A MULTI-SVM BASED DIABETIC RETINOPATHY SCREENING SYSTEM

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ABSTRACT

Diabetic Retinopathy (DR) is an abnormality of the eye in which the human retina is affected due to an increasing amount of insulin in the blood. The early detection and diagnosis of DR is vital to save the vision of diabetic patients. The early signs of DR which appear on the surface of the retina are microaneurysms, haemorrhages, and exudates. This paper presents an automated screening system for Diabetic Retinopathy using Kirsch's edge detection algorithm. Kirsch template technique is used for the extraction blood vessels from retinal images. The Kirsch edge detection algorithm uses a single mask of size 3x3 and rotates it in 45 degree increments. Since the retinal blood vessels can be considered as required foreground information from fundus images, Kirsch algorithm can be effectively applied. The proposed multi-Support Vector Machine (SVM) based system detects new vessel formations in retinal images following preprocessing, vessel extraction, feature extraction, and classification of retinal fundus images.

Keywords : Fundus Images, Haemorrhages, Lesions, Microaneurysms, Neovascularization, Vasculature.

I INTRODUCTION

Diabetes is a disease caused when the pancreas does not secrete enough insulin or the body is unable to process it properly. Diabetic Retinopathy (DR) is an indication of diabetes leading to the deterioration in the level of eyesight of the patient due to the unusual growth of retinal lesions, viz. exudates, haemorrhages and microaneurysms. The blood vessels in the retina swell and leak fluid or even close off completely. In some cases, neovascularization occurs which is the abnormal or excessive growth of blood vessels in the retina.

Diabetic retinopathy usually affects either or both the eyes, damaging the tiny blood vessels inside the retina. People with DR does not usually notice the changes in vision in the initial stages. The symptoms of DR include :

- Blurry vision.
- Rings or blank spots.
- Pain or pressure in one or both the eyes.
- Vision through the corners of the eyes are affected.

DR is analyzed by the abnormal growth of retinal lesions. Microaneurysms are tiny swellings in the walls of the blood vessels which appear as small, round, red spots. They arise due to the rapid growth of weakened capillaries attempting to revascularize the affected retina. Microaneurysms are not permanent features appearing on the retina due to retinopathy, they may even disappear. Sudden appearance of numerous microaneurysms is an indication of worsening of the disease. Exudates are fluids that have been slowly discharged out of the tissues due to rupturing of the walls of blood vessels. Hard exudates consist of lipoproteins and other proteins leaking through abnormal retinal vessels. They appear as yellow organic deposits which may include fats, oils, waxes etc. Haemorrhages occur due to the bursting of weakened capillaries. They appear as small dots, or larger blot haemorrhages present within the densely packed deeper layers of the retina. Microinfarcts or soft exudates appear in the advanced stages of the disease due to vascular occlusion and they appear as white lesions with vague margins and forms a depressed area when healed, due to tissue loss.

Diabetic retinopathy is divided into several stages such as mild, moderate, severe and proliferative DR as explained below :

(a) Mild non-proliferative retinopathy: Microaneurysms, i.e., small swellings in the tiny blood vessels of the retina will be formed in this stage.

(b) Moderate non-proliferative retinopathy: As the disease progresses, some blood vessels that nourish the retina are blocked.

(c) Severe non-proliferative retinopathy: Many more blood vessels are blocked, depriving several areas of the retina of their blood supply. The affected areas of the retina begin to show sign of ischemia (lack of oxygen) such as blot hemorrhages, bleeding of the veins and intra-retinal micro-vascular abnormalities.

(d) Proliferative diabetic retinopathy (PDR): At this advanced stage, the vasoproliferative factors produced by the retina begin to trigger the growth of new blood vessels. These new blood vessels are abnormal and fragile.

The disease/no disease automated grading system do provide benefits, but an additional objective is to develop a system capable of triaging images. This should include the ability to detect and prioritize DR images to ensure immediate attention and treatment. The automatic detection of DR has received a lot of research attention, with studies investigating microaneurysms and haemorrhages and exudate detection [1-12].

Zhang[13] proposed a modified matched filter that used double sided thresholding. The main emphasis was not on the increased segmentation of new vessels, but instead the reduction of the false response to exudates which can cause large local densities on the segmented map and therefore can be mistaken for new vessels. B.Zhang [14] applied the matched filter with the first-order derivative of the Gaussian to reduce the false response to exudates. Ramlugun [15] described a small vessel extraction technique, the main contribution was the varying of the clip limit for contrast limited adaptive histogram equalization (CLAHE) to allow more contrast for small vessels. The following new vessel detection methods applied vessel segmentation prior to the described analysis methods.

