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Binary Classification of Diabetic Retinopathy Detection and Web Application

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***Abstract*: Nowadays with increasing cases of diabetes one should control the blood sugar as well as should perform regular examination of eye, which can prevent the person from blindness. Any person having diabetes can develop Diabetic Retinopathy (DR). DR is triggered by high blood sugar due to diabetes. After some time having excessive amount of sugar in blood can damage retina. When sugar jams the tiny blood vessels the eyes are damaged affecting the blood vessels in leakage of fluid. Millions of working aged adults suffer from loss of sight due to diabetic retinopathy. DR cannot be treated completely but early detection of DR prevents the person from vision loss. We proposed a deep learning model for detection of Diabetic Retinopathy. Detection of DR is a slow process. Physical detection of DR involves a trained clinician to study and estimate the color fundus photographs of the retina. Normal process of identification takes minimum two days. In our project we used Convolutional Neural Network architecture is used to classify images into two classes which is no-diabetic retinopathy and with diabetic retinopathy. APTOS-2019 Blindness Detection dataset is used from Kaggle which contains high resolution Retinal images. Those images are used to train the model. Web based interface is created for easy interaction with the model.**

***Keywords*: Contrast Limited Adaptive Histogram Equalization (CLAHE), Convolutional Neural Network (CNN), Deep Learning, Diabetic Retinopathy (DR), Gaussian-blur filter.**

1. Introduction

Diabetic retinopathy is a diabetes problem that effects eyes. It is affected due to the damage of blood vessels to photosensitive tissues in retina. Some of the symptoms are blurred vision, vision loss, dark or empty area of vision or dark strings floating in your vision. Timely detection of diabetic retinopathy precludes the person from vision loss. Manual detection of diabetic retinopathy takes more time and requires a trained clinician for detection. Convolutional Neural Network architecture model is used to train the model. High resolution retinal images are used to train the model.

Web based interface is used as front end of the model, which interacts with the model. The web page takes high resolution retinal images as input. The image is than pre-processed and enhanced then result is predicted. The predicted result is displayed in the web page. In our project we used Convolutional Neural Network architecture to train the model. The trained model predicts the result as no-diabetic retinopathy and with diabetic retinopathy. The predicted result is displayed in the web page. Fig. 1 displays the retina image which shows the normal image as well as the retina image having diabetic retinopathy, where we can see the swelling and blood clot in the blood vessels.

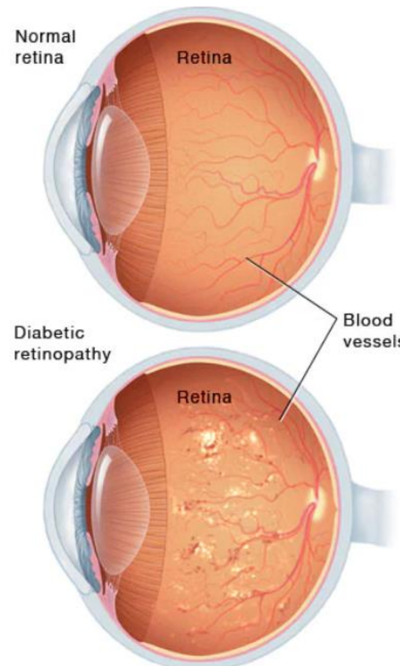

Fig. 1. Retina image before and after diabetic retinopathy

In our project we used 3600 high resolution retinal image from APTOS_2019 Blindness Detection dataset to train the model. These images taken to train are pre-processed and enhanced before training the model. The enhanced images are used for classification of the image as no-diabetic retinopathy and with diabetic retinopathy. In pre-processing high-resolution images are cropped, resized and converted to gray scale image. Grayscale images are blurred using Gaussian-blur filter. CLAHE is implemented to enhance the image and to remove noise and increase contrast of the image.

