Hierarchical Model For The Detection Of Exudates Based On Retinal Features Analysis

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Abstract:

In recent years exudates are emerged as most prominent signs of diabetic retinopathy in diagnostic measurements, and its detection has been investigated in many works for most appropriate diabetic retinopathy CAD system. Here, super pixel segmentation is formulated with most relevant multi-feature set extraction for accurate and fully automated network based classification for the detection of exudates. The process begins with segmentation of super pixels followed by generation of 20 features from two different channels each belongs to different intensity levels namely contextual features. The supervised classification algorithm is used to discriminate the exudates from other classes. Experimental results prove that the proposed models offer improved detection and classification performance in terms of accuracy. Performance validation is carried out over two well known publicly available bench mark datasets namely, DiaretDB1, and e-ophtha EX to prove the effectiveness of the proposed framework.

Keywords: Diabetic Retinopathy, CAD system, color retina fundus image, exudates, local luminosity, pixel and feature classification etc.

1. INTRODUCTION

Diabetic Retinopathy (DR) is an abnormality that occurs in eye region which caused blindness by long-term diabetes around the world. Moreover the significance of detailed analyzes of this disease has been emerged with the rising prevalence of diabetes notably in Asian and European countries [1] and also to detect the severe vision-threatening stages which includes proliferative DR (PDR) and diabetic macular edema (DME) etc. In general, Diabetic Retinopathy early detection can avoids any sort of vision problems for many patients but initial phase of the disease is quite difficult to detect. During advancement of the disease, vision loss due to diabetic Retinopathy is unavoidable in most cases. To overcome this, it is essential to conducts frequent examination for all patients to avoid progression of blindness and vision loss [2-3]. But specialists are not readily available to monitoring the DR patients as with the cases is rapidly increasing in every years which leads fully automatic detection technique over digital fundus images to accommodate any number of patients.

On the other side to detect the early stages of diabetic retinopathy, the significant contribution of inflammation which is developed from the initial reports of the diabetic patients those who took salicylates for rheumatoid arthritis [4]. In addition to this different molecular abnormalities are also noted down which is related to the inflammation in the retinas. Exudates also considered as prominent factors in some CAD system and used most prominent signs of regular examination of DR which can overcome vision loss problem in the range of 90-95%. Microarray analyses also used to accomplish the exploration of the inflammatory response in retinas from diabetic rodents.

Several existing works [5-6] proved that the detection of exudates can give a significant contribution towards early diagnoses of eye abnormalities caused by Diabetic Retinopathy (DR) to produce the most appropriate impairment and preservation. In this paper, we propose super pixel ROI segmentation and multi feature extraction followed by classification for color retinal images which has metrics as follows:

- To carry out highly robust and invariant detection of the exudates using super pixel model that utilize appropriate residual blocks.
- To validate the statistical significance of contextual feature analyzes and its relevant exploration Metris in terms of discrimination between lesion and retina region.

This paper is organized as follows: Section 2 discusses various image processing techniques for the detection of exudates in retina images and its metrics in overall clinical measurements. Various stages of proposed image computation and its statistical measures have been analyzed in Section 3. Section 4 includes the performance validation and its associated efficiency, followed by the conclusion.

1. RELATED WORK*:*

To assist the accurate diagnosis of diabetic retinopathy it is essential to incorporates all eye abnormalities which include various non linear transformations and feature attributes for reducing the diagnostic errors. But due to its poor-resource formulation and its sensitiveness to illuminations highly robust segmentation methods that are required for modelling the CAD system still has several limitations due such as:

Illuminations occur at lesion region causes minima in edges and also cause high contrast.

Segmentation of super pixels gives promient influence on the overall detection performance of the retinal lesion and exudates, which requires some finite approximation.

Feature extraction always produces variance which cause inters class and intra class issues that required unique solutions.

The super pixel Segmentation in retinal images can be done by using different methods namely i) Rule Based [7] ii) Pixel Based iii) Deformable based and iv) region growing based etc. In this research Novel pixel segmentation method is proposed by utilizing some of the pre processing image transformation Model and multi feature based approach with machine learning algorithm method to improve the accuracy of classification.

And for automated detection system both the Segmentation models and the feature values used to explore the abnormal behaviours of exudates region is difficult task to accomplish. Though various models [8-9] are investigated for appropriate Segmentation and attributes extraction process still prominent techniques are required to reduce the performance gaps. Among other features attributes texture traits are widely used in recent years in medical imaging for its invariance nature. And finite detection rate for improved classification largely depends on classifier models used at the final stage.

