Haemorrhages and Micro- aneurysms Diseases Detection using Eye Fundus Images with Image Processing Techniques

S.Megala, T.S. Subashini

Abstract: The micro-aneurysm and haemorrhages are considered to be earliest possible signs of diabetic retinopathy (DR). The weak blood vessel generates a swelling due to accumulation of leaking lipids termed as micro-aneurysm (MA). The swelling ruptures and leaking blood results in to haemorrhage. Haemorrhage is a major problem of the eye after diabetic retinopathy, in this disease bleeding occurs into the interior portion of the eye. The following are main reasons for Haemorrhages such as hypertension, retinal vein occlusion and diabetes mellitus. The exact detection of haemorrhages is more helpful for protecting the vision of diabetic patients as well as earlier diagnosing of diabetic retinopathy. In this paper work, we suggest an innovative method that expose and reveal diabetic retinopathy in fundus color images.

Keywords: Fundus image, Green channel, Relative entropy thresholding, Top –hat transform, Connected Component Labeling.

I. INTRODUCTION

Diabetic Retinopathy is a primary disorder in which the eye retina gets damaged due to leakage of blood. Consequence of this may leads to vision loss. Haemorrhages identification in the retinal eye is the foremost sign of diabetic retinopathy such earlier detection of haemorrhage can help to avoid blindness. Haemorrhages are nothing but leaking of blood from the vessels lying in imminent closeness to blood vessels that initiate their delineation from blood vessels alleging the entire fundus retinal image. The algorithm works by segmenting the image into small partitions covering the entire retinal images.

II. DISEASE INVESTIGATION AND METHODOLOGY

A. Fundus Image having Haemorrhages

Retina is the endogenous portion of the eyeball, which includes the optic disc the top-most nerves part of the eye, and the macula which is the tiny part in the eye oculus where visibility is more. The back end of the retinal eye fundus is the part of the visual organ that should be palpable all along an eye investigation by notify through the pupil.

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In this the images from the DIARETDB0 fundus image database [2] is used to detect and classify. Fig.1 shows a fundus eye image taken from DIARETDB1 fundus image database.
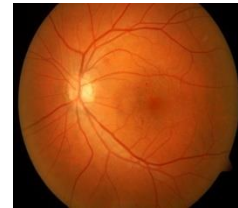

Fig.1. Normal image of an eye

Extreme vision loss and complete blindness occurs due to many of the eye disease.

B. Haemorrhages and Micro-aneurysm

The recurrence of Haemorrhages in the eye is the common effect of diabetic retinopathy. The number of Haemorrhages and its position are used to show the exposure of the disorder.
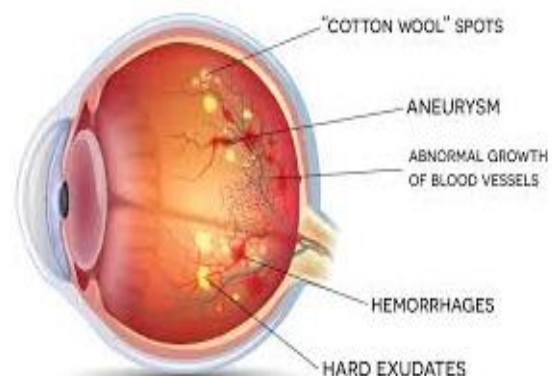

Fig. 2. Haemorrhages and aneurysm affected eye

The major sign is a powerful red spot in the eye that may disperse and sometimes seems to be green or yellow in color. Sometimes it happens after an immediate sneeze or cough, lifting heavy objects, straining, vomiting or even rubbing one's eyes too roughly. After surgery in the eye, due to some allergy it comes as a side effect of eye. Probably it may gone within one or two weeks and it is treated us mild haemorrhage, Whereas if it causes due to diabetic retinopathy or high blood pressure, it need to be considered severe and requires immediate proper treatment. The Haemorrhages are mainly of two types: Dot and Blot Haemorrhages. Dot haemorrhages are red in color, small in size, circular and many times confused with Micro-aneurysm. Blot haemorrhages are also red, bigger, and show corner points. A retinal micro-aneurysm is a smaller portion of blood comes out through the artery or vein from the internal portion of the eye.

