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DIABETIC RETINOPATHY

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***Abstract*— One of the most common causes of vision impairment in the developed world is diabetic retinopathy (DR). It is brought on by complications from type 2 diabetes. Although vision impairment is not always a complication of diabetes, roughly 2% of those with this illness are blind, and 10% experience vision loss after 15 years of diabetes as a result of DR consequences. Patients with DR do not experience symptoms until visual loss begins. Therefore, diabetic individuals need annual eye fundus examinations utilising digital retinal photography to make sure the therapy is administered on schedule. The goal of screening programmes is to identify potentially blinding disorders early enough to allow for prompt and efficient treatment. By 2030, there are expected to be 336 million people with diabetes, up from the estimated prevalence of 171 million in 2000. In order to reduce this anticipated rise in the screening workload, there is consequently a lot of interest in the possibilities of automated retinal picture analysis. Assessing the treatments and risk factors for this common complication of diabetes requires categorization of the severity of diabetic retinopathy and quantification of diabetic alterations. The use of digital images for eye disease diagnostics vii may be utilised for automated early identification of DR. A system that non-specialists might use to screen out cases of patients who weren't sick would lighten the load on the experts and improve the efficacy of preventive measures and early therapeutic interventions. Additionally, it would benefit public health systems financially because early sickness identification and cost-effective treatments result in significant cost savings.**

I. INTRODUCTION

Retinopathy is a serious illness that affects diabetes patients and accounts for 5% of all cases of blindness worldwide. Blood flow is altered by a high blood sugar level, which harms the retinal blood vessels. Since diabetic retinopathy (DR) has no symptoms in its early stages, a physical exam is required to diagnose the condition. One of the primary indicators of the existence of DR is exudates, which are caused by the leakage of lipids and proteins as yellow masses of different sizes. The buildup of exudates in the fundus oculi could cause total blindness if the exudates are not identified at an early stage. To find DR early on, screening procedures must be conducted often. The screening of several photos, which is expensive and prone to human mistake, is a significant barrier for clinicians. A Computer Aided Diagnosis (CAD) is required to determine the stages of DR in order to fix this issue. The purpose of this effort is to create a CAD system to classify abnormal images as mild, moderate, or severe, and to distinguish them from normal fundus images.

II. RELATED WORKS

A. Fast and Accurate method for early detection of Exudates in Fundus Photographs

Authors: Nahed Solouma and Doaa Youssef. Top hat transform is used to improve contrast while median filter is used for noise reduction. The Hough transform is used to retrieve the optical disc. The snakes algorithm is utilised since this method is based on contour detection. Morphological operations are used to find the blood vessel. To get a preliminary estimation of the exudates, the blood vessels and optic disc are removed from the edge detected image. The final estimate of exudates is obtained using a morphological reconstruction technique. The photos were gathered from the STARE database, Cairo University in Egypt, and the NILES..

B. A computational-intelligence-based approach

Author: Alireza Osareh, Bita Shadgar, Richard Markham. This method uses colour normalisation and contrast enhancement as pre-processing steps. Fuzzy C Means clustering is used to segment the preprocessed images. Colour, size, edge strength, and texture are a few of the initial parameters that are taken to categorise the segmented sections into exudates and non-exudates. To rank and identify a subset of features for improved classification outcomes, a genetically based algorithm is applied. For classification, a multilayer neural network classifier is employed. The Bristol Eye Hospital provided the photos that were used to test the algorithm.

III. METHODOLOGY

- *3.1 Image Pre-Processing*

The photos are pre-processed to improve contrast and brightness, as well as to get rid of any noise and artefacts that may be present. Since it provides more details than the red and blue bands, the green band is primarily utilised to identify exudates. A morphological opening is applied to the green channel picture as a structural element to remove the vessel central light reflex, which could lead to the incorrect

identification of exudates. Using an arithmetic mean kernel, background homogenization uniformly smoothes the intensity measurements.

