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DIABETIC RETINOPATHY DETECTION USING RETINAL IMAGES

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ABSTRACT

Diabetes occurs when the pancreas fails to secrete enough insulin, slowly affecting the retina of the human eye. As it progresses, the vision of a patient starts deteriorating, leading to diabetic retinopathy. In this regard, retinal images are collected from DRIVE dataset images which are analyzing the consequences, nature, and status of the effect of diabetes on the eye. The objectives of this work are to (i) detect blood vessel, (ii) identify hemorrhages and (iii) classify different stages of diabetic retinopathy into normal or abnormal. The basis of the classification of different stages of diabetic retinopathy is the detection and quantification of blood vessels and hemorrhages present in the retinal image. Retinal vascular is segmented utilizing the contrast between the blood vessels and surrounding background. Hemorrhage candidates were detected using density analysis and bounding box techniques. Finally, classification of the different stages of eye disease was done using Random Forests technique based on the GLCM and LBP features of the blood vessels and hemorrhages. The proposed methodology for detection and grading of Diabetic Retinopathy is divided into following stages such as preprocessing, Optic Disc Removal, Blood Vessel Segmentation and Removal, Features Extraction and classification.

1. INTRODUCTION

The purpose of this work is to directly compare the methods developed for automatic image grading of Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME). One of the common diseases all over the world is diabetes in which the lack of insulin causes high blood sugar in humans. Long-term diabetes also affects the human retina resulting in a condition known as diabetic retinopathy (DR). This condition damages the retinal blood vessels causing them to leak which ultimately leads to blindness. The patients of different types of diabetes develop some form of retinopathy after 20 years of this chronic disease. DR of any stage develops in nearly all of the patients having diabetes of type 1 and about 60%of the patients with diabetes of type 2. The percentage of diabetes patients is high in almost every region of the world especially in industrialized countries which makes a high chance of DR sufferers.

Diabetic retinopathy is the leading cause of blindness in adults around the world today . The International Diabetes Foundation reports that India has the largest share of this population with over 50 million people and growing rapidly (IDF 2009a). Health care costs motivated by diabetes are also increasing around the world. In the United States alone, projected costs of 376 billion are expected to rise to 490 billion by 2030 (Unwin et al. 2009). Despite the disease's alarming growth on the global scale, diabetic retinopathy often strikes with few initial symptoms before invoking irreversible damage. Many patients are unaware of the problem before its diagnosed.

2. LITERATURE REVIEW

1] Diabetic retinopathy is a chronic progressive eye disease associated to a group of eye problems as a complication of diabetes. This disease may cause severe vision loss or even blindness. Specialists analyze fundus images in order to diagnostic it and to give specific treatments.

This method is divided into two stages: in the first one, we have used local binary patterns (LBP) to extract local features, while in the second stage, we have applied artificial neural networks, random forest and support vector machines for the detection task.

[2] Diabetic retinopathy is one of the most common causes of blindness in Europe. However, efficient therapies do exist. An accurate and early diagnosis and correct application of treatment can prevent blindness in more than 50% of all cases. Digital imaging is becoming available as a means of screening for diabetic retinopathy.

[3] Diabetic retinopathy is considered as the root cause of vision loss for diabetic patients. However, if the symptoms are identified earlier and a proper treatment is provided through regular screenings, blindness can be avoided Subsequently nonlinear diffusion segmentation is employed to encapsulate the variation in exudates and lesion boundary criteria pixels.

[4] The manual strategy evaluated by clinicians is a tedious and asset concentrated procedure. Programmed retinal picture examination gives a prompt recognition and portrayal of retinal highlights preceding a pro investigation. reduce the dimensional space based on image resolutions thus, enhances to speedup of the HE detection. strategies.

[5] Diabetic retinopathy (DR) is one of the most common reasons for blindness in the working-age population of world. Diabetic Retinopathy is an eye disease, which occurs with long-standing untreated diabetes. Progression to vision impairment can be slowed down or stopped if DR is detected on time; In detection or screening of DR, automatic methods can play an important role.

[6] The retinal fundus image is partitioned into four sub images. Various features are extracted from the retinal fundus image. Haar wavelet transformations are applied on the features extracted

[7] Visual perception is very important for human life. Although several medical conditions can cause retinal disease, the most common cause is diabetes. Diabetic Retinopathy (DR) can be identified using retinal fundus images. Detection and classification of deformation in Diabetic retinopathy is a challenging task since it is symptomless.

