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AUTOMATED DETECTION AND DIAGNOSIS OF DIABETIC RETINOPATHY

 Dr. B. Shoba, Associate Professor, Department Of Electronics and Communication Engineering, KGiSL Institute of Technology, Coimbatore, India.
M. Preethi, UG Scholars, Department Of Electronics and Communication Engineering, KGiSL Institute of Technology, Coimbatore, India.

P. Kamala Nethra, UG Scholars, Department Of Electronics and Communication Engineering, KGiSL Institute of Technology, Coimbatore, India.

M. Vinoth, UG Scholars, Department Of Electronics and Communication Engineering, KGiSL Institute of Technology, Coimbatore, India.

A. Vishnuraj, UG Scholars, Department Of Electronics and Communication Engineering, KGiSL Institute of Technology, Coimbatore, India.

Abstract

Diabetic Retinopathy (DR) is a leading cause of vision loss worldwide. In the past few years, Artificial intelligence (AI) based approaches have been used to detect and grade DR. Early detection enables appropriate treatment and thus prevents vision loss. Both fundus and optical coherence tomography (OCT) images are used to image the retina. With deep learning / machine-learning-based approaches is possible to extract features from the images and detect the presence of DR. Multiple strategies are implemented to detect and grade the presence of DR using classification, segmentation, and hybrid techniques. This is caused when sugar levels cause damage to blood vessels in the retina. These blood vessels can swell and leak. It is the most common reason for vision loss among people with diabetes and the leading cause of vision loss and blindness among working-age people. Here we have proposed a system where eye disease can be detected with extracted retinal blood vessels. At first retinal blood vessels from images are extracted. Then noise and environmental interference from the image are removed using filtering methods. Local entropy thresholding for the segmentation of images has been adopted in this system. The user will input the retina image into the system. The system applies filtering techniques. Image pre-processing procedures are applied to get accurate and clear results. All unwanted objects from the image are removed. The system will apply the algorithm to extract retinal blood vessels. Finally, diabetic retinopathy is detected.

Keywords: Diabetes, retina, blindness, filtering, retinal images, retinal blood vessels, diabetic retinopathy, proliferative, non-proliferative.

I. Introduction

The entire globe continues to be worried and is working hard to develop screening techniques to treat hazardous eye defects including Diabetic Eye Illness. In any case, there are a lot of challenges when attempting to apply these kinds of techniques to precisely and accurately detect the defect. Diabetic retinopathy (DR) is the primary cause of blindness in those of working age and is a defect with a growing frequency. It is a diabetic condition that mostly impacts the eyes. Damage to the blood vessels in the tissue behind the retina is the root cause of it. Early diagnosis and treatment can greatly reduce the chance of developing serious vision loss. The high degree of diabetes mellitus is the cause of this impairment. The duration of the person's diabetes and their glycemic control levels determine how severe this problem is.

It has been acknowledged that systematic DR screening is an economical approach to reduce the burden on health care. In addition to saving time and money on diagnosis, automatic retinal image processing is emerging as a key screening method for early DR identification. This can lessen the



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Figure 1: Difference between NPDR, PDR, & Normal

workload associated with manual grading. In the past several years, a lot of research has been done to create automatic technologies that would aid in the identification and assessment of DR lesions.

It has been established that damaged blood vessels are extremely dangerous since they can cause adult blindness. Some symptoms of DR in its early stages include floaters, trouble distinguishing colors, and even total loss of color and vision. Proliferative Diabetic Retinopathy and Non-Proliferative Diabetic Retinopathy are now recognized as the two advanced forms of DR, and early identification and flaw detection would be the only means of curing these.

It is possible to avoid visual loss and lower costs for health systems by screening for DR and tracking the progression of the disease, particularly in its early asymptomatic phases. Non-mydriatic digital color fundus cameras are used in the majority of screening programs to take color images of the retina. The lesions that are suggestive of DR, such as cotton wool spots (CWSs), hemorrhages (HEMs), exudates (EXs), and micro-aneurysms (MAs), are next looked for in these photos of individuals enrolled in any DR screening program, around two-thirds do not have a diabetic retinopathy defect. By reducing the number of photos that need to be manually graded, the application of automated image analysis to digital fundus images may minimize expenses and workload.