In this paper, as shown in Figure 1we carried out hierarchical process for extracting potentially useful information's, series of multiple features and network classifiers to exploit fine details about abnormal retinal image for following advantages.

1) Finite super pixel ROI model incorporates the various forms of spatial details from transformed input images.

2) Based on consistency measures multiple contextual features are extracted for lesion detection process.

3) Classification using network model reduce false rate with improved detection rate.

In addition, to optimize the negative impacts during classification process proposed model also includes simplified redundant removal blocks in all stages for reducing the sensitiveness to complex boundary variations and illuminations CAD system.

2. SUPERPIXEL MULTI-FEATURE DIABETIC RETINOPATHY

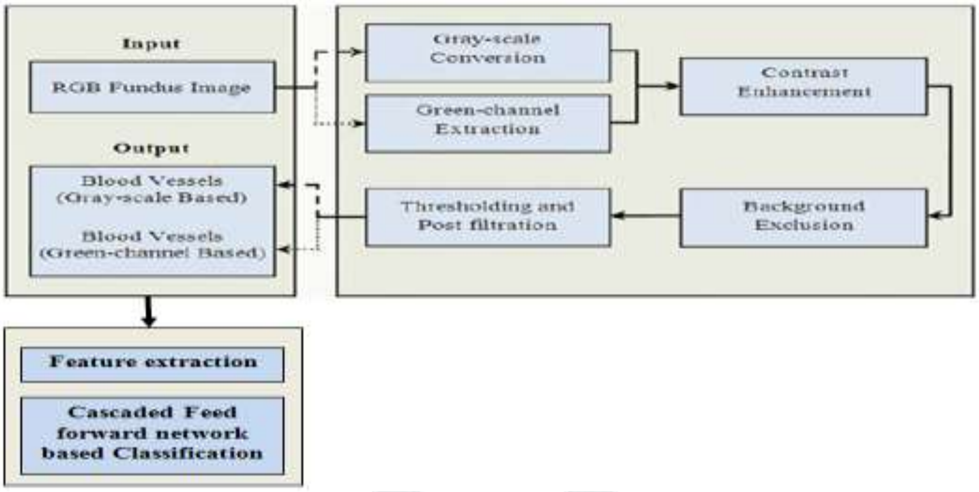


Fig .1. Proposed Multi-Feature Framework for Retinal CAD System

3.1 PRE-PROCESSING:

A. RGB to Gray/Green Conversion:

Here initially input retinal set is first transformed into a gray-scale/green-channel to carry out the blood vessels ROI and to reduce the overall computational time. Gray-scale image explores only the luminance values from the input retinal input while suppressing the hue and saturation, whereas the green-channel offers maximum contrast information between the background and lesion region. The ROI results are formulated using these two channels namely gray and green-channel and the results are analyzed using other forthcoming process. The transformation from the input retinal into gray-scale image is accomplished using a weighted sum of the primary channels as in Eq.(1)

$$g = 0.2989*R + 0.5870*G + 0.1140*B \qquad (1)$$

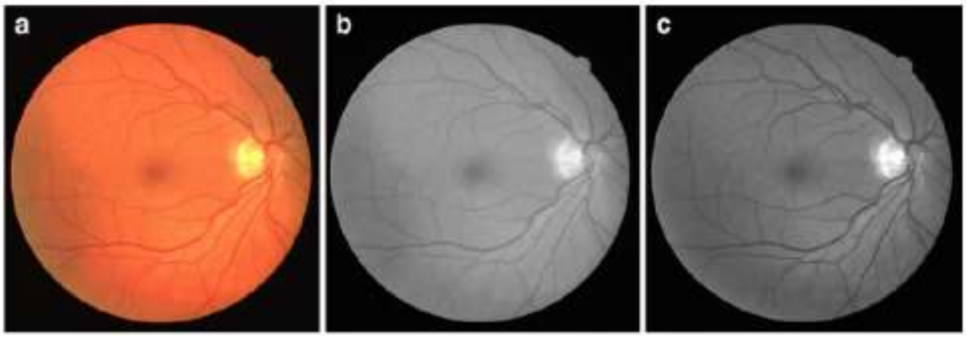


Fig. 2. Input retinal image, b gray-scale channel, c green-scale.

B,Contrast Enhancement

Low contrast input leads several complications such as uneven lighting condition, scale variations or dynamic variations caused by sensor models in general illumination is often unevenly across the lesions. To overcome this problem it is essential to suppress the contrast to ensure the better transform for complete component analysis. The contrast normalization used both the gray- scale/green-channel in Fig.2, where $T(r)$ refers the conversion model which controlled by the spatial points (r_1, s_1) and (r_2, s_2). And other techniques are used to modulate the contrast with some range of intensity values to control the dynamic ranges. Techniques like decor relation stretch transform, non uniform mask, histogram equalization, contrast-limited dynamic control driven adaptive histogram equalization (CLAHE) is incorporated for improving the lesion region contrast as shown in Fig.3.

