Detection of Diabetic Retinopathy in Fundus Images using Extreme Learning Machines

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***Abstract*— Diabetic Retinopathy (DR) is the term used to describe the retinal damage due to diabetes.**

Initially, diabetic retinopathy may cause none to mild symptoms but sight loss at an advanced stage.

Hence detecting lesions automatically in retinal images can assist in diagnosis and screening of DR at an early stage.

The detection of the different lesions in fundus images is therefore of interest. This project proposes thepre-processing of the image using a Median Filter and Contrast Limited Adaptive Histogram Equalization(CLAHE), optic disc detection using Hough Transform, feature extraction using Gray-Level Co-Occurrence Matrix (GLCM)and Extreme Learning Machines (ELM) for classification.

***Keywords*— Diabetic Retinopathy, Median Filter, Contrast Limited Adaptive Histogram Equalization (CLAHE), Gray Level Co-Occurrence Matrix (GLCM), Extreme Learning Machines (ELM).**

I. INTRODUCTION

When one has diabetes, the body’s ability to produce or respond to the hormone insulin is impaired. Diabetic retinopathy is a diabetes complication that affects eyes. It damages the blood vessels of the retina. At first, diabetic retinopathy may cause none or mild vision problems. However, eventually causing blindness. Imaging of fundus helps in identifying and further classify the DR. The spatial distribution of exudates and microaneurysms and hemorrhages, can be used to determine the severity of the DR. Color retinal images are studied closely by ophthalmologists.

II. RELATED WORK

With the increasing study in this field, a number of methods have been proposed for the study of fundus images. Elbalaoui, M. Fakir, and A. Merbouha [1] proposed a method for Optic Disc detection with the help of Hough Transform & Graph cuts. Alpha-Expansion algorithm is used to achieve this. Further, classification is performed using a Neural Network Classifier. Amin Dehghani [2] proposes obtaining the histogram and extracting RGB components and which is then utilized as template to find the correlation with the moving window in order to localize the center of OD. Amit Ashok Kamthane [3] examines the removal of OD and detection of exudates using Morphological Closing Operator, Thresholding Previous output image, Inversion Operation, Morphological Reconstruction and Thresholding Previous Result Image using Otsu’s Algorithm. Exudate detection is laterachieved with the help of Closing Operator, Local Variation Operator, Dilation Operator and then Flood Filled. A. Aquino, M. E. Gegúndez-Arias, and D. Marín [4] describe a template-based methodology for segmenting the OD using morphological and edge detection methods. This is followed by the HoughTransform for circular objects. A location based methodology on a voting-type algorithm is then proposed to locate a pixel within the OD as initial information (Optic Disc Pixel ODP). OD Boundary Segmentation includes elimination of blood vessels, obtaining OD boundary candidates & finally the segmentation of OD boundary.

III. METHODOLOGY

A. Image Acquisition

In comparison to a direct examination, retinal details may be easier to visualize in fundus photographs.

Fundus imaging is the 2D picture of the 3D retinal tissue. It is captured using specialized fundus camerasconsisting of a flash enabled camera with a highly intricate microscope attached to it.

The camera gives a magnified and upright view of the fundus. It views 30° to 50° of retinal area with a magnification of 2.5x; using zoom or auxiliary lenses 15° area and 5x magnification can be obtained; similarly 140° can be obtained with a wide angle lens which minifies the image by half.

B. Database

TABLE I DATABASE

Database	No. of normal images	No. of affected images	Total No. of images
Diaretdb0	20	110	130
Diaretdb1	5	84	89
Drive	7	33	40
Total:	32	227	259

C. Pre-processing

1) RGB to HSI Conversion: RGB (red, green, blue) model interprets colors as a combination of their primary colors, while HSI (hue, saturation, intensity) model describes it as how the human eye would perceive color.

HSI model is preferred when color description or luminance of an image is of importance.