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These swellings may peel and blood starts to leak into the retinal tissue around its surroundings. Mainly diabetes mellitus is the common cause for this disease as well as vascular disease or high blood pressure may also leads to a retinal micro-aneurysm. Good control of diabetes and high blood pressure helps to reduce retinal micro- aneurysms and improves life span.

III. LITERATURE REVIEW

This section describes literature regarding to haemorrhages identification and classification from fundus eye images for diagnosing. The following sub-sections give a detailed report on techniques seen in the literature and elaborate about the identification of haemorrhages.The preferable method for detecting haemorrhages in the retina is simple by using morphological operation on binary image for selected candidates. One of the most popular morphological operation such that linear top hat approach helps to detect mild dot haemorrhage [1] and the same would be fitted to multiple scales for detecting larger haemorrhages. Complement image function followed by multiple linear top-hats operation has carried out to de-enhance blood veins in each and every extent. Morphological opening can be achieved in Acharya et al. [2] performed with required changes using fundamental components for extracting vasculature automatically along with dark formation including hemorrhage and vessels. Haemorrhage affected people were obtained by subtraction followed by demonizing. A modernistic method for large haemorrhage detection [3] uses gradient scale-space and watershed transform, achieve segmenting of image regions, and recognize partitions correlative to haemorrhages employing supervised machine learning. On the other hand, the methods that does not use morphological method for candid genuine detection uses a multi-scale gaussian matched-filter with entropy thresholding used in [4] for identification of haemorrhages. Haemorrhages can be mainly differentiated using the following characteristics: dark appearance typically low intensity and uneven, unstructured shape. However, intensity in haemorrhages is identical to vessel structures and polymorphic shape of haemorrhages makes exhaustive modelling intractable. Blood vessel and fovea is the two notable false portions that may give headache in haemorrhage detection [5]. Haemorrhages are also a symptom of blood-related pathology, may appear in close adjacency to vessels, and sometimes fold over or occlude them.

IV. PROPOSED WORK

A. Pre-Processing

Haemorrhage detection and classification methodology for the proposed method is shown in Fig. 3. Pre-processing and detection of Haemorrhages, extraction and classification are the major processes considered in this work.
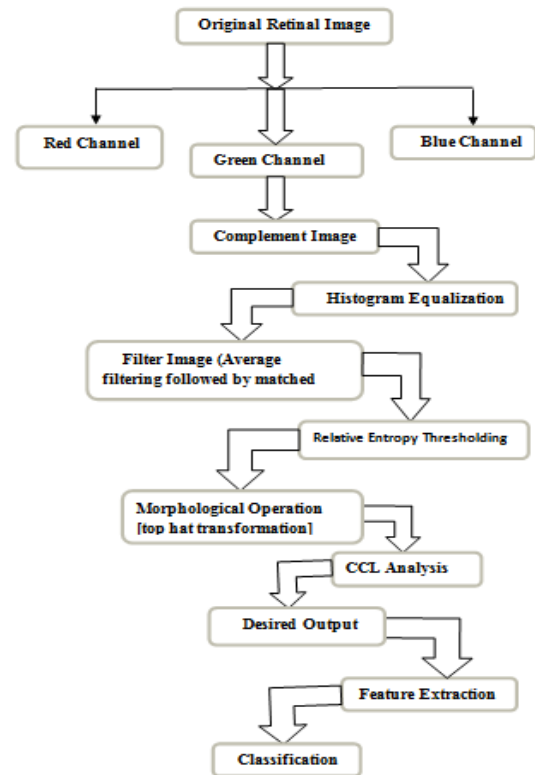
Fig. 3. Block diagram of the proposed haemorrhage detection and classification method

In this work, to detect and classify haemorrhages images from the DIARETDB0 database fundus images were used. The optic disc portion of an eye is brighter likewise blood artery in an eye extent from the optic disc portion has the equal illumination as that of the optic disk. Fundus image is a image with colour pigment of optic disk image and among the three channels, the green channel image is isolated here because the blood veins get highlighted from the original image accurately.