This proposed system has created A DR detection method, whereby the fundus picture is acquired from the patient's retina. Here, the fundus image obtained with the Peek retina coupled to the smartphone camera lens has been analyzed using a CNN-based approach. The objective of this suggested work is to analyze whether the retinal condition is in the proliferative or non-proliferative stage of diabetic retinopathy (DR) by segmenting the fundus image into exudates, microaneurysm, optical disk, and hemorrhage.

II. Literature

A. Diabetic Retinopathy Detection Using Matlab:

Using Matlab to Identify Diabetic Retinopathy - Hamood This work was written by Ali Hamood Al Shamaly, Sumesh E P, Vidhyalavanya R, and Jayakumari C - This paper

provides a MATLAB-based analysis and fundus classification into a hemorrhage, optical disk, microaneurysm, and exudates. The proliferative and non-proliferative stages of DR are also covered. Morphological processes including erosion and dilatation were also carried out for the goal. In just 39 seconds, the suggested technique saw 98% accuracy in the detection DR.

B. Micro-Aneurysm Detection and Symptom Analysis:

Micro-Aneurysm Detection and Symptom Analysis of Diabetic Retinopathy – This Paperwork was written by Tajbia Karim, Md. Salehin Riad, Rehnuma Kabir – This Paper suggested work compared to the SVM classifier and Naïve-Bayes approach, which show misclassification rates of 46.6% and 49.6%, respectively, using MATLAB Neural Network Pattern Recognition (NPRTOOL) with misclassification rate of 43.7%. It was shown to have 61.6% sensitivity, while the SVM classifier approach yielded 5.8% and the Naïve-Bayes method produced 54.8%. Conversely, 42.85% and 44% specificity are offered by the SVM classifier and the Naïve-Bayes approach, respectively. The suggested method's sensitivity rate is 61.6% as well. The achieved accuracy of 26.3% is higher than that of the SVM classifier and the Naïve-Bayes approach, which have respective accuracy of 53.3% and 50.4%. The suggested method yields satisfactory results based on sensitivity and accuracy.

C. Digital image processing for Automated Detection of Diabetic Retinopathy:



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Digital image processing for automatic detection of diabetic retinopathy -This Paperwork was written by Kranthi Kumar Palalasa and Bhavani Sambaturu - In this Paperwork, exudates are found by combining the fundus picture background subtraction with exudate candidate extraction and other anatomy detection techniques. The suggested method can identify the hard exudates present in the fundus pictures with easy and acceptable sensitivity and accuracy when compared to the other stateof-the-art segmentation techniques. By choosing the appropriate features for the exudates and applying a machine learning-based technique, performance might be improved.

D. Diabetic Retinopathy Detection :

Diabetic Retinopathy Detection by Extracting Area and Number of Micro-aneurysms

from Colour Fundus Image - Shailesh Kumar and Basant Kumar - This method presented an improved scheme for the detection of diabetic retinopathy by precisely determining the quantity and area of microaneurysms, this method gave an improved scheme for the identification of diabetic retinopathy. The obtained sensitivity and specificity values demonstrate how superior the suggested diagnostic method is at detecting non-proliferative diabetic retinopathy.

E. Automated Detection of Diabetic Retinopathy using Support Vector Machine :

Diabetes-related retinopathy is automatically detected with support vector machines - Enrique Ricardo Carrera, Andres Gonzalez, and V. Carrera Several algorithms have been presented that are effective in detecting hard exudates, microaneurysms, blood vessels, and the optic disc. There is a lot of promise for DR detection and categorization with the suggested features. SVM has an average accuracy of 85% and a sensitivity of nearly 95% when it comes to DR detection.

SVM routinely outperforms other machine learning algorithms in terms of performance.