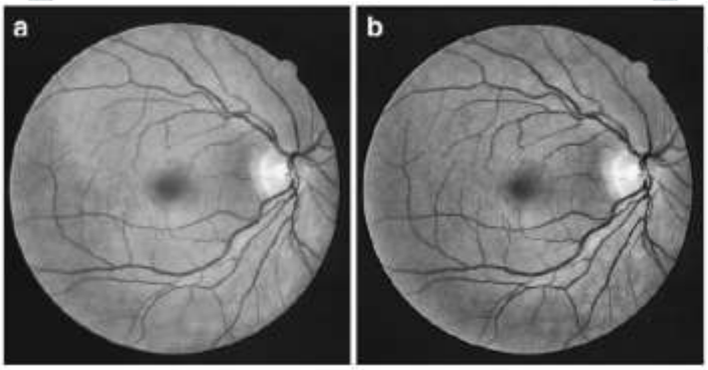


Fig.3. Contrast enhancement a Gray-scale model, b Green-model.

C.Background extraction

This step is evaluated by eliminating all non linear background variations due to illumination to isolate the foreground objects and to explore the lesions for detailed analyzes. Here image filtering is performed to suppressing the original intensity from results generated.

As shown in Eqn. (2) average filter is formulated using some local operations over input image, which is referred as" neighborhood average method". The principle behind this model is to carry out standard moving average filter instead of the pixel values compound from the center pixel g'(x,y) and neighboring pixels gi(x, y) are predefined accordingly as shown in Fig.4.

$$\widehat{g}(x,y) = \frac{1}{N \times M} \sum_{i=1}^{N \times M} g_i \qquad (2)$$

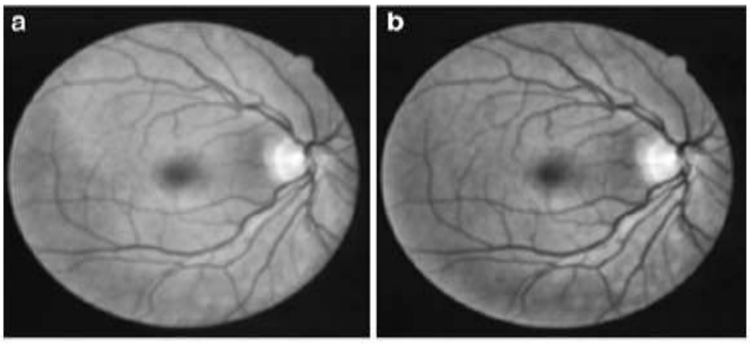


Fig.4. Average-filtered images with 9×9 pixels a Gray-scale image, b Green-channel

D.Thresholding

At final stage the binary images are generated from enhanced version of input retinal images where the pixel values of blood vessel and background regions are discriminated using thresholding technique with pre-determined threshold value for all classes.

E. Post-Filtration

Here for both noise suppression and shade normalization Fleming model is proposed based on Gaussian matched filter to enhance circular dark regions. And the detected blood vessel and its associated cross-sections are comes with different intensity profiles which is well matched with MAs and detected using morphological operations as shown in Fig.5.

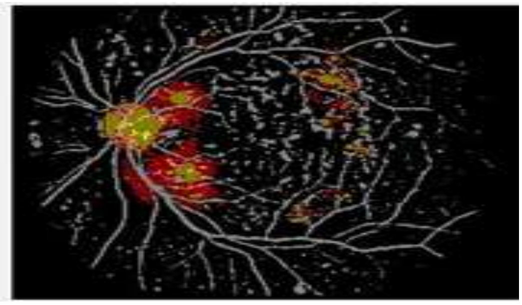


Fig.5. Detection of micro aneurysm

3.2 CONTEXTUAL FEATURE:

After image pre processing and super pixel isolation, the proposed contextual feature in output green channel *I* is computed. And for spatial compact (*P*) candidate regions *Ri*(i=1; 2; 3; :::; P) with relative consistent size. Here, let *Mean_Ri*and *pi* refers gray scale average and bary center position of the *i*-th super pixel region. Let us considered

