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Detection of Diabetic Retinopathy Using CNN

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ABSTRACT

Diabetic Retinopathy is a significant cause of blindness and vision impairment among middle-aged people worldwide. It occurs when high blood sugar levels damage the blood vessels of the retina or prevent blood from passing through in the eyes. These conditions can affect the vision and lead to life long blindness. However, this can be averted if diabetic retinopathy is detected and treated in time. In this project, Convolutional Neural Networks(CNN) with ResNet architecture on color fundus images is used for the recognition task of diabetic retinopathy for staging accuracy. Retinal images obtained using fundal cameras provide information about the type, nature, consequences, and effect of diabetes on the eye. The objective of this project is the detection of blood vessels, and hemorrhages, classification of the detection and accuracy assessment. It aims to detect and prevent this disease among people living in rural areas where medical tests are difficult to conduct. It will help hospitals to detect DR in very little time. Moreover, the explications will be disseminated to other Ophthalmologists through the 4th Asia Pacific Tele-Ophthalmology Society (APTOS) Symposium. In the future, this model can also be used for detecting other diseases such as glaucoma and macular degeneration

Keywords: - Diabetic Retinopathy, Convolutional Neural Networks, fundus images, fundal cameras, ResNet architecture, hemorrhages, glaucoma, macular degeneration

I. INTRODUCTION

The complexities of diabetes mellitus induce the degeneration of the retina. This affects the blood veins in the retina, causing them to swell or burst, thus leaking retinal fluids and distorting vision. This is known as Diabetic Retinopathy (DR).Diabetes is a disease which impacts body parts like kidneys, eyes, sensory system, heart, etc. Moreover, other eye diseases such as Glaucoma, DR, Cataracts, Occlusions in the retinal arteries and Occlusions in the veins of the retina can also affect the people having diabetes [1]-[15].

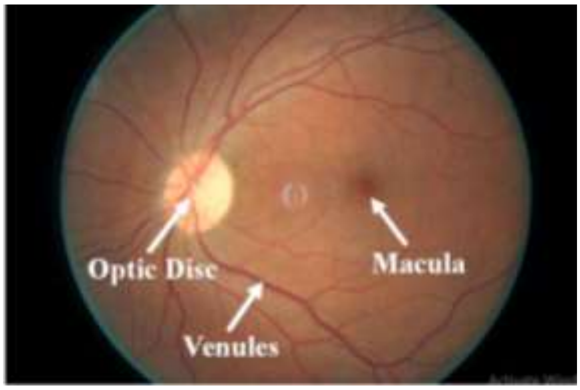


Figure 1: Fundus image of a normal eye

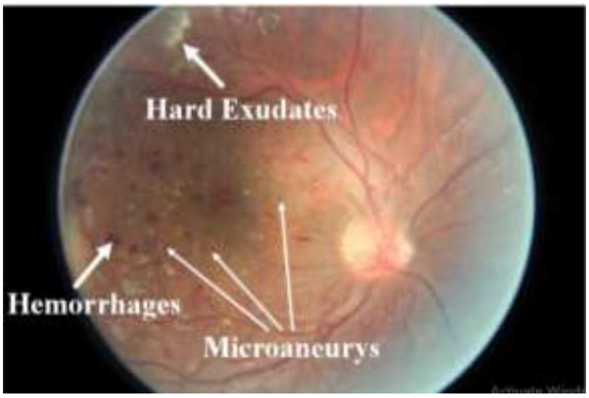


Figure 2: Fundus image of a diabetic eye showing lesions

At an early stage, diabetic retinopathy might not cause any significant vision loss, but eventually, it might lead to life-loss blindness. This condition is prevalent in working-age adults. In India, about 46% of people suffer from vision loss before even diagnosis. On left untreated, the disease can lead to vision loss. However, this can be avoided if the disease is recognized and treated in time. Blindness due to DR can be prevented at an early stage through routine checks and treatment of rudimentary diabetes [16]-[25].

In this project, a deep learning model is used which is a convolutional neural network with ResNet architecture. In this architecture, the input images are pre-processed, such as the images are cropped and the borders are removed, and enhanced before feeding them to the residual network in order to remove redundant information. Instead of adopting fundus images of a single eye as input, the ResNet architecture accepts images of both the eyes and outputs the classification result of each eye at the same time.