The most sensible human eye is always sensitive to green, so green channel image is an effective replacement for doing an rgb to intensity conversion. The blue cones are also very much sensory to light, but they are out of the area of fine core so the all over significant addition to the process is commensurable to the remaining two types.

$$gr = \frac{G}{(R1+G1+B1)} \qquad (1)$$

Here 'gr' is a Green channel and R_1 G_1 and B_1 are Red, Green and Blue respectively. Because green channel shows the more hue, intensity and saturation when compare to red and blue channel respectively.

$$Ac = \{\omega \,|\omega \notin A \} \qquad (2)$$

Here Ac is a complement ω is the element of A, $\notin$ stands for not an element of A and A is set. Complement function is used on histogram equalization for enhancement.

$$H(k) = \left\{ \frac{round(cdf1(k) - cdf1}{(X \times Y) - cdf1_{min}} \right\} * (J-1) \qquad (3)$$

Here $cdf1_{min}$ is the minimum value of the cumulative distribution function, $X \times Y$ gives the image's number of pixels and J is the number of grey levels.

Histogram equalization is used for enhancement of a green channel image to extract more fine details nothing but the pixel values of fundus image.

The process of enhancing a digital image for further crystal clear results those are further advisable for image analysis. Using the enhancement techniques it is possible to clear noise, brighten an image, sharpen an image thus helps greater to find key features. Next, two dimensional median filtering process has been performed which helps to reduce salt and pepper noise without affecting edges. After enhancing the pixel values clearly, that would be reflects in the gray scale image.

Filters plays a vital role in image processing to perform image smoothing that is either suppress the higher level of frequencies in the image as well as to detect minute edges and to enhancing the image, the low frequencies can be used, which helps to emphasizing or identifying edges in the image. Any fundus eye image can be filtered in the frequency domain else in the spatial domain. Mainly filtering operation performed here is to detect the edges of nerves and diseases affected part from the obtained image. The matched filter concept is used for further enhancing which focus to detect red patches in retinal fundus images. Red patches always have low level contrast. The two dimensional matched filter kernels are constructed to wrap around with the original image in order to enhance the red spots. A prototype-matched filter kernel is expressed as

$$f(x,y) = -exp\left(-\frac{x^2}{2\sigma^2}\right) for \ mod \ of \ Y \ \leq L/2 \quad (4)$$

During this process, along with red patches the appearance of the blood vessels is also enhanced. To extract the required red lesion segments in the matched filter response images obtained as shown in figure 4(e), an impressive powerful thresholding operation is necessary.

B. Red Lesion segmentation using Entropy Thresholding

Inconsistency or discrepancy is minimized with the use of the relative entropy thresholding. The relative entropy process has been executed between the co-occurrence matrix of the original image and that of the binary image. Hence, the threshold image should be the best resemblance to the original image. Due to the obstructed intensity distribution of opacity region (red spots and blood vessels), the co-occurrence matrix of opacity region has stable and restricted peaks, and the relative entropy-based thresholding was good enough to keep all red patches along with blood vessels. In order to detect the candid red patches effectively, the enhanced blood vessels in relative entropy-threshold image must be abolished. Morphological top-hat transformation is used for this purpose.

C. Morphological Operations for detecting Haemorrhages

Top-hat morphological operation was carried out on the binary image as it identifies more haemorrhage disease affected parameters. For effective detection of candidate red lesion segments, the enhanced blood vessels in relative entropy - threshold image must be trampled. Morphological top-hat transformation is used for this purpose which helps to extracts small elements and details from given image. To get the candid red patches segmentation, the difference

between top-hat transformed image and the relative entropy threshold image needs to be obtained. In general, red lesions does not come out on bigger visible blood vessels, they are de-attached from the vasculature. Afterwards, connected component analysis was implied on the binary objects to get probable candid locations. Most of the vasculature may be connected which forms images having larger around 300 pixels and should need to be removed using this step. Only minimal count of tiny blood vessel fragments and those red lesions that are not inter-linked to the vasculature remains and forms an object. The results of remaining connected components object are shown in figure 4(h).
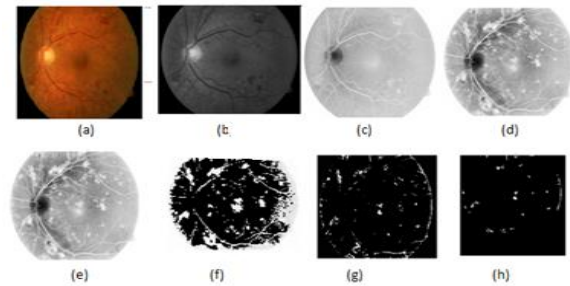

Fig. 4. (a) Original image (b) Green channel image (c) Complement image (d) Histogram image (e) 2D Matched filtering image to detect red lesion (f) Relative entropy thresholding (g) Top- hat transformation (h) CCL analysis for Hemorrhage detection.