[8] Diabetic retinopathy (DR) is a major microvascular complication resulting from diabetes and continues to have a serious impact on global health systems. Globally about 95 million people suffer from DR. This paper focuses on detection aspects of a mobile application developed to perform DR screening in real time. The application is powered by a tensorflow deep neural network architecture that is trained and tested on 16,798 fundus images.

[9] Early detection of diabetic retinopathy is of critical importance. In this study, a deep learning-based approach is presented for the early detection of diabetic retinopathy from retinal images. The proposed approach consists of two steps. In the first stage, pretreatments were performed to remove retinal images from different data sets and standardize them to size.

[10] Exudate detection is an essential task for computer-aid diagnosis of diabetic retinopathy (DR), so as to monitor the progress of DR. In this paper, deep convolutional neural network (CNN) is adopted to achieve pixel-wise exudate identification. The CNN model is first trained with expert labeled exudates image patches and then saved as off-line classifier.

3. METHODOLOGY

The approach presented in this paper for detecting hemorrhages is based on three major steps. The first step is to preprocess and enhance the image quality in case of low illumination and contrast. The subsequent step is to remove blood vessels from the fundus image. This is a good starting point which will assist in not detecting blood vessels as hemorrhages. Both blood vessels and hemorrhages share the same color so it is important to detect the blood vessel first and then segment it from the fundus image. After the blood vessel segmentation, the later steps mostly employ the morphological operations and thresholding. All steps will be performed on the input image as shown in Fig.

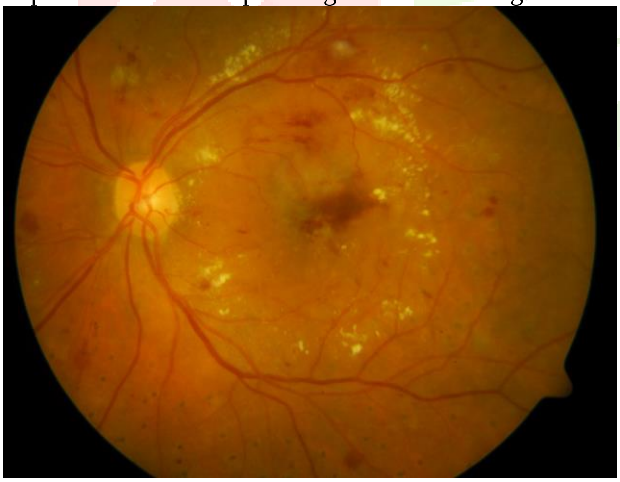

Figure 1 Input Image

Preprocessing

There might be cases when the fundus image suffers from poor illumination and contrast. In such cases, before detecting the hemorrhages, the preprocessing of the fundus image becomes indispensable. The purpose of preprocessing is to enhance the image contrast and its brightness. To increase the contrast of the fundus image, we first extracted the green channel response of the image as it provides a better contrast as compared to the other two color channels, i.e., blue and red. Although we increased the contrast of the image, the contrast alone is not sufficient to detect the hemorrhages.

Equation 1 Gaussian Filter

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}}$$

The green channel response of the image was further normalized using Eq. 1:
$n(x, y) = (g(x, y) - G1) \div$ _G2, (1)
where $n(x, y)$ is the normalized image, $g(x, y)$ is the input image, and $G1$ and $G2$ are the Gaussian filters. Equation 1 can be comprehended more easily by Fig. 2.
$G1$ is the Gaussian filter of $g(x, y)$ with sigma $\sigma 1$, and size of the filter is the double of normal inverse cumulative distribution function of $\sigma 1$ with mean 0 and probability $1e - 1$.
$G2$ is the Gaussian filter of square of $g(x, y)$ with sigma $\sigma 2$ and size the double of normal inverse cumulative distribution function of $\sigma 2$ with mean 0 and probability $1e - 1$. Figure 3 shows the preprocessing result.

