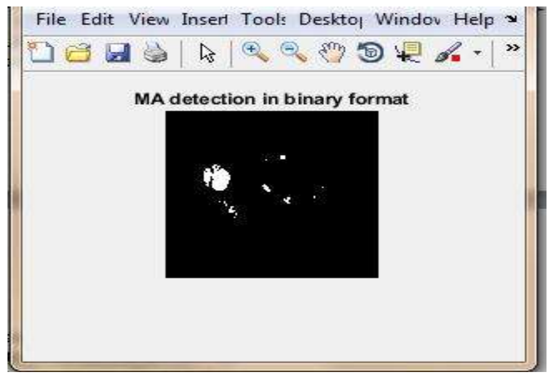

Fig. 11. MA Detection in binary format.

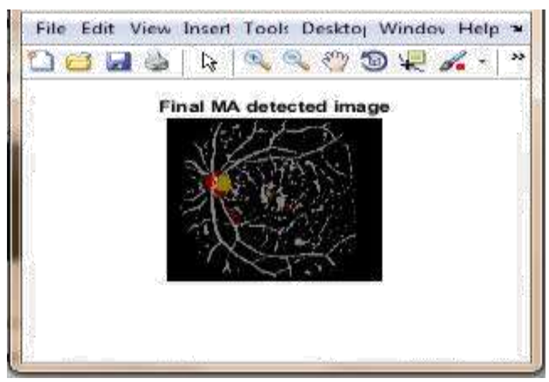

Fig. 12. Final MA detected image.

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Fig. 13. Exudate detection using DCNN.

Using DCNN technique the results obtained are specificity 0.95, sensitivity 0.99, area under the curve 0.95 and accuracy 0.89.

V. COMPARISON RESULTS

The comparison of results for classified output using FDA [12], proposed SVM and DCNN techniques are presented in table1.

TABLE 1: Comparison of results

Metric	FDA[12]	Proposed method using SVM	Proposed method using CNN
Sensitivity	0.8950	0.9810	0.9996
Specificity	0.9270	0.8537	0.9570
AUC	0.9510	0.9268	0.9560
Accuracy	0.8445	0.87818	0.8978

For the same input image using DCNN technique better results are obtained compared to SVM technique and FDA.

VI. CONCLUSION

In this paper, SVM and DCNN techniques are proposed. DCT based enhancement method is used for image enhancement to improve the vision of an image. SVM classifier is used to improve the results. The sensitivity, accuracy, area under the curve and specificity of SVM technique is 0.98, 0.87, 0.92 and 0.875 respectively. DCNN technique is implemented to further improve the results for non-illumination images. For DCNN technique accuracy, specificity, area under the curve and sensitivity is 0.89, 0.95, 0.956 and 0.99 respectively. It is evident that DCNN techniques yields much better results.

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