After finding the haemorrhages affected area, to get the desired size of an output image, we have to implement image resize option that requires us to specify number of rows and number of columns of the binary image. Then calculate area of haemorrhage after extraction of haemorrhages.

D. Feature Extraction

The Haemorrhages show dark red appearance surrounded by lighter background. They appear in irregular shape and thus their shape modelling becomes difficult. For each segmented region, the features were computed from red channel intensity. For the regions segmented, then enumerate the specified features below.

Red intensity based: the minimum, maximum, and red intensity average of the region were computed. The results were shown in the following figure.
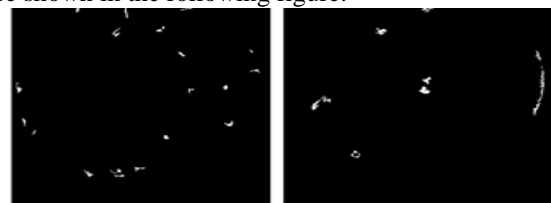
Fig. 5. (a) Minimum red intensity region (b) Maximum red intensity region

Solidity of region: the ratio of pixels in the area proportional to the convex hull pixels. To calculate it, the rectangular bounding box was constructed around the detected region. It is a tiny bounded area, which is rectangular in shape to

encompass all the pixels under detected region.

$$Sr = \frac{\text{Number of pixels in the area}}{\text{Number of pixels in the bounded box}}$$

Calculation of red profile region: We here developed the profile of detected regions by summing the red channel intensities for rows and columns. Using the rectangular bounding box constructed which helps to encompassing the segmented region. Usually, the profile of an image is computed for a particular row or column of the image. It gives idea of intensity or color level distribution at cross section. The results were shown in the figure 7. Area of pixel is calculated using number of non-zero function. If the total number of pixel range is smaller in size it is consider being micro-aneurysm and if the total number of pixel range is larger in size and the disease may be considered as haemorrhages.

E. Classification

In this section, ANFIS classifier is used to classify the retinal fundus images which are affected by eye diseases and provides the experimental results in a proper way. With normal and abnormal images the performance evaluation can be done with the help of confusion matrix on usual metrics such as accuracy, sensitivity, and specificity shown in below table. For the statistical process especially in machine learning confusion matrix is a specific tool used to identify the performance of our algorithm. During the classification process, normal and abnormal eye images are classified as actual true positive condition, actual true negative condition as well as predicted positive condition, predicted negative condition.

True positive (TP): Haemorrhage part correctly marked as haemorrhage.

True Negative (TN): Normal area correctly unmarked as haemorrhage.

False positive (FP): Normal part unfairly marked as haemorrhage.

False Negative (FN): Haemorrhage part unfairly unmarked as haemorrhage.
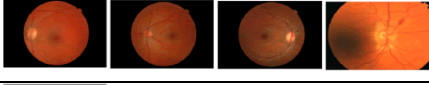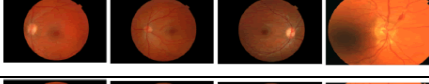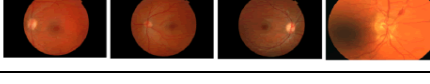
$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN}$$

$$sensitivity = \frac{No. of\ TP}{No. of\ TP + No. of\ FP}$$

$$speccificity = \frac{No.\ of\ TN}{No. of\ TN + No. of\ FP}$$

To calculate the percentage all the metrics results such as sensitivity, specificity and accuracy should need to be multiplied by 100.The DIARETDB0 database totally consists of 130 colour fundus eye images in that images only 27 are normal images and the remaining 103 images contain signs of the diabetic retinopathy (hard exudates, soft exudates, micro-aneurysm, haemorrhages and neo-vascularization). Normal images are taken as testing dataset and abnormal images are taken as training dataset. The total training and testing dataset can be split equally into three

folds. Accuracy, sensitivity and specificity can be calculated for each fold.