F. Diabetic Retinal Fundus Images:

Diabetic Retinal Fundus Images - Preprocessing and Feature Extraction for Early Detection of Diabetic Retinopathy - Dilip Singh Sisodia, Shruti Nair, and PoojaKhobragade - Using machine learning approaches, the diabetic retinal fundus image was pre-processed and its features were extracted to detect diabetic retinopathy. The method of pre-processing

such as resizing, histogram equalization, and green channel extraction were carried out using MATLAB's DIP toolbox. Two distinct datasets containing retinal pictures altered by diabetes and a normal stimulus were created from the images. The normal and diabetic retinal fundus imaging data sets are used to derive 14 physiologically distinct characteristics. Seven of the most distinctive aspects from the entire set of extracted features are used for comparison; rating these features is a straightforward and essential step in differentiating between a normal and a diabetic fundus image. G. Diabetic Retinal Fundus Images:

Detection of retinal blood vessels and reduction of false micro-aneurysms for diagnosis of diabetic retinopathy - Rahul Chauhan, Anita Uniyal, and V.P Dubey – This system focuses on the detection of microaneurysms utilizing a thresholding factor and a Gabor filter, which only performs better when the Gabor filter is utilized. We obtain various outcomes for different levels of sigma. altering the parameter value and evaluating the outcome. There is a trade-off involved in choosing Sigma. Although larger values are more resilient to noise, the resulting image is more likely to contain spurious rings and lower values.

H. Automated Detection of Neovascularization for Proliferative Diabetic Retinopathy Screening: Automated Detection of Neovascularization for Proliferative Diabetic Retinopathy Screening - Sohini Roychowdhury1, Dara D. Koozekanani2, and Keshab K. Parhi - The best feature sets in this method have been determined for the classification of minor and major vessel segments in the Optic disk area. It has been found that intensity-based characteristics from morphologically enhanced fundus images and vessel structural features are more discriminating in detecting DR for NVD classification.

I. Automated Detection of Neovascularization for Proliferative Diabetic Retinopathy Screening: Comparative study of imaging transforms on diabetic retinopathy images - Rakshitha T R, DeepashreeDevaraj, Prasanna Kumar S.C. - In this study, three enhancement techniques have been analyzed and the comparison of all three techniques has been computed by using PSNR. The

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transformation techniques used are as follows: Wavelet Transform, Curvelet Transform, and Contourlet Transform. The main problem in wavelet is, with the missing data while reconstructing the image and those data cannot be regained. In the case of curvelet transform, the image is improved and it helps to amplify the noisy images but it loses its geometric shape and information and later it is very difficult to identify the edges and the noises in the image. These are the drawbacks faced in these two transforms. Hence the Contourlet Transform is introduced to overcome the drawbacks of these two transforms and this technique gives a better performance when compared to the other two transforms.

2.1 EXISTING SYSTEM

The majority of screening programs take color pictures of the retina using a digital color fundus camera. After that, these photos are manually inspected to check for retinal abnormalities. This process took a long time and needed experts to look through the pictures and determine if the subject was infected or not. Consequently, automated image analysis emerged, which tends to minimize the number of photographs that require manual examination, reducing expenses and workload.

Generally speaking, some technologies are meant to identify the diabetic retinopathy defect by utilizing the retinal images offered as input. Furthermore, distinct approaches are employed to identify diffuse retinal deformity (DR) based on various attributes such as exudates, micro-aneurysm, optical disk, and hemorrhage. Our goal is to create a system that distinguishes between proliferative and non-proliferative stages of the condition and can identify DR.

2.2 PROPOSED SYSTEM

Our suggested classification tool will help determine the illness as accurately as possible. The framework applies filtering methods and finds the faults associated with diabetic retinopathy. It determines whether a defect is in a proliferative or non-proliferative stage based on its severity and shows the users the results.

- a) The Use Cases system :
- Uploading the Retinal fundus images to the system.
- Viewing the lesions caused in the patient's retinal area.
- Viewing the stage and severity of the disorder caused in the patient's retinal area.
- Viewing the type of the disorder based on the distinct features.



- a) Use case diagram :
- b) Sequence Case :

The following is the sequence in which the system's functions are performed:

• The first module receives the input photos and processes and normalizes them using a range of visionbased tasks.

• To guarantee that the supplied image has the best resolution possible, pre-processing must be done next.

This can be achieved by resizing the provided image. Next, an automated, unsupervised blood vessel segmentation-based technology has been used to enhance the image's attributes. Anatomical components can be removed to produce a clear image. Subsequently, it pinpoints the problematic attributes and presents the result to the user.

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2.3 WORKING PRINCIPLE

The provided block diagram gives a visual depiction of this tool's operation. The four components that make up the system are the acquisition, segmentation, feature extraction, and classification modules.