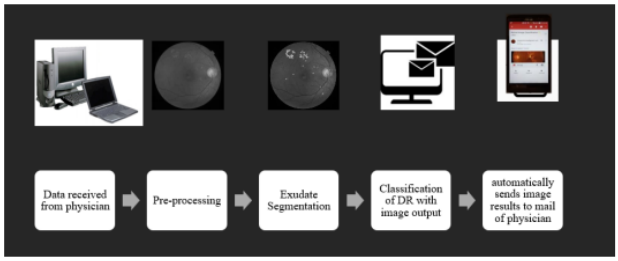

Figure 1: Methodology

- 3.2 Exudate Detection

An entropy-based segmentation method is used to segment the exudates from the preprocessed images. This method is designed to handle the low-contrast and varying illumination conditions of the images. The exudates are segmented by removing blood vessels and optic disc from the green channel image extracted from the fundus image. The steps for exudate detection are as follows. Step1. Blood vessel segmentation Blood vessels are prone to cause bright lesion like appearance during the segmentation of exudates. Hence it is removed in order to reduce false positive and to improve the accuracy of exudate segmentation. Fuzzy C-Means (FCM) clustering algorithm is used to segment the blood vessel since it can retain more information of the dataset. FCM is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. Step2. Optical disc segmentation the segmentation of optic disc is crucial since it is circular in shape with high contrast and is similar to exudates. The optic disc is removed using a circular mask. Step3. Exudate segmentation an entropy filtering is performed on the pre-processed image clearly segments blood vessels, optic disc and exudates. For detecting the exudates, the blood vessels segmented in step 1 and the optic disc obtained in step 2 are subtracted from the filtered image.

- 3.3 Feature Extraction

The segmented exudate regions are characterized by extracting relevant features such as area, perimeter, compactness, etc. The extraction of features is essential in order to extract the desired information and discard the undesired information. The textural feature utilizes the contents of the GLCM to provide the measure of variation in intensity at the pixel of interest. The features are extracted by pairwise spatial cooccurrences of pixels separated by some angle and distance which are tabulated using the GLCM. The GLCM consist of an NxN matrix, where N is the number of gray levels in the image. The Four GLCM features that are selected as the feature set are correlation, cluster shade, dissimilarity and entropy. Correlation is the gray level linear dependence between the pixels at a specified position to each other as in equation.

Cluster shade is a measure of the skewness of the matrix or lack of symmetry. When the value of cluster shade is higher, the image is not symmetric with respect to the texture value. Dissimilarity is a measure that defines the variation of grey level pairs in an image. It is expected that these two

measures behave in the same way for the same texture because they calculate the same parameter with different weights. Contrast will always be slightly higher than the dissimilarity value. Dissimilarity ranges from [0, 1] and obtain maximum when the grey level of the reference and neighbour pixel is at the extremes of the possible grey levels in the texture sample. Entropy shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information in a transmitted image as in equation. A completely random distribution would have very high entropy because it represents disorder. Solid tone image would have an entropy value of 0.

- *3.4 Classification*

Classification helps to identify the classes with similar features. GLCM features such as correlation, cluster shade, dissimilarity, and entropy are extracted. Based on the features the classifier classifies the images as normal, mild, moderate and severe. The classifier is selected by testing different classifier performances. A support vector machine (SVM) classifier is trained on the extracted features to classify the images into normal and DR classes. The SVM classifier is chosen due to its ability to handle non-linear decision boundaries and high-dimensional feature spaces. The classified DR images are further graded into mild, moderate, and severe DR classes using a decision tree classifier.

- *3.5 Results Reporting*

The results of the classification and severity grading are reported to the ophthalmologist through email or any kind of media, along with the classified fundus images.