Table 1. Classification results of ANFIS

Metrics	Number of images	%
Accuracy		91.00
Sensitivity		93.05
Specificity		87.60
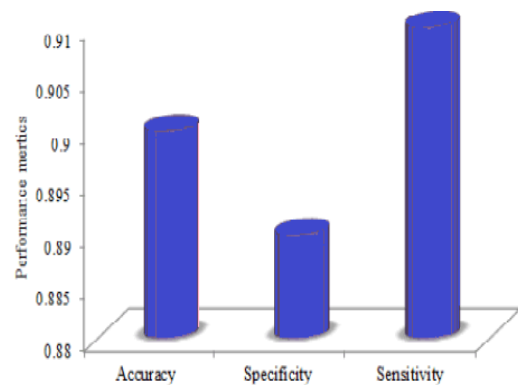
Fig. 6. Pictorial representation of results.

| Table 2. Comparative analysis with other methods			
Method	Sensitivity	Specificity	Accuracy
Zohu et al. [14]	80.37	91.53	89.12
Tang et al. [3]	93.00	66.00	–
Garcia et al. [7]	100.00	56.04	83.08
Kande et al. [4]	89.22	82.53	–
Our method	93.05	87.60	91.00

First fold images were taken for validation that reveals the accuracy of 0.89 % in first level process, and then in the second level process, 0.91% maximum accuracy has obtained using ANFIS classifier associated with other validation. Likewise, the process of validation has performed until the last image of the database. Resultant range of sensitivity and specificity also gets good percentage in haemorrhage detection procedure.

V. EXPERIMENTAL RESULTS

In this work apart from the other images green channel image only is examined for haemorrhage detection because in that image blood vessels are highlighted properly. Then complement function is used in the image pixel that changes the value reversibly as the resultant all the black background changed into white and vice-versa. Histogram equalization

helps to enhance the image. Image filtering removes the boundary pixels that are eliminated using the suggested method and to segment red lesions from blood vessels relative entropy thresholding followed by morphological operation has made to identify haemorrhages. To procure desired region, connected component analysis was called upon on the binary image. After identification of haemorrhages, its feature extraction process has been performed based on the red intensity and bounded box image and results are shown in the following figure.
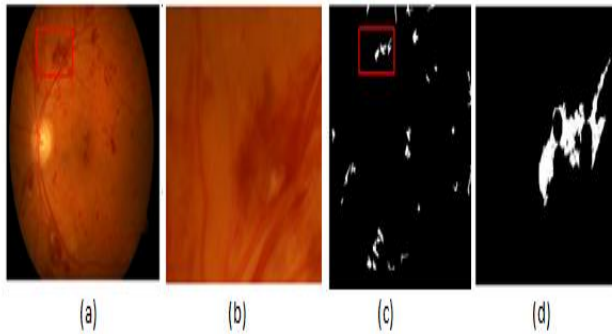
Fig. 7.(a) Bounded box image (b) Segmented ROI (c) Binary bounded box image (d) BW Segmented ROI .

It was observed that the Haemorrhages being irregular in shape does not have any standard pattern to these profiles. The automated red spots detection illustrates the different limits of options in identifying the proportion between sensitivity and specificity.

VI. PERFORMANCE EVALUATION

The performance of proposed haemorrhage detection and area calculation is tested with publicly available dataset DIARETDB0. With the help of relative entropy thresholding and morphological operation followed by connected component labeling approximate coefficient matrices for haemorrhage affected region has traced for the given input binary image. Thus resultant implicates that the proposed method could be employed automatically detect haemorrhage from color fundus images, earlier detection helps to prevent vision loss.

Table 3. Results obtained for random images with proposed methodology

S.No.	Image	Area of white pixel
1.	image008	0.0687
2.	image019	0.0258
3.	image026	0.0457
4.	image032	0.0754
5.	image051	0.0484
6.	image072	0.0528
7.	image089	0.0659
8.	image096	0.0787
9.	Image100	0.0872

Table. 3 summarizes the results of this proposed work on randomly selected 10 fundus images containing Haemorrhages.

VII. CONCLUSION

Eye vision shows vigorous role in our senses. In our research work fundus images in the databases has been classified as either eye gets damaged due to haemorrhages and nor in normal condition are completely examined with clear segmentation procedure. Thus the determined innovative method for red lesion layers detection in fundus images based on pixel analysis and morphological operation.

FUTURE SCOPE

Using this retinal image scan and also with the help of artificial intelligence cardiovascular events can be predicted instead of MRI, X – ray and CT scan. Doctors can get clear view of what is inside the body of a patient.

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