Daxer[16] and Karperien [17] both described the retinal vasculature as a fractal and used the fractal dimension to quantify its complexity to indicate the presence of new vessel growth. Jelinek[18] extracted morphological features based on data obtained from the application of the derivatives of Gaussian wavelets to the vessel skeleton. Goatman [19] developed a comprehensive set of 15 features including the number of vessel segments,

the mean vessel wall gradient and various tortuosity measures to detect new vessels on the optic disc. Akram [20] proposed a Gaussian mixture model based classifier with a 5 dimensional feature set based on intensity and gradient values. Hassan[21] used just two local features, the number of vessels and the area of vessels within a small scanning sub-window to indicate new vessels.

R.A. Welikala, V. Tah, T.H. Williamson [22] proposed a method in which the majority of normal vasculature was removed from the vessel map to simplify new vessel detection. Statistical texture measures calculated using the grey level co-occurrence matrix (GLCM) were applied by Frame [23] to identify irregular distributions of pixel intensities associated with neovascularization. Acharya [24] calculated texture features from the GLCM and the run length matrix to identify the stage of DR. Agurto [25] utilized multi-scale amplitude modulation frequency modulation (AM-FM) methods for spectral texture analysis to characterize differ-ent retinal structures, including new vessels. However, later work by Agurto [26] involved AM-FM along with granulometry and vessel segmentation to detect new vessels on the optic disc.

M.Usman Akram, Shehzad Khalid, Anam Tariq and M.Younus Javed [27] proposed a new method for detection of abnormal blood vessels and grading of proliferative diabetic retinopathy using multivariate m-Medoids based classifier. The system extracts the vascular pattern and optic disc using a multilayered thresholding technique and Hough transform respectively. It grades the fundus image in different categories of proliferative diabetic retinopathy using classification and optic disc coordinates.

True comparisons on the results are difficult to make in some of the above papers as no standard datasets have been used for testing. Also, the testing becomes too slow as the number of hidden layers increases in the back-propagation algorithm used and the algorithm diverges unless the covariance values are regularized.

II PROBLEM DESCRIPTION

Diabetic Retinopathy is a complication of diabetes which causes vision impairment on patients with diabetes for 10 years and above. The disease affects the circulatory system of the human body, including that of the retina. Thus oxygen supply to the visual system is reduced to a bigger extent and it causes swellings on the retinal vessels. Also retinal lesions are formed which includes haemorrhages, microaneurysms and exudates. These are the symptoms for the disease, which will not be visible in the initial stages of the disease. Therefore, unless the patient takes regular examination of the disease, it cannot be identified and thus not cured.

This paper puts forward a system with which the severity of the disease can be identified by examining the retinal photograph of the patient. The retinal photograph of the patient is examined by this automated system and by studying the retinal features of the patient from this retinal photograph, the disease classification will be done by this system.

For this purpose, the authors have implemented a technique called Kirsch's edge detection algorithm which automatically detects the newly formed edges in the retina. The method also sets and resets new threshold values by itself which helps in this automated detection technique.

Retinal features are extracted to analyze the changes in each stage of the disease. So by using these feature values, the threshold can be set such that the proposed multi-SVM based system automatically classifies the stages of the disease by analyzing the particular range of feature values.

III METHODOLOGY

As the number of diabetes affected people are increasing worldwide, the need for automated detection methods of diabetic retinopathy is very much significant. In order to have an automated system to automatically detect diabetic retinopathy, a computer has to interpret and analyze digital images of the retina. Fig.1 shows the flow chart of the proposed system.

As said in the flowchart, the steps followed include preprocessing, vessel extraction, feature extraction and classification. The preprocessing is done to enhance the data images prior to computational preprocessing. Preprocessing commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles in images, removing reflections and masking portions of images. Preprocessing of the fundus image can significantly increase the reliability of an optical inspection.

Vessel extraction step extracts the blood vessels from the retinal images and helps for extracting the features from them. The classification process categorizes the disease into the corresponding severity stages by the feature values obtained by performing feature extraction. This paper presents a multiple-Support Vector Machine (SVM) learning technique by which the weakness of simple SVM classifier of just clustering into two data-sets has been overcome.