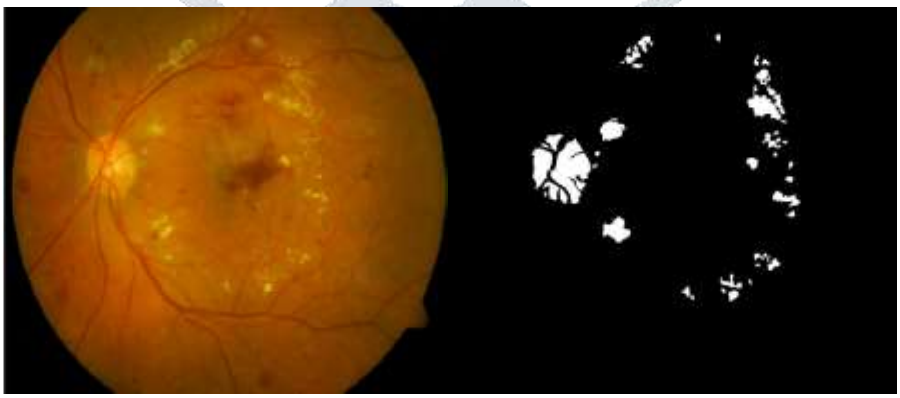
Mean - Global mean value
Si - Contextual feature

$$S_i = \frac{1}{N_i} \times \frac{Mean\_R_i}{Mean} \times \sum_{j \in N(i)} \left(\frac{d_j}{D_j} \right)$$

$$d_j = Mean\_R_i - Mean\_R_j$$

$$D_j = sqrt\left(\|p_i - p_j\|_2^2 \right) j \in N(i)$$

N (i) is the set of spatial region Ri and Ni is the pixels count over candidate region Ri



Input Image Exudates part

Fig.6.Final MA detected image

3.3 Classification:

Alex Net:

AlexNet CNN model is used to perform image classification over a collection of sets as shown in Fig,7. Alex Net network is trained using several images and can classify images into maximum number of classes up to 1000 object categories.The network has learned rich feature representations for a wide range of images. Here the CNN network consider whole image region as input and labels the different object based on the probabilities for each classes. Machine learning can be used as deep learning with some pretrained network and appropriate starting point to learn for every task. Fine-tuning of a CNN network also requires some transfer learning to run at faster and simpler as compared to other training a network which are randomly initialized with different weights.The following shows the architecture of Alex Net.

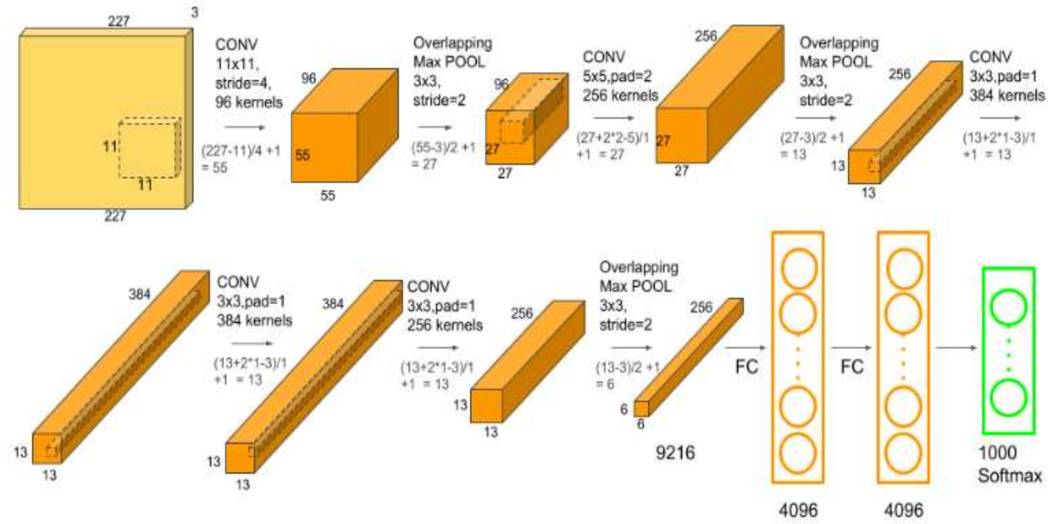


Fig.7. Architecture of AlexNet

3. EXPERIMENTAL RESULTS

Experiments are carried over on the publicly available data sets. This algorithm has been tested over different set of retinal images, which belongs to both normal and abnormal DT images with manifestations of various clinical stages. Here Exudates regions are detected with range of illumination conditions using Matlab software.

Algorithms validated iteratively based on the retinal spatial model reports improved performance as shown in Fig.8.to detect the exudates regions in the retinal images to achieve a improved classification. The British Diabetic Association recommends a minimum standard of 98% sensitivity and 98% precision during the detection of retinopathy signs. It is also reported that sensitivity values is accumulated with ranges from 80% to 98% and also results shows that the detection of exudates offers an acceptable eye-screening programme as shown in Fig.9.