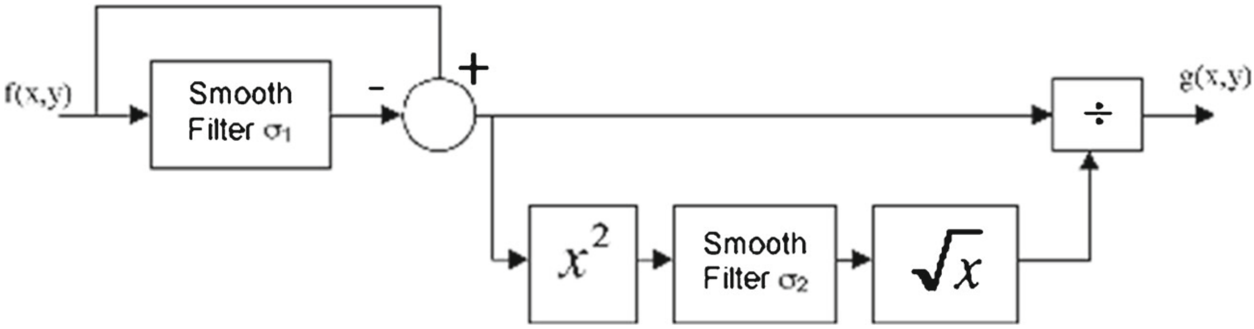

Figure 2 Image Normalization

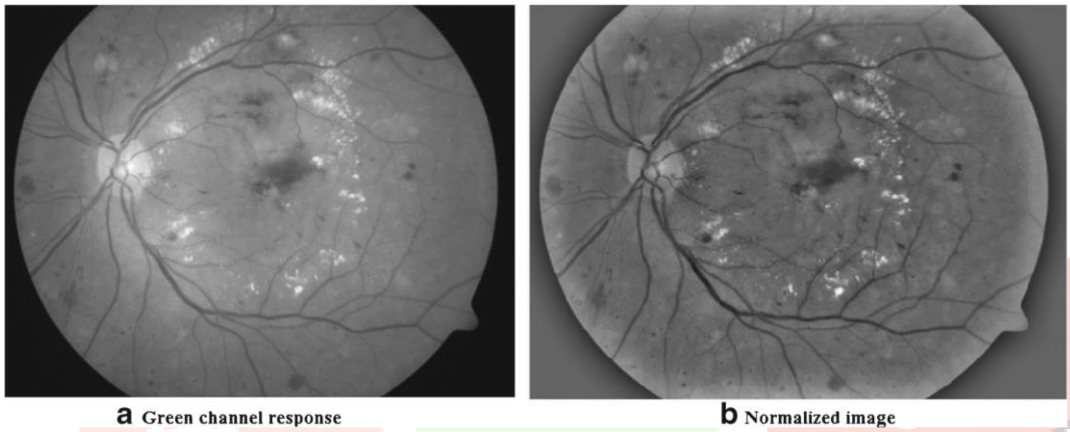

Figure 3 Preprocessing

Blood vessel segmentation

After preprocessing, the blood vessel segmentation is performed. It is a prerequisite in detection of hemorrhages and a complex problem. We used the method proposed by Vlachos and Dermatas , in which multi-scale retinal vessel segmentation has been performed using linetracking. The line-tracking process begins from a small cluster of pixels, acquired from a brightness selection rule, and aborts when a cross-sectional profile condition is eventually invalid. The multi-scale image projection is obtained after combining each image map along scales, encompassing the pixels confidence to exist in a vessel. The foremost network of vessels is obtained after performing map quantization of the multi-scale confidence matrix. Then, median filtering is adapted in the foremost vessel network, rebuilding disjointed vessel lines and removing the noisy lines. Eventually, post processing eliminates the erroneous areas by applying the directional attributes of the vessels and the morphological reconstruction
The image obtained after blood vessel segmentation is further processed using morphological opening operation with square structuring element. With morphological opening, the entire foreground morphology which is smaller than the structuring element is removed by applying erosion, and then, the residual structures are softened or smoothed by using dilation and then restored to their original size (Fig. 4b).

Localization of hemorrhages
The method of localization of hemorrhages is based upon the combination of mathematical morphological operations and image enhancement techniques. Hemorrhages, which are dark spots in fundus image, are brought to foreground by taking complement of the out put (Fig. 5a) of the preprocessing stage defined in section "Preprocessing". The intensity values are adjusted using gamma correction, and this adjustment is with the shape of curve in which mapped values are weighted towards brighter intensities Gamma correction is described by using power-law expression given in .
Iout = $AI\gamma$ in (2)
Vout is the output image and Vin is the input image, where A is constant and γ defines the nature of the gamma curve.
In general case, A is 1, which is also true for our proposed method. We did not perform gamma correction on all intensity values present in the image. Intensity values of the input image to be used in gamma correction are clipped
between low intensity values INlow and high intensity values INhigh. INlow and INhigh are selected by saturating the

upper 1% and the lower %intensity values present in the input image. The shape of gamma curve was specified using $\gamma = 10$.