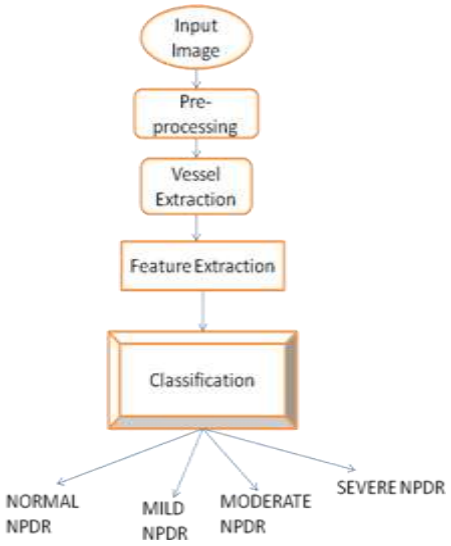

Figure 1: Flow-chart of the proposed system.

3.1 Vessel Extraction

The extraction of retinal blood vessel is an essential step for the diagnosis of various eye diseases. Retinal images of humans play a crucial role in the detection and diagnosis of several eye diseases by the oculists. The information about blood vessels, such as length, width, diameter and branching pattern, can help to diagnose the symptom of diseases. With the help of computer aided diagnosis (CAD), the success rate of the treatment of these diseases may increase significantly.

3.1.1 Kirsch's Method of Edge Detection

Edge detection is a process of identifying the pixel values in order to get frequent and abrupt changes. Kirsch templates of size 3x3 are used for the extraction of blood vessels from retinal image. Edge information of a

particular and target pixel is checked by determining the brightness level of the neighboring pixels. If there is no major difference in the brightness levels then there is no possibility of edge in the image.

In this paper Kirsch template technique is used for the extraction blood vessels from retinal images. The Kirsch edge detection algorithm uses a single mask of size 3x3 and rotates it in 45 degree increments through all 8 directions.

The edge magnitude of the Kirsch operator is calculated as the maximum magnitude across all directions. The matrix contains the information of a pixel and its neighbors. The Kirsch algorithm detects direction of the edge as well as an edge. Accordingly, there are eight possible directions : South, East, North, West, North-East, South-East, South-West and North-West. Out of the several templates the biggest one is considered for the output value and later the edges are extracted. Kirsch template can set and reset the threshold values to obtain most suitable edge of images. Kirsch template works well for images having clear distinction between the foreground and background. Since the retinal blood vessels can be considered as required foreground information from fundus images, Kirsch algorithm can be effectively applied.

3.2 Feature Extraction & Classification

Features are the individual measurable properties which help for classification. A good feature should be consistent over several images of the same scene. Features should be invariant towards certain transformations and should also be insensitive to noise. Feature extraction is the process of generating features to be used in the selection and classification tasks which constructs a set of application-dependant features.

Classification is a process in which individual items are grouped based on the similarity between the item and the description of the group. The classification task determines which parts of the image belong to the object of interest. This paper presents a multi-SVM based diabetic retinopathy screening system. SVM normally classifies data into two clusters. The main advantage of this multi-SVM based system is that it can be used to classify the object of interest into two or more clusters by which the normal, mild, moderate, severe and proliferative stages of the disease can be distinctly classified.

IV RESULTS & DISCUSSIONS

In this section, the simulation results are presented. The fundus images has been collected from the Diabetic Retinopathy Database, DRIVE Database and from **Vasan Eye Care Hospital**, **Chaithanya Institute of Ophthalmology and Visual Sciences, Trivandrum**.

The input retinal image is in the RGB format, which is shown in Fig.2. The image in Fig.2 is converted into the grayscale range as shown in Fig.3.

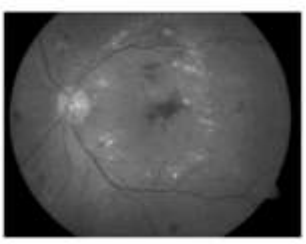

Figure 2 : Input fundus image. Figure 3 : Gray-scale Image.

The RGB to Grayscale conversion is done to increase the dynamic range of the image. Also, the retinal features can be analyzed much easily using the grayscale form of the image.

Fig.4a) shows the histogram of the grayscale image shown in Fig.3. The histogram of the image is taken to represent the intensity values of the image graphically. Histogram equalization is performed to represent the scattered average values in the original histogram. Fig.4b) shows the equalized histogram of the input inamge.