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Figure 2: Block Diagram:

To achieve optimal resolution, the input images are digitalized and pre-processed in the first module, known as the Acquisition module. After that, these pictures are kept to go through additional procedures. The segmentation procedure is carried out in the following module, the Segmentation module, to identify and distinguish between cases based on crucial classifying features such as microaneurysms, exudates, hemorrhages, and optic disks. When segmenting the images using an unsupervised blood vessel segmentation methodology, these morphological features are useful. Additionally, in very rare circumstances, morphological procedures like dilation—which adds pixels to the image and increases object visibility-and erosion-which removes pixels from the boundaries of the object—are carried out to produce findings that are far more accurate.

The pathogenic components are used in the Feature Extraction module to extract the salient features, which are further classified according to the nature and severity of the defect, i.e., whether the patient is in the Proliferative or Non-Proliferative Diabetic Retinopathy stage. The user is presented with the final product following each of these phases.



Figure 3: Extraction:



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Figure 4: Different stages of Diabetic Retinopathy

2.4 EXPERIMENTAL SETUP

Installing and running Python IDE version 3.9 or higher is required for this experiment. It is recommended to install high-quality package libraries in a runnable interface, such as Scikit, Matplotlib, TensorFlow, and Kera. It is also necessary to install the CNN network VGG16 model, which is utilized for feature extraction. The working directory file contains the input photos, which are prepared for the training process.

2.5 RESULTS

As a result, our system can able to fetch the images from the database and predict the result, whether the person is affected with Diabetic Retinopathy or not.

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Figure 5: Output of the Project

Kera's model VGG16 is loaded in the above Figure, which displays the outcome with the fetched image being accurate for the label Diabetic Retinopathy. The steps involved in training and testing the model are explained in detail in the screenshots below.



Figure 6: VGG16 model loaded



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Figure 7: Login Page

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Figure 8: After Successfully Logged in to the page

In this phase, there are five Epochs (the total number of iterations of the training dataset that the machine learning algorithm has finished). It is trained in 29 seconds with an accuracy of 0.5250, beginning with epoch 1. The time required to train the datasets after Epoch, or Epoch 5, is 22 seconds, with an accuracy of 0.5750.



Figure 9: Uploading the Retinal Image and the results of the image, shows in which stage the person suffers.

The photos that are put into the system are essentially three-dimensional figures. An additional dimension is introduced to achieve greater resolution and clarity. Four values make up the column output structure as a result. One by one, the images are trained using several layers of max-pooling and convolution. The method continues to remove undesirable elements, including blood vessels and tissues, from the dense layer until it extracts the morphological features needed for classification.



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Figure 10: Confusion Matrix



Figure 11: Chart of Severity of each stage

III. Conclusion

Diabetic Retinopathy is recognized as a potentially fatal eye condition that, if untreated, results in irreversible blindness. Therefore, prompt monitoring of the retinal area would be the only viable way to correct this abnormality. If this defect is addressed in its early stages, it may very possibly be healed. The disadvantage of manual screening would be that it is extremely difficult for ophthalmologists to identify retinal lesions. Therefore, we can effectively diagnose the condition by using an automated approach for the diagnosis of diabetic retinopathy. Generally speaking, automated technologies are suggested to identify retinal abnormalities. However, it uses certain features, such as exudates or micro-aneurysms, to identify the illness. Our project involves analyzing a model to determine the diabetic retinopathy severity based on fundus photos. We found that our method outperformed other approaches. It is a known truth that the treatment plan will be more precise the better and more accurate the diagnosis. Therefore, the goal of diagnostic procedures should be precision to provide a successful treatment plan. We were able to demonstrate a good level of accuracy in the diagnosis outcomes in our investigation. Using the four primary distinctive features — hemorrhages, exudates, micro-aneurysms, and optic disks — our suggested system can identify the illness. It further categorizes the problem as Proliferative or Non-Proliferative Diabetic Retinopathy according to its nature and severity. Additionally, our method correctly and precisely classifies the issue.

3.1 FUTURE WORKS

We have developed a tool accessible as a web application. In the Future, we would like to improve using mobile applications so we may provide a much more user-friendly and integrated platform.

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