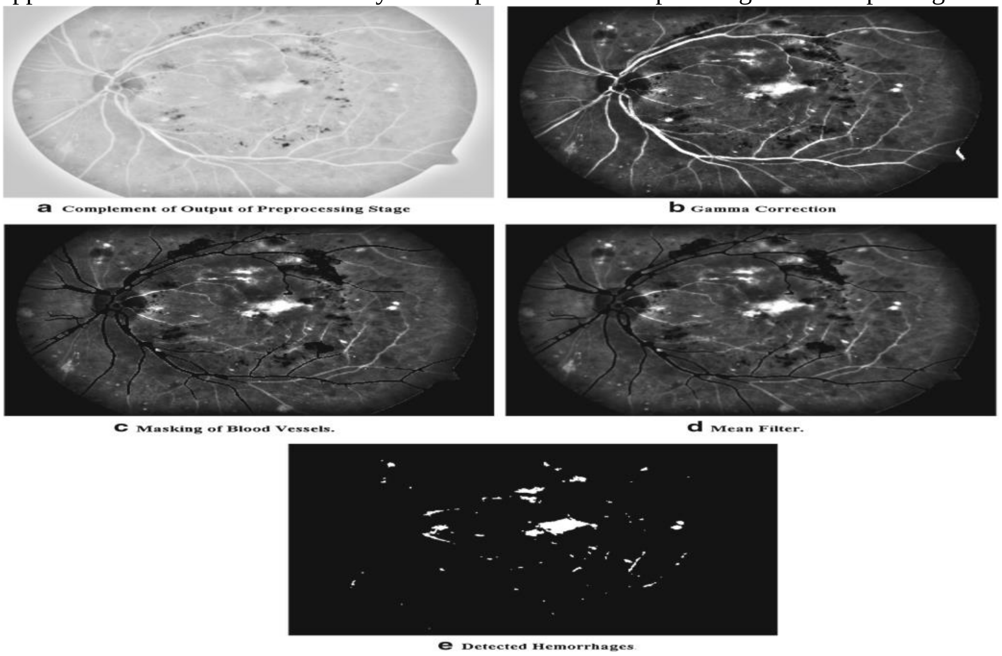

Figure 4 Localization of Hemorrhages

complement of the detected blood vessels has been taken and is then masked onto the image (Fig. 5c). Mean filter is necessary to smoothen the image after the blood vessels have been segmented out of the image. For calculating the mean filter at the boundaries of the image, intensity values outside the bounds of the image matrix are considered to be equal to the nearest border value (Fig. 5d). The final binary image highlighting the detected hemorrhages is then calculated using global thresholding (Fig. 5e). Thresholding creates binary images from gray-level ones by making all pixels below some threshold to zero and all pixels about that threshold to one. If *f (x, y)* is the input image, the image obtained after thresholding *g(x, y)* is given by Eq. 3 .

$g(x, y)$ = _ 1, if $f(x, y) \geq t$

0, otherwise (3)

The localization of hemorrhages was performed by using Matlab "im2bw(I, level)" function, where *I* is the input image and *level* is the normalized intensity value in the range [0,1]. This function converts an image into a binary image based on some threshold or level.

PERFORMANCE ANALYSIS

The potential of our proposed method has been determined by the performance metrics like sensitivity (SN), specificity (SP), and accuracy as shown in Table 1. For any binary classifier, the output can be termed either as positive or negative. Both outputs again can be either true or false, which gives four different possibilities. If the output of the classifier is positive and the actual value is also positive, it is called as true positive (TP), and if the actual value is negative, this output is termed as false positive (FP). If the output of the classifier is negative and actual value is also negative,

it is called as true negative (TN), and if the actual value is positive, this output is termed as false negative (FN). SN is the ability of an algorithm to detect a pixel as a point of interest. It is the ratio of TP and conditional positive values. SP is the ability of an algorithm to detect a pixel as a point of the background pixel. It is the ratio of TN and conditional negative values.

The accuracy of the proposed model is estimated by calculating the proportion of true positive and true negative in all evaluated images.

The classification task is to generalize well on unseen/independent data. A classifier is learned on training/learning data and then tested on data that has not been used for learning (unseen test data). There exist many measures to assess performance of a classifier and a lot of techniques to create training and test data in order to estimate generalization ability of a classifier on test (unseen) data.

