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Self Activating Grading of Diabetic Retinopathy Images using Hybrid Neural Network

Saurabh Soni[1], Abha Choubey[2], Siddharth Choubey[3]

Computer Science and Engineering, Shri Shankaracharya Technical Campus, Bhilai

Durg, India

Email: [1]ssoni4289@gmail.com, [2]abha.is.shukla@gmail.com

Abstract

In order to classify diabetic retinopathy grades from images, a deep learning architecture is presented in this research. Different steps make up the suggested structure. Firstly, intensity normalization and augmentation are used to preprocess the retina images. Second, to extract a compact feature vector for grading, the pre-processed images are fed into a proposed Hybrid Convolutional Neural Network model. Detection and gradation of retina images are done in this research which shows the severity of the diabetes. The difficult Diabetic Retinopathy Image Dataset is used to train the suggested framework. The proposed method effectively classifies the retina dataset into different grades.

Keywords—*Diabetic retinopathy, diagnosis of DR, uncontrolled diabetes, image processing, medical imaging.*

I. INTRODUCTION

The World Health Organization (WHO) estimates that diabetic retinopathy (DR) caused 5 million blind cases, or approximately 5% of all blind cases worldwide. Blindness can be prevented with early detection. A deep learning system for the early detection and grading of DR is presented in this research. [1]

Type 1, type 2, and gestational diabetes are the three main types of diabetes. Type 1 diabetes is thought to be caused by an autoimmune reaction. The liver finds it difficult to utilize insulin correctly and maintain normal blood sugar levels when you have type 2 diabetes. Gestational diabetes can occur in pregnant women without a history of the disease. [2]

Retinopathy, a disorder brought on by diabetes, affects your eyesight. This disorder results in damage to the blood vessels of the retina, a photosensitive area inside the eye. At first, DR might not cause any symptoms or might just cause little visual problems. But blindness might be the outcome. [3]

Both type 1 and type 2 diabetics are susceptible to developing the disease. The longer you have diabetes and the more closely you control your blood sugar, the more likely it is that you may acquire this eye condition. Early signs of DR might not show up right away. It is possible that you will feel it when things go worse. As time goes by, the diabetic patient may notice spots of blackness or emptiness, as well as hazy or fluctuating vision. [4]

By 2030, 19.1 crore individuals are expected to have DR. Irreversible vision loss brought on by DR appears during puberty and the aging process. (5)

The visual impairment may be significantly reduced if detected in its early stages. [6]

Stopping the progression of DR can be achieved by lowering the risk factors, especially hypertension and hyperglycemia [7].

Both an automatic and manual diagnostic may be made using computerized diagnosis. Manually reviewing the retinal images takes time. Identifying every patient by hand is difficult for ophthalmologists since there is only one physician for every 10,000 patients.

The proposed approach uses various grading which are presented in TABLE I. These grades will identify the retina images.

Table: Grading of DR.

Grade	Clinical Features
0	No symptoms observed means no DR
1	MAs present means mild or early symptoms
2	MAs, HEM and HEX present means moderate symptoms
3	Microvascular anomalies inside the retina, venous beading and HEM larger value indicates severe symptoms

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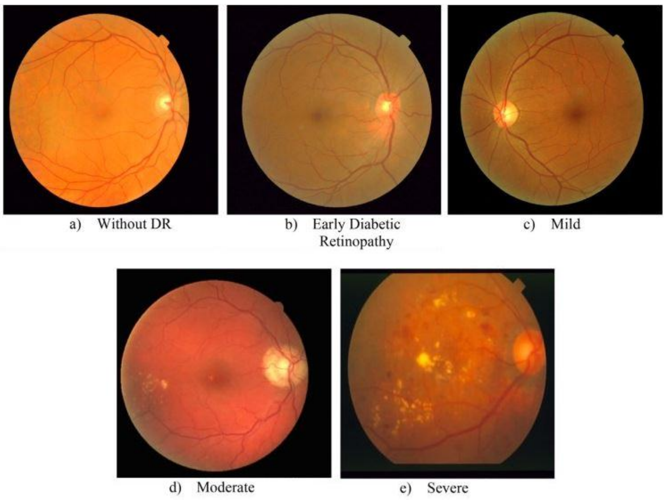

Fig. 1. Stages of DR

II. LITERATURE REVIEW

Four general practitioners and three retinal specialists evaluated 1589 fundus pictures from Wang et al. The findings show that when it comes to rating the severity of DR as well as the existence of DR-related characteristics, retinal specialists are more reliable than ordinary ophthalmologists.

