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AN AUTOMATED LEARNING APPROACH FOR DETECTION OF DIABETIC RETINOPATHY USING DEEP LEARNING

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Abstract - *Diabetic retinopathy (DR) is an across the board issue for diabetic patient and it has been a primary explanation behind visual deficiency in the dynamic populace. A few troubles looked by diabetic patients in view of DR can be disposed of by appropriately keeping up the blood glucose and by auspicious treatment. As the DR accompanies various stages and differing challenges, it is difficult to DR and furthermore it is tedious. Right now, build up a computerized division based order model for DR. At first, the Contrast restricted versatile histogram evening out (CLAHE) is utilized for portioning the pictures. Later, deep belief network (DBN) is employed for classifying the images into different grades of DR. For exploratory investigation, the dataset is gotten from Kaggle site which is open source stage that endeavors to construct DR recognition model. The highest classifier performance is attained by the presented model with the maximum accuracy of 84.35 over compared models.*

Key Words: **Classification, DR, Segmentation, Deep Learning, Histogram**

1. INTRODUCTION

Diabetic retinopathy (DR) generally occur to patients who acquires diabetes for long time and because of retinal damage, it causes blindness[1]. By utilizing the strategy of fundus imaging, the DR influenced retinal structure of eyes may be recognized. By centering the eye, the fundus pictures will be commonly caught through fundus camera. The interior surface of eye is exhibited through fundus pictures which involve fovea, retina, veins, optic circle and macula[9]. A typical retina includes veins which conveys supplements and blood required for eye. Ordinarily, the veins are sensitive and in light of extra circulatory strain, they may barge in diabetic patients. Through additional small blood vessels count, the diabetic retinopathy progress because of additional pressure might be found from retinal surface

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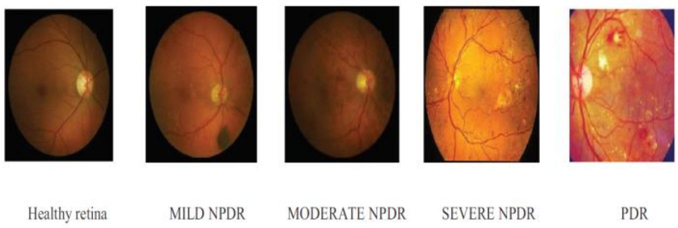

Fig -1: Stages of Diabetic Retinopathy

2. DIABETIC RETINOPATHY DETECTION TECHNIQUES

In the section below, different fire detection techniques are discussed in detail.

2.1 Classification of Diabetic Retinopathy using ANN

To separate the exudates and veins, morphological administrators are utilized by this strategy. In addition, an accuracy of 96% is attained by the methods like genetic algorithm (GA) and fuzzy c means (FCM) [4]. The technique of multilayered thresholding is projected through for blood vessels segmentation in retinopathy images. For retinal structure analysis, ridgelets, curvelet and wavelet transforms are employed additionally with fundus images [6].

Drawbacks:

- This is not a reliable method since the images is not morphed those specific fundus areas.
- The loss of information in the interface between the classifiers is detrimental to accurate classification.

2.2 Modified Alexnet architecture for classification of diabetic retinopathy images

The present research aims to classify the fundus images with high accuracy into various stages of diabetic retinopathy. There is a massive growth in patients affected by diabetic retinopathy. It is necessary to categorize the patients into different stages of diabetic retinopathy in a swift manner. Through the present research with the application of a modified Alexnet architecture we have striven to increase the classification accuracy in the study of DR images.

Among different CNN structures, Alexnet is one of the most effective designs that are broadly utilized to address issues in picture characterization [8]. The first step is to resize the input fundus image to the size of 259 □259 pixels corresponding to the breadth and height and the three color channels representing the depth of the input fundus image. The output of neurons is computed as a scalar product of a small portion of the image with their corresponding weights. This process is repeated along the length and breadth. This operation is performed in convolutional layer. In Rectified Linear Unit (RELU) layer, an element-wise activation function is employed. This layer replaces all the negative activations with 0 by introducing nonlinearity to the system and by applying the function $-f(k) = \max(0, k)$. In pooling layer, the samples are reduced along the spatial coordinates. This process is known as decimation. Fully Connected (FC) layer computes the Class scores for each image and gives the prediction. The probability score for each of the prediction class is computed and the class that is scoring maximum probability score is chosen as the predicted class.

Drawbacks:

- The results can be improved by increasing the size of the dataset.
- There is lack of augmentation and normalization in the images.

2.3 Classification of DR using CNN

We bring convolutional neural systems (CNNs) [5] capacity to DR recognition, which incorporates 3 significant troublesome difficulties: arrangement, division and detection. Coupled with move learning and hyper-parameter tuning, we embrace AlexNet, VggNet, GoogleNet, ResNet[2], and examine how well these models do with the DR picture classification. We utilize openly accessible Kaggle stage for preparing these models. The best classification accuracy is 80.62% and the results have demonstrated the better accuracy of CNNs and transfer learning on DR image classification. Studies in this domain involve feature segmentation and blood vessels [4].