7.1 Performance Evaluation

This is a measurement tool to calculate the performance

$$\text{Accuracy} = \left[\frac{TP+TN}{TP+TN+FP+FN}\right]$$

$$\text{Sensitivity} = \left[\frac{TP}{TP+FN}\right]$$

$$\text{Specificity} = \left[\frac{TN}{TN+FP}\right]$$

$$\text{Positive Predictive Value: } PPV = \left[\frac{TP}{TP+FP}\right]$$

$$\text{Negative Predictive Value: } NPV = \left[\frac{TN}{TN+FN}\right]$$

Where

- The *recall* or *true positive rate* (*TP*) is the proportion of positive cases that were correctly identified
- The *false positive rate* (*FP*) is the proportion of negatives cases that were incorrectly classified as positive
- The *true negative rate* (*TN*) is defined as the proportion of negatives cases that were classified correctly
- The *false negative rate* (*FN*) is the proportion of positives cases that were incorrectly classified as negative
- The *accuracy* (*AC*) is the proportion of the total number of predictions that were correct.
- The *Sensitivity or Recall* the proportion of actual positive cases which are correctly identified.
- The *Specificity* the proportion of actual negative cases which are correctly identified.
- The *Positive Predictive Value or Precision* the proportion of positive cases that were correctly identified.
- The *Negative Predictive Value* the proportion of negative cases that were correctly identified.
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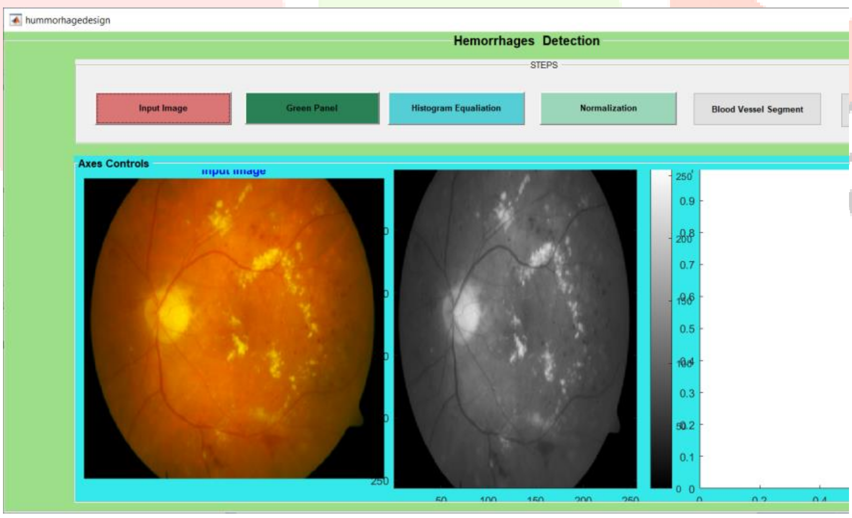

Automatic hemorrhage detection method proposed in this paper was tested over a large database containing 219 colored fundus images of 1500×1152, in which there are normal and varying lesion degrees images and corresponding ground-truth images manually marked by experts, thus it is of a certain representation. Parts of experimental results are shown in below