The grayscale image is adjusted such that it becomes considerably sharp and retinal features are displayed more clearly, which is shown in Fig.5a). Contour mapping of the adjusted input is showed in Fig.5b) which clearly depicts the retinal lesions.

Fig.6 shows the 8 possible vessel extracts of the input retinal image, obtained by using the Kirsch's Template or Kirsch's edge detection algorithm.

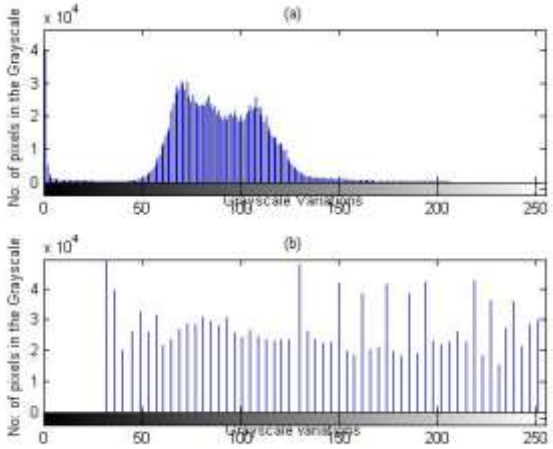

Figure 4 : a) Histogram of the grayscale image, b) Equalized histogram of 5 a).

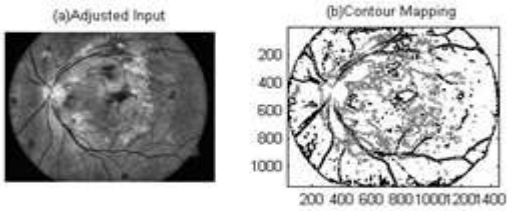

Figure 5 a) Adjusted input. b) Contour Mapping of the adjusted image.

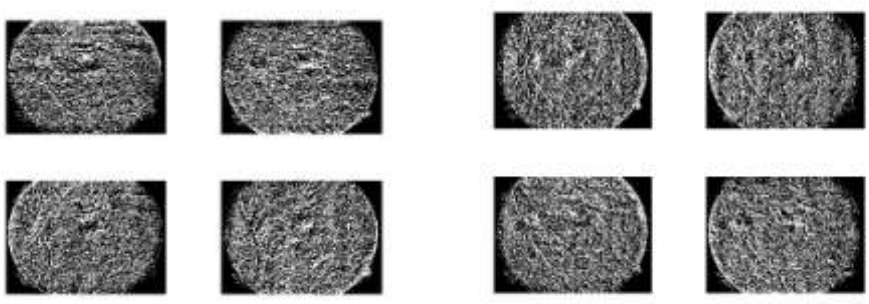

Figure 6 : Eight Possible Vessel Extracts of the input image using Kirsch's Template.

The difference in the major stages of the disease can be figuratively represented as in Figures 7-11 along with their graphical histogram and equalized histogram representations. The changes in the histogram are due to the variations in the texture and feature values of the different images used. Fig.12 represents the outcome of the multi-SVM based classification process.

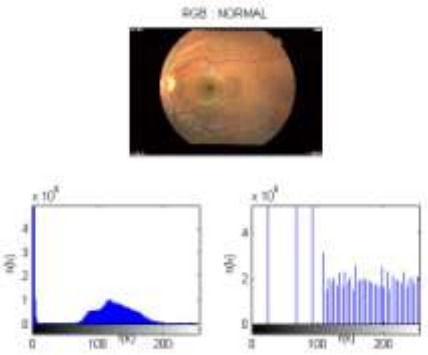

Fig 7 : Representation of the Normal stage of DR.

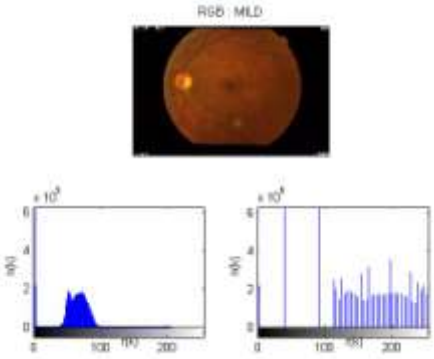

Fig 8 : Representation of the Mild stage of DR.