It is necessary to first normalize the RGB component since it is in the range of (0, 255) this is achieved by:

$$r = \frac{R}{R+G+B}, \qquad g = \frac{G}{R+G+B}, \qquad b = \frac{B}{R+G+B}$$

Then the normalized H,S,I components areobtained:

$$h = \cos^{-1}\left\{\frac{0.5[(r-g)+(r-b)]}{[(r-g)^2+(r-b)(g-b)]^{1/2}}\right\};\ b \le g$$

$$h = 2\pi - \cos^{-1}\left\{\frac{0.5[(r-g)+(r-b)]}{[(r-g^2)+(r-b)(g-b)]^{1/2}}\right\};\ b > g$$

$$s = 1 - 3min(r, g, b)$$

$$i = \frac{R+G+B}{3 * 255}$$

2) Median Filtering: Filtering is necessary for noise removal simultaneously preserving the characteristics of the image.

Algorithm:

First step is to define a “window” of a fixed size. All pixels within the window are considered a part of the neighborhood.

The window is then run through the image, pixel by pixel, replacing the center pixel of each neighborhood by the median value of the neighborhood. Hence forcing the pixel to have an intensity value like its neighborhood.

It helps in reducing salt and pepper noise.

3) Contrast Limited Adaptive Histogram Equalization (CLAHE): Histogram Equalization improves the contrast of an image by evenly spreading the histogram among its intensity levels. This can be achieved by the following ways:

Histogram Equalization: It improves the contrast globally. Being an ordinary histogram equalization technique, it redistributes the intensity of the histogram of the entire image. Adaptive Histogram Equalization (AHE): It differs from the ordinary histogram equalization in a way that, it first divides the image into distinct sections and then computes several histograms with respect to these sections. This improves the contrast locally, as well as, enhances the edges in each region of the image.

However it tends to overamplify the contrast of regions where the intensity levels are nearly constant. This amplifies the noise in these regions.

Contrast Limited Adaptive Histogram Equalization (CLAHE): Here the over amplification of noise is prevented by defining a limit to the amplification. The histogram is clipped at a predefined value called the clip limit. The clipped part is not discarded but redistributed among all histogram bins. This results in an effective clip larger than the prescribed limit and if undesirable, recursive redistribution can be performed.

4) Concatenation

The resultant I component after median filtering and histogram equalization was then combinedwith theH and S component for further processing.

D. Optic Disc Detection

Most OD detection methods have a low success rate when pathological regions exist in afundus images. Aconcept of histogram matching is proven to be more effective.No preprocessing algorithms are included in this technique, hence computational cost is low.

The filter utilized here is the average filter.

First a template is formed by taking the R, G, B components and averaging them.

The correlation $C_{i,j}$ between the histogram of the R/G/B channel in the moving window and the histograms of its corresponding R/G/B channel in the template is obtained. The resultant correlation lies between [0,1].

The result of histogram matching is the weighted sum of the 3 correlation values.

$$c_{i,j} = t_r \times c_r + t_g \times c_g + t_b \times c_b$$

The histogram of the pixels having an intensity value lower than 200 are chosen. Hence eliminatingany pathological regions and exudates which are bright regions.

E. Feature Extraction

It is a method of capturing visual content of images for indexing & retrieval. Gray Level Co-Occurrence Matrix (GLCM) extracts second order statistical texture features for motion estimation of images.

1) Partitioning of ROI: We begin by dividing the input image into several smaller blocks of sizes 36X37 pixels. The blocks are categorized based on their content.

   The blocks are divided into four categories namely, Normal blocks (Blocks containing Normal Retinal background part), Exudates blocks (Blocks containing exudates), Vessel blocks (Blocks containing vessels) and OD blocks (Blocks containing part of Optic disc.)

2) Grey Level Co-occurrence Matrix (GLCM): It examines the textures and gives the spatial relationship between the pixels. It calculates how often pairs of pixel with specific values and in a specified spatial relationship occur in an image.This creates the GLCM. Then statistical measures are

extracted from the matrix.

3) GLCM matrix calculation: Various second order features i.e., energy, entropy, contrast and homogeneity are computed from the GLCM. Thus out of the sixteen features 4 are being chosen.

Contrast: $\sum_{i,j} |i-j|^2 p(i,j)$

Correlation: $\sum_{i,j} \frac{(i-\mu i)p(i,j)}{\sigma_i \sigma_j}$

Energy: $\sum_{i,j} p(i,j)^2$

Homogeneity: $\sum_{i,j} \frac{p(i,j)}{1+|i-j|}$

F. Classification using Extreme Learning Machines(ELM):

A feedforward neural network learns at a relatively slower speed and hence is a drawback in most applications. The key reasons for this being the slow gradient-based learning algorithms that are extensively utilized to train neural networks, and also all the parameters of the networks are tuned iteratively.