The model accepts two fundus images corresponding to the left eye and right eye as inputs and summarises the presence of detected features, i.e, blood vessels and hemorrhages, in the input images. The information from two eyes is passed through the pooling layer into the fully-connected layer and finally, the model will output the diagnosis result of each eye respectively, i.e., the five classes of DR.

II. LITERATURE SURVEY

Over the year, many research and projects have been developed to automatically detect Diabetic Retinopathy, in order to reduce the detection time. Since DR affects the blood veins and capillaries in the eye, most of the research focuses on the automatic detection of blood clots, hemorrhages, microaneurysms, and hard exudates in the fundus images [26]-[50].

The paper "Automated Diabetic Retinopathy Detection Based on Binocular Siamese-Like Convolutional Neural Network" [1] describes a novel CNN model to automatically detect DR based on deep learning method. This model uses Siamese-like architecture which accepts binocular fundus images as inputs and predicts DR for each eye. The model has a high score of 70.7% specificity and 82.2% sensitivity which is much greater than the monocular model. The model is more dynamic and has an enhanced method for screening.

Chavan et al.[2] in "Enhancement and Feature Extraction of Fundus Images" aims at studying and analyzing the fundus images using tools that work on image processing algorithms to detect macula and hemorrhages. The paper describes fundus image examination with various types of processing methods for pre-processing, feature extraction and classification. The pre-processing methods include noise removal, color space conversion, smoothing, and thresholding.

In "A Brief Review of the Detection of Diabetic Retinopathy in Human Eyes Using Pre-Processing & Segmentation Techniques" [3], Kumaran, gives a short acumen into the detection of Diabetic Retinopathy using different types of pre-processing and segmentation techniques. Information present in this paper is just the work done by various researchers till date so that the researchers can know about the various advances in this field. The paper explains the several stages of DR and the process of detection.

Gulshan et al.[4], in his paper describes the automated grading of DR using machine learning algorithms. The paper focuses on "feature engineering" which involves the extraction of features such as specific lesions. The algorithm uses an optimization technique called 'back-propagation' which details how the machine learning algorithm adjusts its internal weights in order to match the desired output. The paper concentrates on improved efficiency, coverage of screening exams and enhancing patient outcomes.

Quellec et al. [5] proposed a system to detect referable DR by exercising a deep convolutional neural network (CNN) and automatedly segment DR lesions such as micro-aneurysms, hemorrhages, exudates and cotton-wool spots. They adopted ConvNet architecture using competing heatmap generation. The paper used the dataset from Kaggle Diabetic Retinopathy Competition that contained almost 90,000 fundus photographs. The suggested detector outperforms numerous algorithms trained to detect those lesions precisely.

Geetharamani et al [6], in her paper, describes the technique of image processing and data mining to perform blood vessel segmentation. Blood vessel segmentation was performed using color space conversion and color channel extraction, image pre-processing, Gabor filtering, image postprocessing, feature construction through the application of principal component analysis, k-means clustering and first-level classification using Naïve–Bayes classification algorithm and second-level classification using C4.5 improved with bagging techniques. The results reported high accuracy of 95%.

III. PROPOSED WORK

For this project, the important parts that we are focusing on are image pre-processing and augmentation, network architecture and implementation and training method. Images that are gathered using fundus cameras are first pre-processed and augmented which is described in section A, network architecture and implementation is described in Section B and Training method are described in Section C.