Drawbacks:

- The segmentation of blood vessel is not accurate
- the precision of the strategy can't be guaranteed as the dataset highlights are inferred exactly and physically
- the datasets are of low quality and comprise small size some fundus images with single collection environment relatively offer complexities to compare the algorithm's performance for experimental purposes

2.4 Classification and Detection of Retinal Changes Due to Red lesions in Longitudinal Fundus Images

This project have presented a robust and flexible multistage approach for tracking retinal changes due to small red DR lesions such as microaneurysms and dot hemorrhages in longitudinal fundus images. The system was applied to both small and large retinal fields of 81 diabetic eyes. Strength to intra and between picture enlightenment varieties was accomplished by misusing fundus pictures that are standardized for glow and differentiation over the whole field of view. The improvement in the visibility and contrast of especially small retinal features in the normalized fundus images enabled our approach to track subtle retinal changes, including those that are visually difficult to detect on the colour fundus images [2].

A simple and effective criterion for blobness (BM) was defined for detecting spatiotemporal retinal change locations from longitudinal normalized fundus images[3]. The BM can likewise be handily adjusted to other related issues for the identification and following of little round articles in a progression of enrolled longitudinal pictures. The proposed approach was assessed with regards to an ordinary diabetic retinopathy screening program including subjects extending from solid (no retinal sore) to direct (with clinically pertinent retinal lesions) DR levels. Evaluation was done on both a large field-of-view fundus mosaics, which consisted of the macula, optic nerve, temporal, and superior fields, and a small field-of-view of the retina consisting only of the macula centered fields[2]. The results show that the system was able to detect retinal changes due to small DR lesions with a sensitivity of 80% from large field fundus mosaics and small field fundus images at an average false positive rate of 2:5 and 1, respectively.

Drawbacks:

- The detection of red DR lesions from single time point images can be very difficult due to the subtle nature of most of the lesions and limited number of lesion pixels

- In contrast to the small fields, the higher false alarm rate gets occurred in the large field fundus mosaics images is mainly caused by the lower image quality
- The presence of significant illumination artefacts such as white spots

2.5 Diagnosis of DR using Machine Learning Classification Algorithm

In this they Proposed a method which we train individual classifier algorithm and not the ensemble of that. The features extracted and will be used to train the classifiers and the best individual classifiers are used to identify DR or non-DR categories by the help of Support Vector Machine, logistic Regression and Neural Network[6]. This paper proposed methods to develop an automated system to detect the case of diabetic retinopathy among the diabetic patients and is aimed at helping ophthalmologists to detect early symptoms of diabetic retinopathy with ease. The ideas proposed for the intelligent system can be understood by this paper[4]. Also this paper highlights various technologies used for diagnosis and detection of diabetic eye disease.

Drawbacks:

- Here by using the machine learning algorithm the extraction of feature and classification are occurred in separate phases and output will be generated.
- It does not work with multiple hidden layer of units.

3. Proposed Method

Keeping the constraints of the current models, right now, present a productive division based characterization model. To approve the exhibited model on the DR grouping process, a benchmark dataset from Kaggle site is utilized. Initially the fundus images from the dataset will get preprocessed by the method of conversion from RGB to grayscale due to detection of the neurons we increase the contrast in the Green fundus area of the images and the images will get preprocessed . The preprocessed image will undergo segmentation process. When the picture is sectioned utilizing CLAHE strategy, the marking of classes happens. Next, DBN based classification model will be built by proper training phase. Once the model is created using DBN, test input images can be provided to attain proper output. The proposed work involves in the process of three stages:

a) Preprocessing b) Segmentation c) Classification of stages.

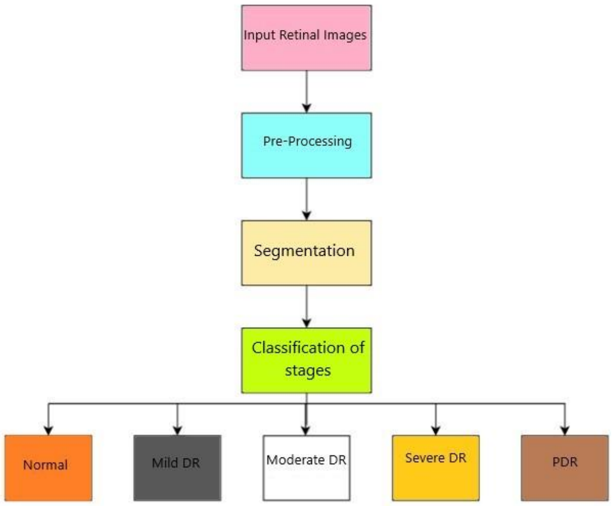

Fig -2: Work Flow of Proposed Method

4. CONCLUSIONS

The motivation of this project work is to implement an automatic diagnosis of DR using fundus images classification. Extreme vision misfortune in diabetic patients can be maintained a strategic distance from by identifying and treating diabetic retinopathy at a beginning period. The method proposed in this paper aims at providing an optimal solution for the classification of diabetic retinopathy patients according to the severity of the disorder. Deep learning is one of the state of the art techniques to address classification problems and it provides better accuracy. Efficient Deep Belief Network architecture to detect and classify the fundus images will be helpful for the ophthalmologist to a greater extent in eradicating the vision loss due to diabetic retinopathy. The testing and training the evaluation of proposed architecture is done using Kaggle dataset. Classifying the images collected from the Kaggle dataset into Healthy retina, Normal, Mild, Moderate, Severe, Proliferate of stages using the proposed work.

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