(ELM) consists of a single-hidden layer feedforward neural networks (SLFNs). It randomly chooses hidden nodes &analytically determines the output weights of SLFNs.It has either single layer or multiple layers of hidden nodes. The parameters of hidden nodes need not be tuned. These hidden nodes can be randomly assigned and never updatedor can be inherited without being changed.

IV. RESULTS

The fundus images are obtained from the database. These images are RGB model images of the fundus.

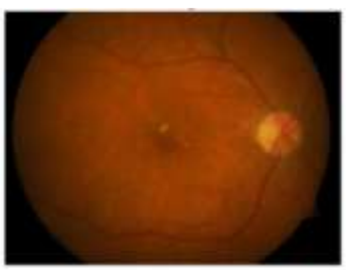

Fig. 1 Fundus image from database

The images in the RGB model are converted to HSI model in Matlab, in order to work on it in it's grey scale.

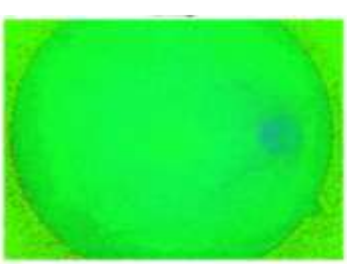

Fig. 2 HSI Model

On application of a Median Filter the following output was obtained.

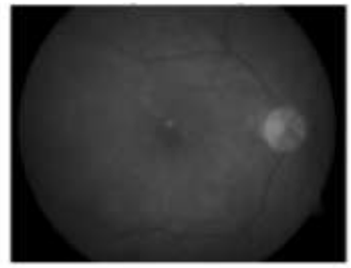

Fig. 3 Median Filtered Image

The histogram of the image was obtained and it was seen that histogram equalization was needed. Hence, Contrast Limited Adaptive Histogram Equalization (CLAHE) was performed.

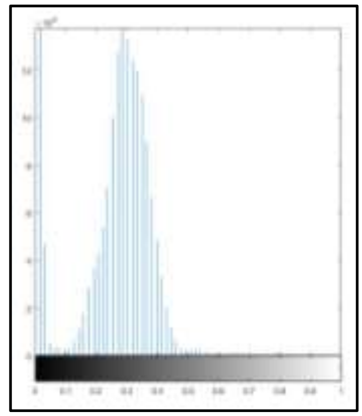

Fig. 4 Histogram of the Image

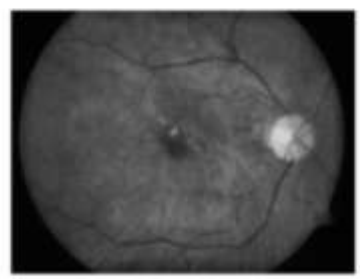

Fig. 5 Image after CLAHE

The image in its grey scale after being pre-processed is combined with its H & S components.

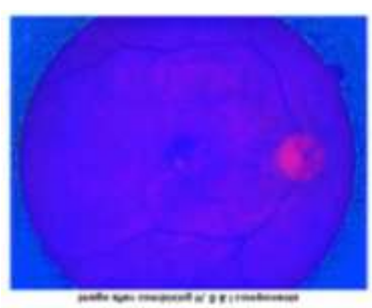

Fig. 6 Final pre-processed image

Optic disc detection using histogram matching was successfully performed. The optic disc was marked with an 'x'.

Fig. 7 Optic Disc Detection

```
glcm =

  Columns 1 through 6

      42971         838          39           4           5          14
       1106       88918        1994           4           5           6
         54        1993       51849         140           6           6
         14           6         133        1011          66           4
         12           0           2          68         323          12
         10           6           6           6           9          28
         15           0           3           2           4          22
        594         590          78          37          32          25

  Columns 7 through 8

          9         896
          1         317
          9          47
          3          35
          6          27
         12          40
          6          32
         38      125996
```

Fig. 8GLCM Matrix

```
stats =

       Contrast: 0.3972
    Correlation: 0.9735
         Energy: 0.2613
    Homogeneity: 0.9582
```

Fig. 9 GLCM Statistics

V. CONCLUSION

In this paper, a fast method of segmentation and recognition of exudates for diabetic retinopathy based on Histogram Matching, Gray Level Co-Occurrence Matrix(GLCM) and Extreme Learning Machines (ELM) is proposed. This approach improved the precision of the diagnosis of the diabetes retinopathy before the stage of complications. First several preprocessing operations improved the image quality by eliminating defects caused by lighting and acquisition processes. Then, since the optic disc disrupts the automatic detection, it was segmented and removed using Histogram Matching Method. In the third step, feature extraction using Gray Level Co-occurrence Matrix (GLCM) detected the exudate regions. Finally, the Extreme Learning Machines (ELM) will be used for classification.