IV. RESULTS & DISCUSSIONS

The proposed approach for the automated detection and classification of diabetic retinopathy (DR) using an entropy-based segmentation method and support vector machine (SVM) classifier is promising. The experimental setup included preprocessing the retinal images, segmenting the exudates, extracting features, and training a SVM classifier to classify the images into normal, mild DR, moderate DR, and severe DR. The system was able to accurately classify the retinal images into normal, mild DR, moderate DR, and severe DR. The system also provided a visualization of the segmented exudates, which can help ophthalmologists in diagnosing DR. A major limitation faced by the clinicians is

screening a large number of images, which is very expensive and also open to human error. In order to solve this problem a Computer Aided Diagnosis (CAD) is necessary to identify the stages of DR. The aim of this work is to develop CAD system to differentiate the abnormal images from the normal fundus images and also grade the abnormal images as mild moderate and severe. Based on the experimental results obtained, it has been observed that the method being evaluated has achieved a performance of 75%. One limitation of the proposed system is that it relies on the quality of the retinal images. If the images are of low quality or have a high level of noise, the accuracy of the system may decrease. Additionally, the proposed system was tested on a limited dataset and may need to be further validated on a larger and more diverse dataset to ensure its generalizability. Overall, the proposed system has the potential to improve the efficiency of DR screening by reducing the burden on ophthalmologists and providing patients with an automated and accurate diagnosis.

Figure 2: Login page

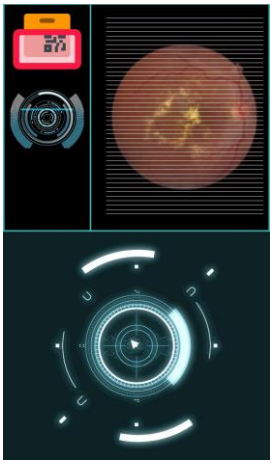

Figure 3: Processing The Image

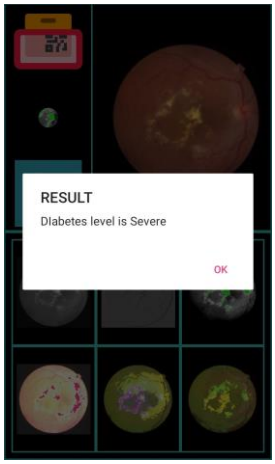

Figure 4: Severity Level Prediction

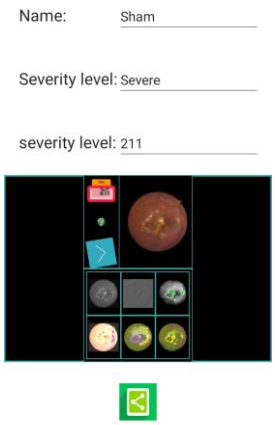

Figure 5: Report

V. CONCLUSION

Early detection of DR can be effective in preventing blindness. The proposed approach is designed for the detection of exudates to diagnose DR. The entropy-based segmentation method segments the exudates precisely and clearly. This automated system can filter out the exudate images and thereby reduces the burden on ophthalmologist in classifying the exudate images manually. It further classifies the given input image as normal, mild DR, moderate DR and severe DR. This provides the patients to get treated according to their severity level. The results are also sent to the physician's e-mail which can be viewed by him in his desktop or mobile phone. This work mainly reduces the time consumption needed for the diagnosis of mass screening processes.

VI. REFERENCES

1. Mariotti S. and Pascolini D: Visual Impairment, Vision Loss and Blindness 2010 global estimates, and VI and blindness causes. Global Data on Visual Impairments 2010, WHO (2010)

2. Kande G. B., Subbaiah P. V., Savithri T. S.: Feature extraction in digital fundus images. In: Journal of Medical and Biological Engineering, vol. 29, No. 3, (2009).

3. Jonas, J., Schneider, U., and Naumann, G. (1992). Count and density of human retinal photoreceptors. Graefe's Arch Clin Exp Ophthalmol, pages 230:505–510.

4. Abramoff, M. D., Garvin, M. K., and Sonka, M. (2010a). Retinal imaging and image analysis. IEEE Reviews in Biomedical Engineering, 3:169–208.

5. Walsh, A. C., Wildey, R., Lara, C., Ouyang, Y., and Sadda, S. R. (2010). Detection of fundus abnormalities using 3d-oct versus mydriatic color fundus imaging. In ARVO 2010.