For the automated identification of hemorrhages and microaneurysms in color fundus photos, Seoud et al. offer a comprehensive and tried-and-true method. Dynamic form characteristics, a novel collection of form parameters that enable precise segmentation without the need to classify the areas, are the primary contribution. These characteristics allow one to distinguish between vascular segments and lesions and show how the shape changes during picture flooding.

Experiments conducted by Esmaeili et al. on 89 retinal pictures of patients with diabetes show that red lesions may be recognized with 87% specificity and 94% sensitivity.

Dorizzi et al. used a deep network patch-based method to create a lesion localization model. It was imperative to simplify the model without compromising its functionality. In order to do this, we successfully developed a procedure for choosing the training patches, ensuring that the difficult scenarios would be given additional attention during the training process. Without specialist training, a DR judgment may be made for the first picture based on the labeling of the area.

A deeply connected patch-based method was used by Dorizzi et al. to create a lesion localization model. Without compromising the model's functionality, its complexity has to be decreased. Our effective technique of choosing the training patches ensured that the difficult scenarios would be given more thought all over training, which is how we were able to do this. One may determine the DR for the first image by using the labeling of the area, without requiring specific training.

Dhara and colleagues demonstrate, using 200 fundus pictures from the MESSIDOR collection, that classification accuracy is expressed in terms of the area (Az) under the receiver operating characteristic curve.

According to Sakshi et al., the image-based DLS outperformed all risk factor-based models in terms of performance. Notwithstanding difficult picture capture circumstances, this DLS showed a clinically acceptable performance for the detection of referable DR. Fundus fluorescein angiography and color fundus pictures are used concurrently by Hajeb et al. to assess the extent of the diabetic retinal degeneration phases. The curvelet transformation is then used to gather six attributes, which are subsequently fed into an SVM.

Using effective image processing and deep machine learning methods, the Rahim et al. work automatically identifies the condition in retinal pictures.

III. METHODOLOGY

This section presents the proposed methodology in detail. Steps involved in the process is presented in figure 2.

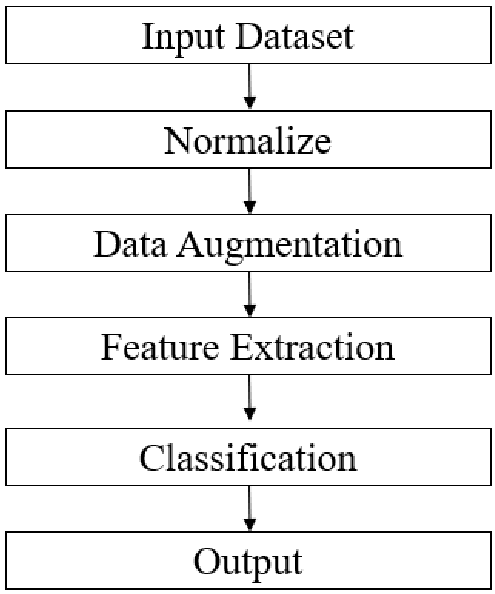

Fig.2:-System architecture

A. *Input Dataset*

A genuine clinical test taken at an Indian eye clinic was used to build the Indian diabetic retinopathy image (IDRiD) dataset. The photos are saved in jpeg format, with a 50º field of view and a size of 4288 × 2848 pixels. 516 photos make up the final dataset, which has been classified into three classes of diabetic.

B. *Image Processing*

The image preprocessing includes the process of normalization. The normalization often changes the pixel values of lesser intensities. Stretching of pixels and improving its quality is also one of the benefits of normalization.

$$Im(x,y)_{norm} = \frac{Im(x,y)-min(Im)}{max(Im)-min(Im)}$$

$$Im_{z-norm} = \frac{Im_{norm}-\mu}{\sigma}$$

Using above equations, the images are normalized which are shown in figure 3.

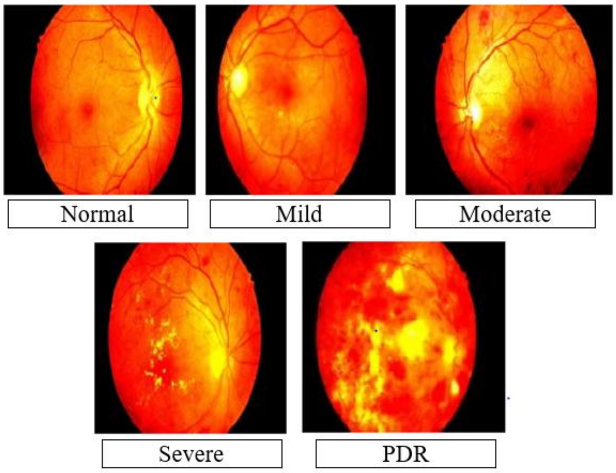

Fig. 3. Normalized Images

C. *Data Augmentation*

For deep networks to function well, a lot of training data is required. To improve the performance of deep networks, picture augmentation is typically needed to create a potent image classifier with minimal training data.