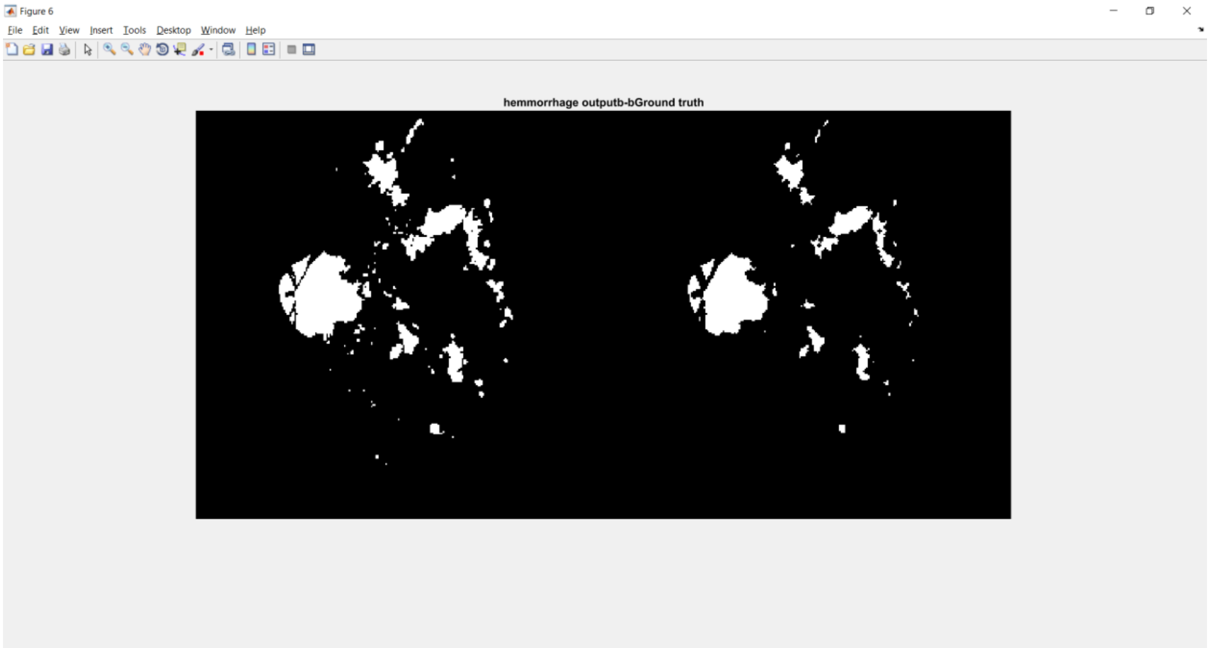
Figure 6
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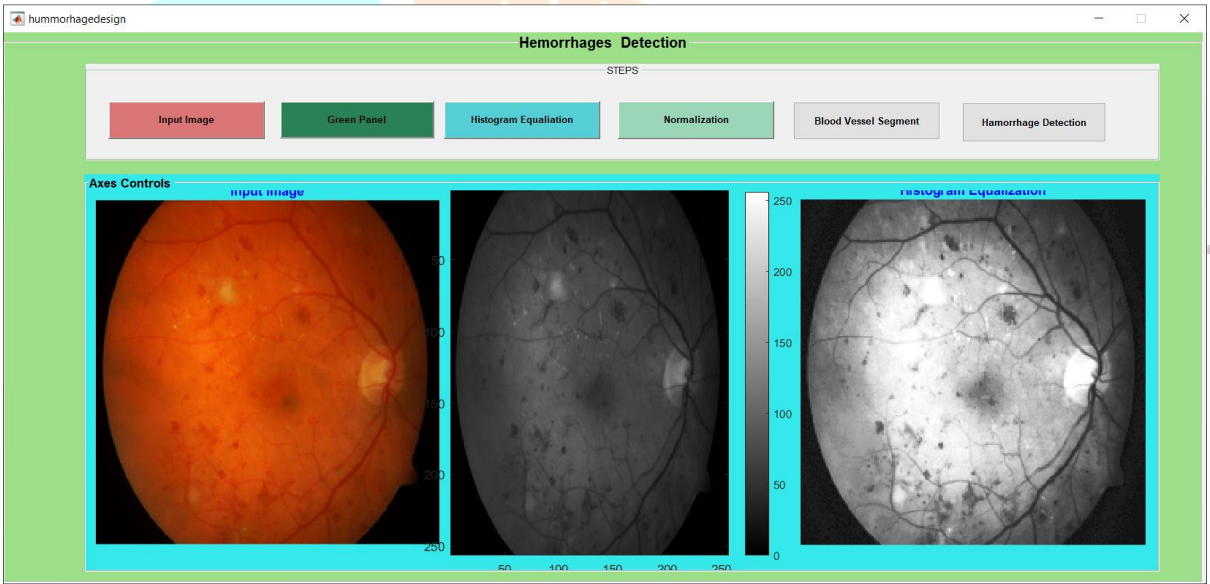
hemmorrhage outputb-bGround truth

