Automated Detection of Diabetic Retinopathy in Retinal Images using Neural Network

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***Abstract* — Diabetic Retinopathy is one of the most dangerous eye diseases that is influenced by working-age people in Sri Lanka that are caused by long term diabetics. It is changed the retinal blood vessels and that leading to vision loss. Ophthalmologist identifies the DR using manual observation of retinal images. It takes lots of time and given inaccurate results frequently. Doctors do lots of errors when detecting Diabetic Retinopathy. To reduce problems that occur in manual checking here introduced the automated computer-based system. This approach is used for the diagnosis of Diabetic Retinopathy using eye fundus images automatically. Contrast Limited Adaptive Histogram Equalization (CLAHE), morphological process, and filtering techniques are used to extract the blood vessel. Convolutional Neural Network is a classifier that is used to detect the right category of the DR. The accuracy of the DR detection system is observed as 93.36% and 90.1% respectively according to CNN architecture.**

Keywords—Diabetic Retinopathy, CLAHE, Morphological

I. INTRODUCTION

Diabetic retinopathy or eye-diabetes is due to diabetes that occurs mostly in the retina eye. In many developed countries, diabetic eye conditions are one of the most leading symptoms of a complete blink[1]. The detection of retinal pathologies has become much easier by using automated retinal image analyses, while other methods such as eye visual disturbances take time and patients have to suffer for a while. Diabetic retinopathy occurs when hyper glucose damages the small vessels that supply the retina with nutrients and oxygen[2][3].

The purpose of this paper is to detect diabetic retinopathy (DR) automatically, using features derived from various algorithms for processing the retinal image such as the circumference of the optical disc, specific to the lesion (microaneurysms, exudates), image level[4]. These features are now being used within an ensemble machine learning system that includes various learning algorithms such as the Neural Network and Convolutional Neural Network[5][6].The idea about research [7] is only provided different image classification techniques and not provided a specific algorithm as proposed paper.

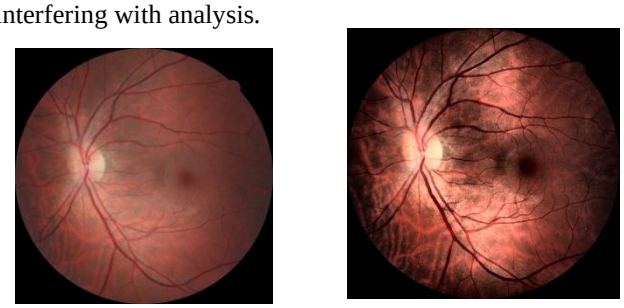
Extracting features through anatomical algorithms of part recognition and lesion detection can be used for the classification of images. A group of classifiers then uses this method to identify whether or not a picture has diabetic retinopathy. The most significant characteristics are the diabetic retinopathy exudates that provide early stages of information. The biggest reason for exudates is protein and lipid leakage into the retina by blood vessels that have been damaged[8]. A machine-learning technique based on the ensemble is used to confirm the location of diabetic retinopathy in a picture.

II. OBJECTIVES

The main objective of this study is to select the best retinal image classification algorithm and guaranteed that any method from both clinical and research experience is appropriate. Automated systems for image analysis typically require large quantities of computational power. In the sense of a diagnostic point of view, any possible classification strategy must be feasible. As sub-objectives, we are decided to develop a mobile application that patient can check their diabetic retinopathy revel without doctors.

III. METHODOLOGY

In the Preprocessing part, for the presence and noisy areas, we generate binary disguises. Different images of the retinal create retinal characteristics difficult to extract and differentiate exudates from other contrasts and brightness in images. The improvement technique is first applied so that the outcome is more useful than the original image for further analysis. Equalization of histograms, which consistently and significantly manipulates histograms. To reduce the processing time of the procedure, Kaggle images [9]were resized to 540 x 340 pixels. However, several strategies for enhancing images are based on structural operations in the local neighborhoods of pixel values. Low quality, such as interfering with analysis.