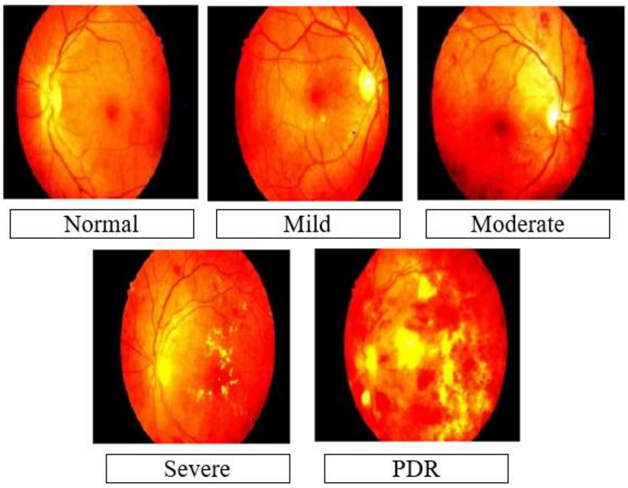

Fig. 4. Augmented Images

D. *Feature Extraction*

By visual inspection, the region of interest is located in accordance with the Iridology chart. The feature is computed such that it quantifies certain important attributes of the item. It is defined as a function of one or more measurements, each of which describes some measurable aspect of an object.

E. *Classification and CNN*

The suggested approach uses the 80 weighted layer of CNN model to apply transfer learning. In order to use transfer learning the fully connected layer is substituted with a shallow classifier that has four class labels, which reflect the DR grades.

IV. Results

This section presents the proposed outcomes of the project. The dataset is split into 7:3 ratio. Where 70% is for training and rest is for testing. The dataset snapshot is shown in fig. 5.

Fig. 4. Dataset snapshot

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The framework output are presented below.

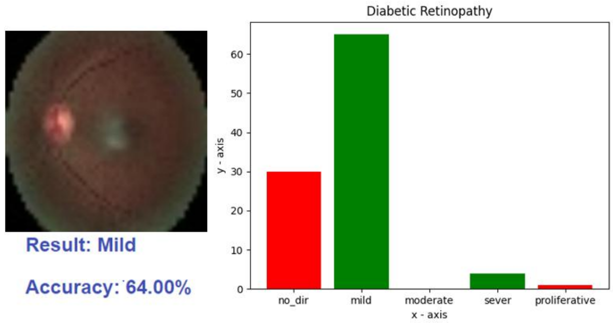

Fig. 5. Retina image with mild grade

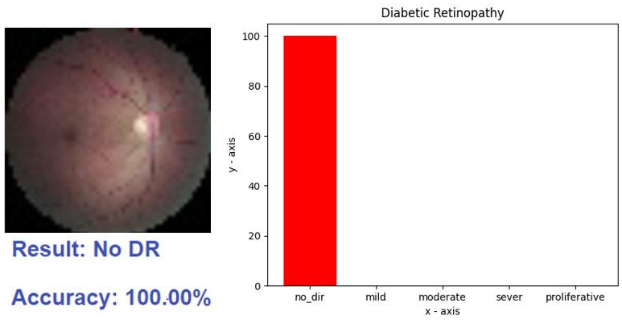

Fig. 6. Retina image with No DR grade

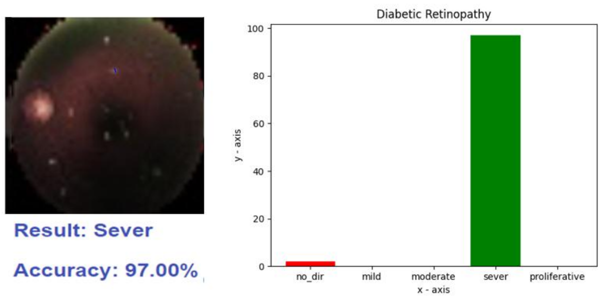

Fig. 7. Retina image with Severe grade

V. CONCLUSION

A three-phase framework for automated DR grading is presented in this research. The three components of the suggested framework are classification, feature extraction, and preprocessing. Based on experimental findings, system performance may be greatly enhanced by employing data augmentation and normalization. The correctness of the suggested framework for DR grading is confirmed by comparison findings with other comparable work on the IDRiD data.

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