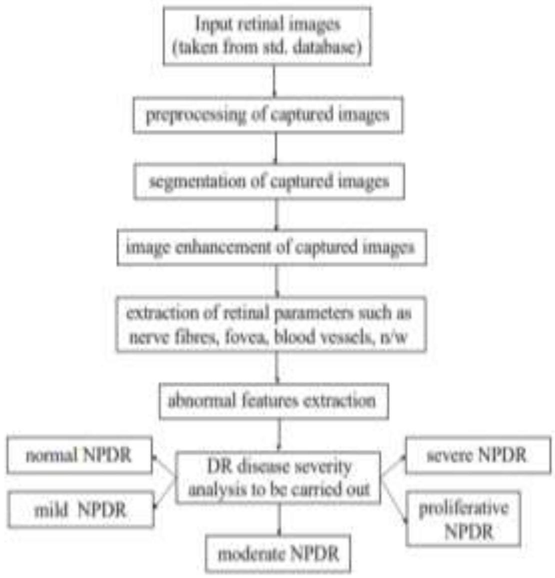


Figure 3: Flow chart of proposed methodology

A. Image pre-processing and Augmentation

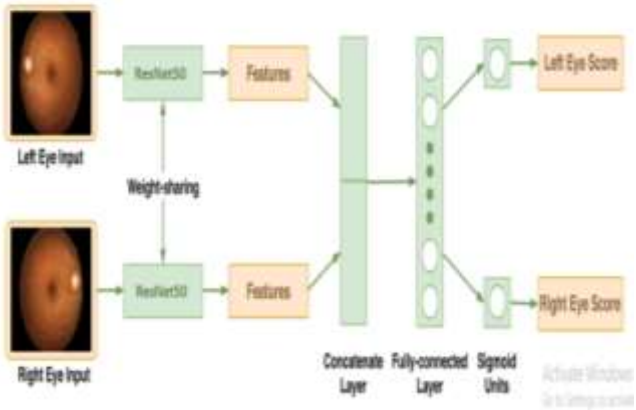
The input images for this project have been gathered from Kaggle Competition. The photographs for the input have been taken with the help of fundal cameras. The fundus photographs in the data set have high variations, such as discrepant brightness or resolution. Therefore, to normalize these pictures, diminish redundant information, numerous pre-processing techniques are applied to the fundus images:

1) Scale down the images according to their original aspect ratio.

2) Remove the black borders from the image
3) Subtract each pixel value of images by the weighted means of its surrounding pixel values, and add it by grayscale.
4) Convert the pixel values of images before feeding images to the network.
5) Flip the images of both eyes horizontally
6) Perform random geometric transmission on images, i.e, cropping and inverting images
7) Change the brightness and contrast of the images.

B. Network Architecture and Implementation

Herein, we are using ResNet 50 architecture which is a 50 layer convolutional neural network. The images after pre-processing are fed into the convolutional layer which applies filters and prepares the feature maps that summarises the presence of detected features in the input. The activation function used here is the Rectified linear unit (RelU)



because of its computational simplicity and linear behavior. The pooling layers then help in compiling the features, into average pooling and max pooling. The end result of the pooling layers is taken to the fully-connected layer which flattens the images, turns them into a single vector, and integrates the information of both eyes. The last layer of the ResNet 5 architecture, however, has been modified to reduce some convolutions, that goes on to become the softmax layer, which classifies the images and gives the final predictions, i.e, with or without DR. In order to further verify the images into the 5 stages of DR, a binocular network is applied. A confusion matrix is generated of the left eye, right eye, and both eyes together. The prediction result will be an integer between 0 to 5 representing the severity of DR.

C. Training Methods

Transfer learning method is a widely used training method of neural network and it is also adopted to make our model trained more efficiently. By loading the weights of ResNet50 blocks pre-trained on ImageNet data set, the model will has a better weights initialization before starting the gradient optimization. Moreover, considering the huge difference between the fundus images data set and ImageNet data set, none of layers in weight-sharing ResNet50 blocks are frozen which means every layer in the blocks can be trained depending upon the weights and bias value.

Beside, the selection of optimizer is significant when training a deep neural network learning model. A good optimizer can amazingly boost up the training process, prevent the bad local optima and provide us a better training result. The optimizer used in this work is called RMSprop. It is a widely-used method similar to the gradient descent algorithm with momentum which has been proven to be effective and practical on deep learning optimization.

Other techniques, such as ‘‘early stop’’ and ‘‘fine tune’’, are also adopted in our work. They are useful to shorten time for training and tuning, helping us to obtain models with better performance.

IV. RESULTS DISCUSSION

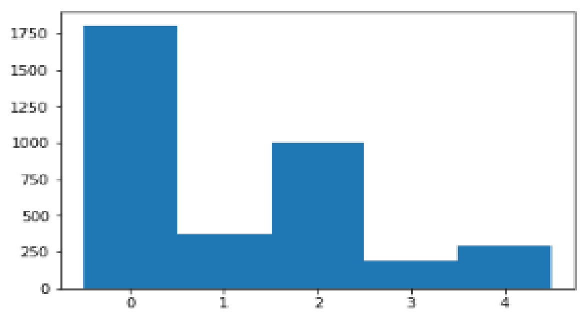
A. *DataSet*

The image dataset used is obtained from the website of Kaggle diabetic retinopathy competition provided by APTOS 2019 Blindness Detection, contains 5592 (3663 for training and 1929 for testing) high resolution fundus photographs taken under a range of imaging conditions. These fundus photographs have been categorized with a scale of 0 to 4 based on the severity of DR. Table 1 shows the 5 classes of DR. According to the International Clinical Diabetic Retinopathy Scale RDR is defined as the presence of moderate and worse DR and/or referable diabetic macular edema.