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REFERENCES

[1]. Elbalaoui, M. Fakir, and A. Merbouha. *Segmentation and Detection of Diabetic Retinopathy Exudates*, International Journal of Computer Applications(0975 8887) Vol. 91, No. 16, April 2014

[2]. Amin Dehghani, H. A. Moghaddam and Mohammad-Shahram Moin. *Optic disc localization in retinal images using histogram matching*, EURASIP Journal on Image and Video Processing 2012, 2012:19

[3]. Amit Ashok Kamthane. *The Lesion Exudate Detection In Retinal Images*, International Journal of Advanced Computational Engineering and Networking Vol.3, Issue-9, Sept.-2015

[4]. Arturo Aquino, Manuel Emilio Gegúndez-Arias, and Diego Marín. *Detecting the Optic Disc Boundary in Digital Fundus Images Using Morphological, Edge Detection, and Feature Extraction Techniques*, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 29, NO. 11, NOVEMBER 2010

[5]. Adam Hoover and Michael Goldbaum. *Locating the Optic Nerve in a Retinal Image Using the Fuzzy Convergence of the Blood Vessels*, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 22, NO. 8, AUGUST 2003

[6]. Salman Sayed, Dr. V. Inamdar, S. Kapre. Detection of Diabetic Retinopathy using Image Processing and Machine Learning, IJIRSET, Vol. 6, Issue 1, January 2017

[7]. Shijian Lu. *Accurate and Efficient Optic Disc Detection and Segmentation by a Circular Transformation*, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 30, NO. 12, DECEMBER 2011

[8]. Thomas Walter, Jean-Claude Klein, P. Massin, and Ali Erginay. *A Contribution of Image Processing to the Diagnosis of Diabetic Retinopathy—Detection of Exudates in Color Fundus Images of the Human Retina*, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 21, NO. 10, OCTOBER 2002

[9]. Dilip Singh Sisodia, Shruti Nair and Pooja Khobragade. *Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction For Early Detection of Diabetic Retinopathy*, Biomedical & Pharmacology Journal Vol. 10(2), 615-626 (2017)

[10]. C. I. Sánchez, R. Hornero, M. I. López, J. Poza. *Retinal Image Analysis to Detect and Quantify Lesions Associated with Diabetic Retinopathy*, 26th Annual International Conference of the IEEE EMBS, San Francisco, USA September 1-5, 2004

[11]. V.Sathananthavathi, G.Indumathi, R.Rajalakshmi. *Abnormalities Detection in Retinal Fundus Images*, International Conference on Inventive Communication and Computational Technologies (ICICCT 2017)

[12]. Akshatha Rao M., Rekha Bhandarkar, T.C. Manjunath. *Automated Detection of Diabetic Retinopathy through Image Feature Extraction*, 2014 International Conference on Advances in Electronics, Computers and Communication (ICAECC) 978-1-4799-5496-4/1/$32.00 2014 IEEE

[13]. Kevin Noronha, Jagadish Nayak, S.N. Bhat. *Enhancement of retinal fundus Image to highlight the features for detection of abnormal eyes*. 1-4244-0549-1/06/20.00 2006 IEEE

[14]. V. Vijaya Kumari, N. Suriyanarayanan, C.Thanka Saranya. *Feature Extraction for Early Detection of Diabetic Retinopathy*, 2010 International Conference on Recent Trends in Information, Telecommunication and Computing, 978-0-7695-3975-1/10 25.00 2010 IEEE

[15]. Ali Shojaeipour, Md.JanNordin, NooshinHadav. *Using Image Processing Methods for Diagnosis Diabetic Retinopathy*, 2014 IEEE International Symposium on Robotics and Manufacturing Automation, 978-479-5765-1114/31.00 2014 IEEE