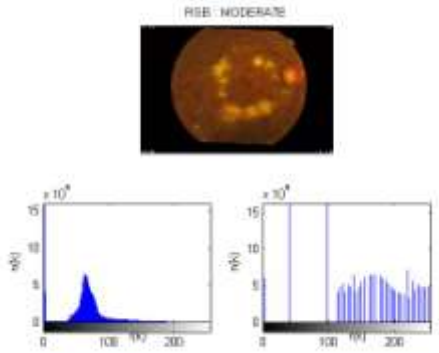

Fig 9 : Representation of the Moderate stage of DR.

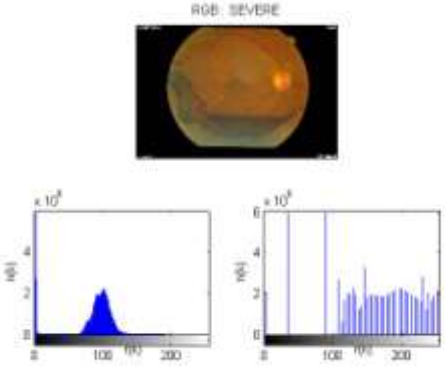

Fig 10 : Representation of the Severe stage of DR.

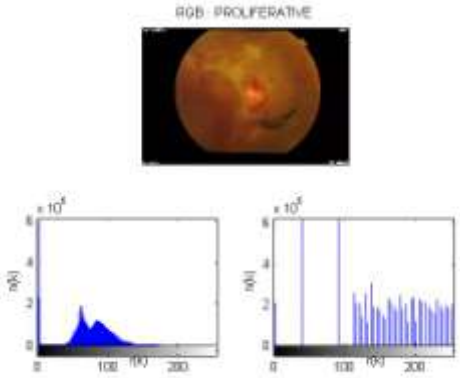

Figure 11 : Representation of the Proliferative stage of DR.

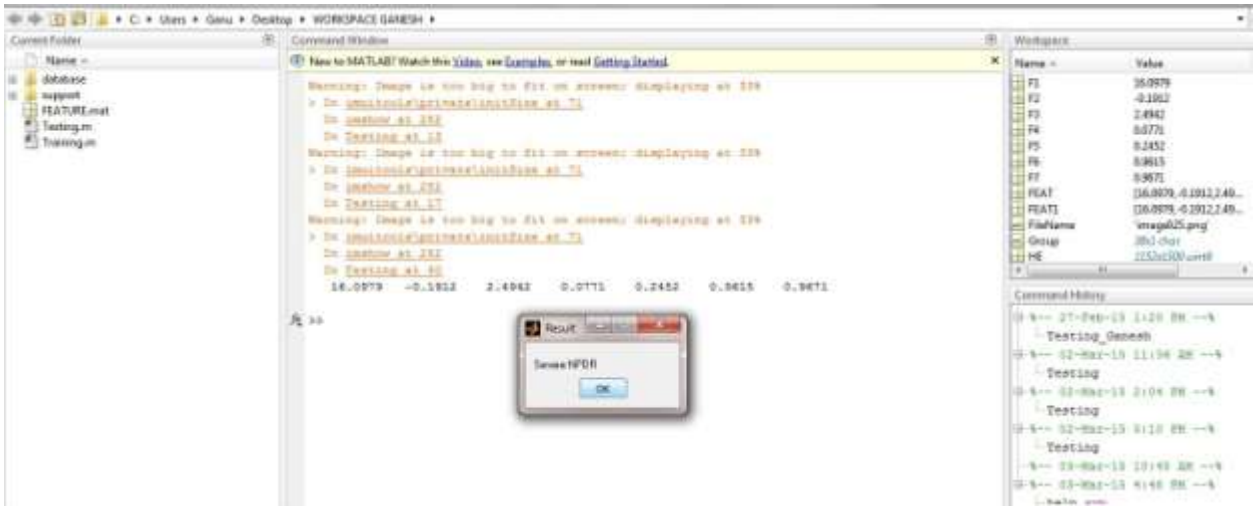

Figure 12 : Result of the classification task.

V CONCLUSION

In this paper, a system for the reliable grading of fundus images has been presented for different stages of DR. A four stage model, comprising preprocessing, vessel extraction, feature extraction and classification, has been proposed. The preprocessing phase extracts background pixels to enable the processing of the further stages on the foreground pixels only. The main components, such as the vascular pattern and optic disc, are also extracted in the first phase to facilitate the later steps. The second phase performs the blood vessel extraction from the retinal images. Feature extraction phase extracts the available features from the retinal images for the purpose of grading of the disease in the final phase. The structural-SVM based classifier classifies the severity of diabetic retinopathy based on the features obtained from the retinal photographs.

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