6. Niemeijer, M., Garvin, M., van Ginneken, B., Sonka, M., and Abramoff, M. (2008). Vessel segmentation in 3d spectral oct scans of the retina. In Proceedings of SPIE, volume 6914.

7. P. Massin, A. Erginay, A. Gaudric, and E. scientifiques et m´edicales Elsevier. R´etinopathie diab´etique. Ed. scientifiques et m´edicales Elsevier, 2000

8. Alireza Osareh, Bita Shadgar, and Richard Markham: A Computational Intelligence Based Approach for Detection of Exudates in Diabetic Retinopathy Images. IEEE Transactions on Information Technology in Biomedicine, Vol. 13, no. 4, pp. 535-545, (2009).

9. Doaa Youssef, Nahed Solouma, Amr El-dib, Mai Mabrouk, and Abo-Bakr Youssef: New Feature-Based Detection of Blood Vessels and Exudates in Color Fundus Images. Image Processing Theory Tools and Applications (IPTA), 2010 2nd International Conference on 7-10, pp. 294 – 299, (July 2010).

10. World Health Organization. Prevention of Blindness from Diabetes Mellitus: Report of a WHO Consultation in Geneva, Switzerland; 2006.

11. World Health Organization. Classification of diabetes mellitus. 2019

12. Al-Goblan AS, Al-Alfi MA, Khan MZ. Mechanism linking diabetes mellitus and obesity. Diabetes Metab Syndr Obes. 2014;7: 587-591.

13. HarryPratt, Frans Coenen, Deborah M Broadbent, et al. Convolutional Neural Networks for Diabetic Retinopathy. Procedia Computer Science. 2016:90:200- 205.

14. Alyoubi WL, Shalash WM, Abulkhair MF. Diabetic retinopathy detec tion through deep learning techniques: A review. Informatics in Medici ne Unlocked. 2020;20 :100377.

15. Xie L. Towards implementation of Al in New Zealand national diabe- tic screening program: Cloud-based, robust, and bespoke. PLoS One. 2020:15(4):¢0225015.

16. Shome SK, Vadali SRK. Enhancement of Diabetic Retinopathy Ima- gery Using Contrast Limited Adaptive Histogram Equalization. nter- 'national Journal of Computer Science and Information Technologies. 2011;2(6):2694-2699.

17. Lindeberg T. Scale Selection Properties of Generalized Scale-Space Interest Point Detectors. Journal of Mathematical Imaging and Vision. 2013:46(2): 177-210.

18. Bay H, T Tuytelaars, L Van Gool. SURF: Speeded up robust features. Computer Vision and Image Understanding. 2006;110(3):346-359.

19. Halil Murat Unver, Yunus Kokver, Elvan Duman, ct al. Statistical Edge Detection and Circular Hough Transform for Optic Disk Localization. Applied Sciences. 2019:9(2).

20. Fabian Pedregosa, Gael Varoquaux, Alexandre Gramfort, ct al. Sciki- t-leamn: Machine learning in Python. The Journal of machineLearning research. 2011512:2825- 2830.

21. Taylor R, Batey D. Handbook of retinal screening in diabetes:diagnosis and management. second ed. John Wiley Sons, Ltd Wiley-Blackwell; 2012.

22. Bourne RR, et al. Causes of vision loss worldwide, 1990-2010: a systematic analysis. Lancet Global Health 2013;1(6):339–49.

23. Harper CA, Keeffe JE. Diabetic retinopathy management guidelines. Expet Rev Ophthalmol 2012;7(5):417–39.

24. Scanlon PH, Wilkinson CP, Aldington SJ, Matthews DR. A Practical manual of diabetic retinopathy management. first ed. Wiley-Blackwell; 2009.

25. Wilkinson CP, et al. Proposed international clinical diabetic retinopathy and di abetic macular edema disease severity scales. Am Acad Ophthalmol 2003;110(9): 1677–82.