(a) (b)

Fig 1: (a) Original Image (b) Enhanced Image

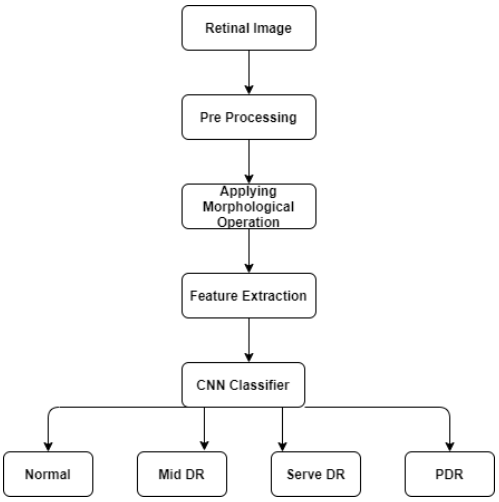


Fig 2: Proposed System

In automated detection of anomalies, pre-processing these images can ensure the appropriate amount of competence. The first step is the Preprocessing part and then captured the features of retinal images using normalization. Most of the retinal images have low image contrast and using the pre-processing part and Morphological operation extract more features in the blood vessels.CLAHE histogram is used to enhance the image. Then using enhances images with different CNN architecture to classify the DR into four stages. Using VGG 16, AlexNet, and Inception V3 as a classifier to get the precious result.

IV. Results and Discussion

In Kaggle Dataset we used 3256 categorize retinal images and enhanced the image stages vices and training the neural network using an enhanced image to get the accurate result. Getting the accuracy according to various CNN architecture and used the best precious architecture as a classifier in the automated system.

The performance of the proposed system is assessed based on four measures: True positive (TP) shows that the data is suffering from the disease and the test result was also positive, false positive (FP) shows that the data is not suffering from the disease and was diagnosed as positive, true negative (TN) indicates that the patient is not suffering from the disease and False negative (FN) was diagnosed as negative and indicates the disease suffering, but diagnosed as negative[10][3]. TP is the fraction of the pixels that are properly classified as pixels of the light lesion. This measure is also called sensitivity. The following calculations are made.

$$\text{Sensitivity} = \frac{TP}{TP + FN} x100 \quad (1)$$

Specificity is defined as the percentage of normal images classified by the system Accuracy in percentage is the measure of

$$\text{Specificity} = \frac{TN}{TN + FP} x100 \quad (2)$$

Accuracy is the percentage of correctly classified normal and abnormal images

$$\text{Accuracy} = \frac{TP+TN}{(TP + FN+TN+FP)} x100 \quad (3)$$

Table 1. Comparison of the DR results with Different CNN Architecture

CNN Architecture	Sensitivity	Specificity	Accuracy
Inception V3	82.8%	82.4%	85.6%
AlexNet	84.2%	83.1%	83.7%
VGG 16	90.1%	91.78%	93.36%

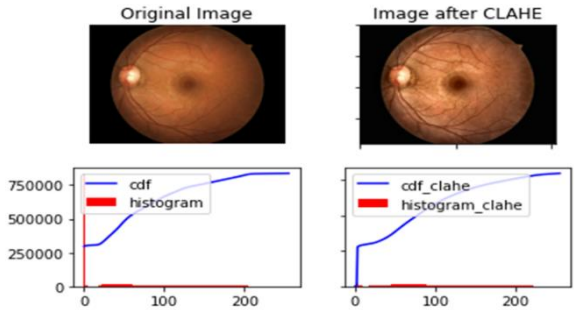


Fig 2: Histogram Graph

According to the results, VGG 16 architecture is more sensitive than other architecture and it is provided better accuracy rather than other architecture. So, we used VGG 16 architecture for automated diagnosis of Diabetic Retinopathy. A computer-based system is provided better accuracy results rather than others. Already published methods do not give much accuracy to our new method.

V. Conclusion

This study presents the automated system that is used to detect the Diabetic Retinopathy. In this work, we have introduced the new feature extraction and classify approach that is used in the computer-based system to identify the severity of retinal images. Early detection of the DR is a vital thing because it voided the blindness and can timely treat that system have 90.1% sensitivity and 93.6% accuracy. The proposed method is provided more sensitivity and accuracy rather than other methods and architecture. This method provided better feature extraction rather than other and accurately grading according to image stages. In the future, we will try to classify using a large image database and real-time dataset.

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