TABLE 1. The distribution of original data.

Label	Class
0	No DR
1	Mild
2	Moderate
3	Severe
4	Proliferative DR

TABLE 2. Percentage of each classification in dataset (bar graph).



B. *Preprocessing And Augmentation*

Two examples of the raw fundus photographs, as well as the corresponding processed images after pre-processing and augmentation, are showed in the given figure below.

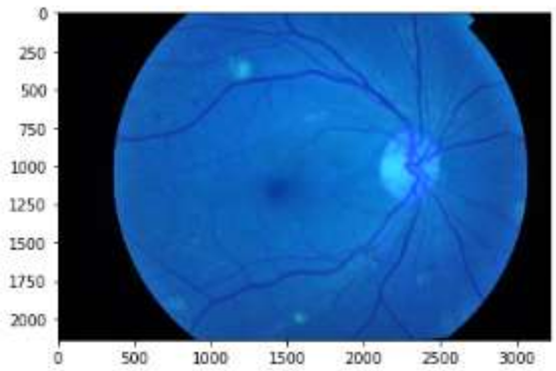


Figure 3: Original Image

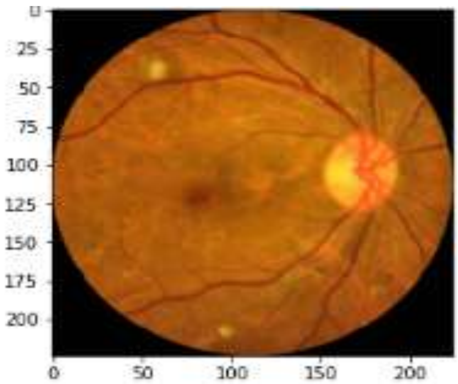


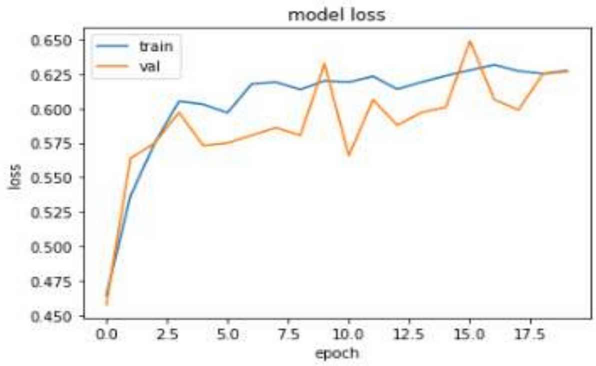
Figure 4: Pre-processed Image

It can be seen that the fundus region in Fig 4 is of well integrity and the imaging quality is high, but the fundus region in Fig.3 is incomplete and there are some illumination artifacts around its edges. After pre-processing and augmenting, the marginal region of retinal fundus in Fig. 3 is clipped, which removes the artifacts and makes the remaining fundus region a complete circle as shown in Fig. 4

Furthermore, the framework color of retina is gradually fainted, while the venules, hard exudates and hemorrhages are highleted.

C. *Result*

Loss vs Iteration graph is plotted to find the accuracy of the model. Because of using method like "early stopping" the model learns within 20 iteration and the learning stops and a loss graph is plotted against each iteration.



V. CONCLUSION

Diabetic Retinopathy (DR) is a result of diabetes and it is the principal cause of blindness and visual disability. Awareness about DR should be spread among the general masses to avoid loss of vision. In this paper, a CNN model is developed to automatically detect DR based on the deep learning method in very little time. The evaluation result shows that the proposed model achieves an accuracy of approximately 75.2% which is higher than any monocular model. Thus the model can help ophthalmologists to diagnose DR more efficiently and can be used for auto-detection of other ophthalmic diseases. However, the model would have issues in training if fundus images are not available. There is furthermore considerable scope for the proposed model to improve if more data are gathered in the future.

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