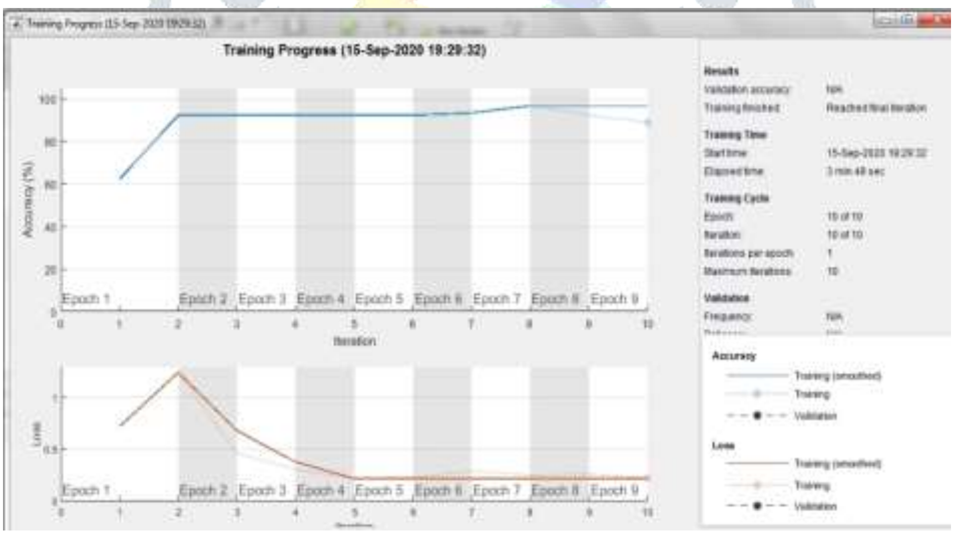
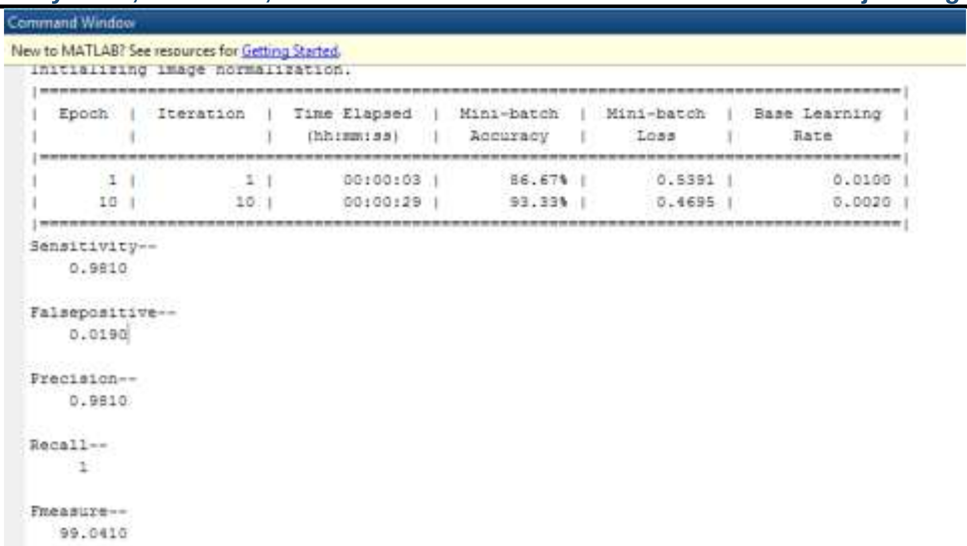


Fig.8. Training progress of network


Command Window

New to MATLAB? See resources for Getting Started.

Initializing image normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:03	86.67%	0.5391	0.0100
10	10	00:00:29	93.33%	0.4695	0.0020

Sensitivity--
0.9810

Falsepositive--
0.0190

Precision--
0.9810

Recall--
1

Fmeasure--
99.0410

Fig.9. Performance measure comparison

4. CONCLUSION

This work presents a novel super pixel segmentation based approach to isolate the lesions from the retinal color fundus image and its abnormal exploration. The proposed method aims to extract multiple contextual feature details from ROI segmented image. The proposed feature attributes interpretation is used in preceding networks layer gives most appropriate outlines; therefore, the proposed method requires least number of layers to incorporate the abnormal details of Exudates in retinal images. By understanding the discrimination of these Exudates regions and its measures are generalized for improved system \performance. Results shows that both the enhancement method incorporated and Alex Net used for classification offers significant contributions for better accuracy.

5. REFERENCE

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