4. RESULTS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Hemorrhages Detection
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Normalization
Blood Vessel Segment
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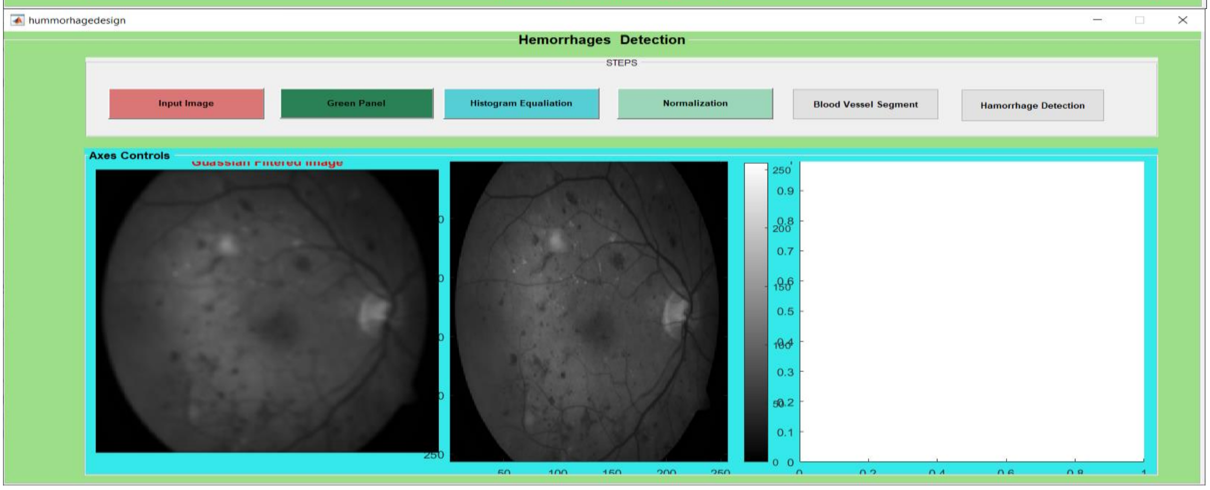
Axes Controls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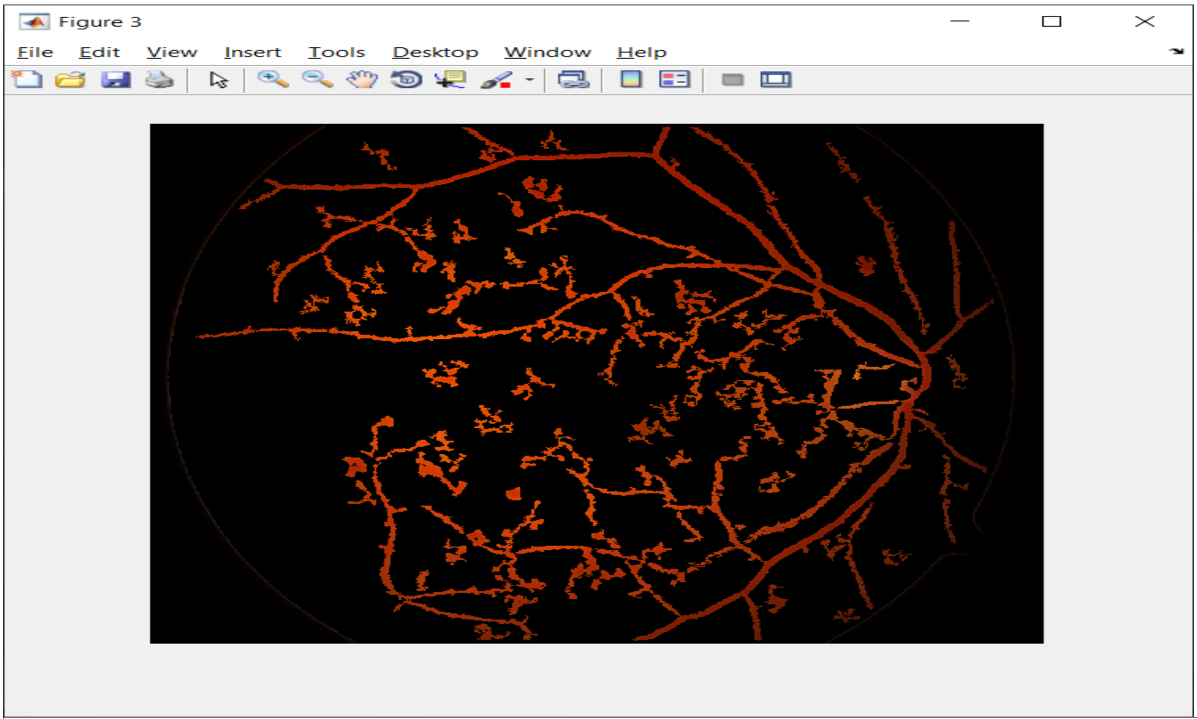
Figure 3
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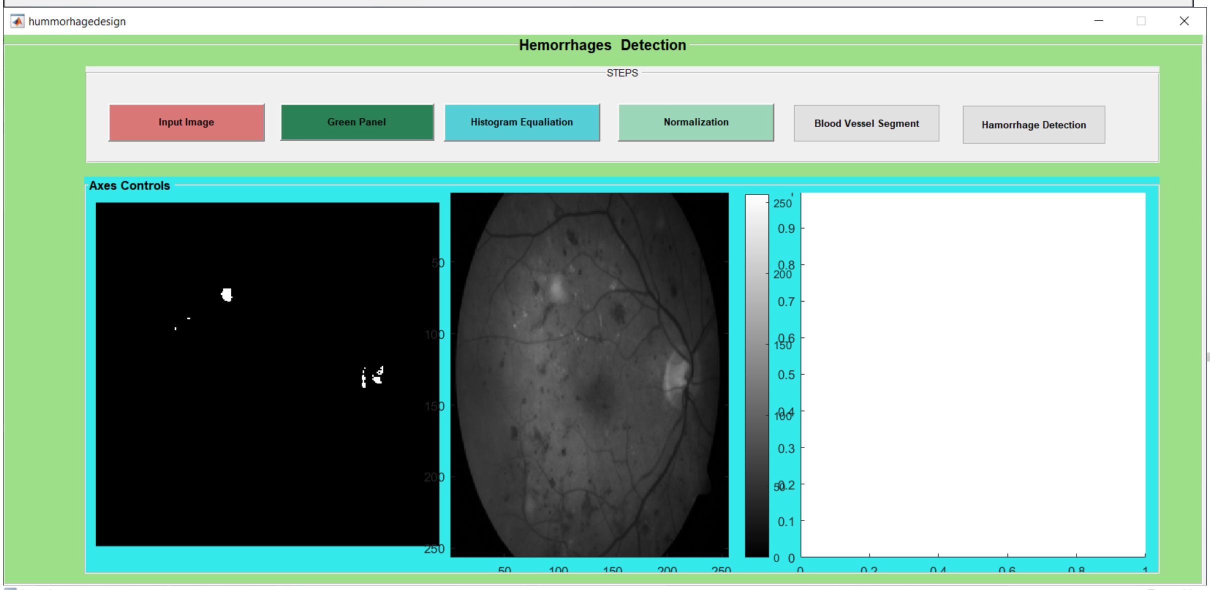
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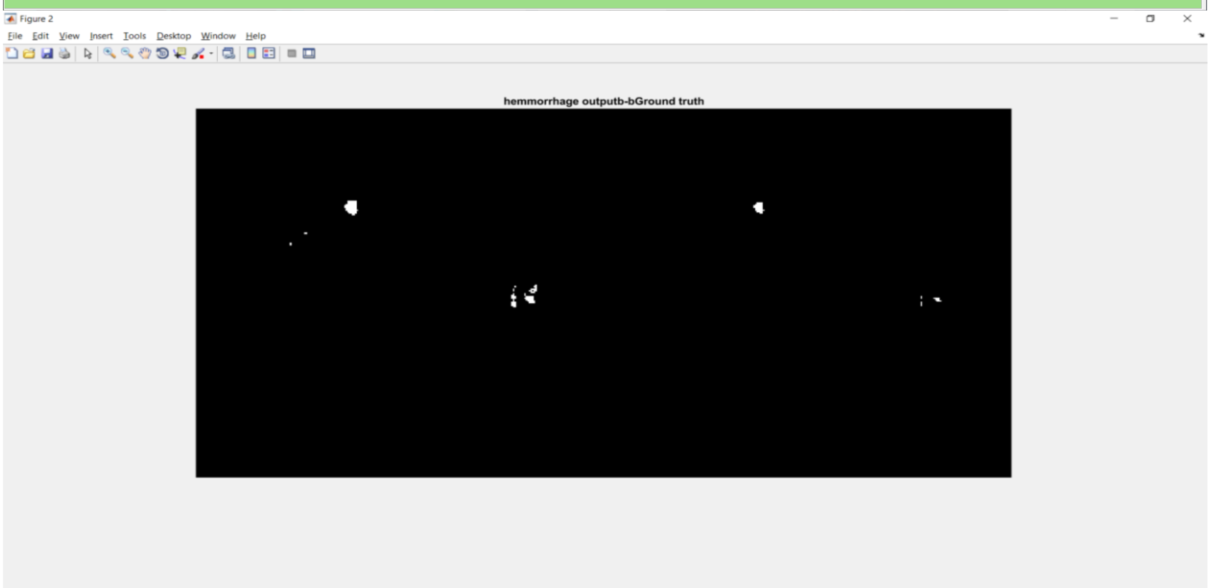
Figure 2
File Edit View Insert Tools Desktop Window Help
hemmorrhage outputb-bGround truth

5. CONCLUSION

The Retinal image analysis through efficient detection of vessels and exudates for retinal vasculature disorder analysis. It plays important roles in detection of some diseases in early stages, such as diabetes, which can be performed by comparison of the states of retinal blood vessels. Intrinsic characteristics of retinal images make the blood vessel detection process difficult. Here, we proposed a new algorithm to detect the retinal blood vessels effectively. Experimental result proves that the blood vessels and exudates can be effectively detected by applying this method on the retinal image with proposed sensitivity, accuracy and specificity.

6. REFERENCE

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