2. Literature Review

Revathy R *et al.* [1] proposed method which detects

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hemorrhages, exudates and microaneurysms. Dilation and erosion operators are performed. The three-classifier used to classify the images are support vector machine, k-nearest neighbour, Random Forest classifies the image as no-diabetic retinopathy and with diabetic retinopathy. In X. Zeng *et al.* [2] the paper proposes CNN model with Siamese-like architecture. The model takes binocular fundus images as inputs. In Borys T *et al.* [3] proposed an ensemble model for final solution. Three CNN architectures are used for transfer learning such as EfficientNet-B4, EfficientNet-B5, SE- ResNeXt50. In A. Biran *et al.* [4] the model used many image processing techniques such as Circular Hough Transform (CTH), Contrast Limited Adaptive Histogram Equalization (CLAHE), Gabor filter and thresholding. Support Vector Machine is used to classify the image. The model. Shu-I Pao *et al.* [6] proposed Bichannel-Convolutional Neural Network architecture used to train the model. The model is trained in this manner, which accepts the inputs of both entropy images and the green component from Unsharp Masking. Yogesh Kumaran *et al.* [7] in their paper they have used Artificial Neural Network and used high resolution retinal image for training the model.

3. Proposed Method

In our project we have trained the model with high resolution retina images. Fig. 2 shows the block diagram of the model. Color fundus retinal images are used for the DR detection. These retinal images are pre-processed, enhanced and classifies it as No DR or with DR.

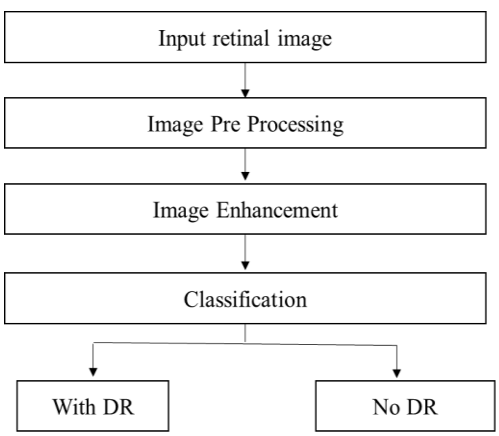

Fig. 2. Block diagram

In our project we have trained the model with APTOS 2019 Blindness Detection dataset from Kaggle, which consists a total of 3662 high resolution retina images. From the total of 3600 retinal images 1800 retinal images are no diabetic retinopathy retinal images and 1800 retinal images are diabetic retinopathy retinal images. The model trained and saved. The saved model is connected to web-based interface. The model extracts the input retinal image from the web application.

A. Pre-Processing

In this method the retinal images are cropped and resized. Cropping is carried out to remove the unwanted noise. The images are resized to new resolution of the image. The new resolution is 224 X 224. The resized images are converted to grayscale. The image is blurred by using Gaussian - blur filter. This filter will smoothen the retinal images. Ben Grahams preprocessing method [5] which helps to improve the lightning condition of the image.

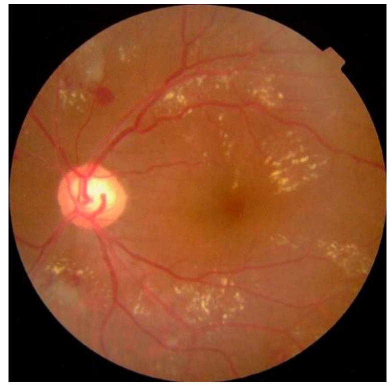

Fig. 3. Original image

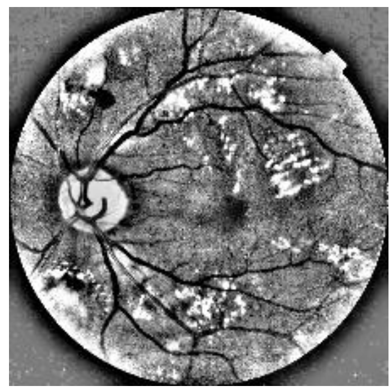

Fig. 4. Image after pre-processing and enhancement

B. Enhancement

In this process the contrast of the image is increased by using Contrast Limited Adaptive Histogram Equalization (CLAHE) filter. This filter is used to increase the contrast of the image and noise amplification problem is decreased. CLAHE does equalization of histogram in small patches or in small tiles with high accuracy and contrast limiting. The function add weighted from cv2 Python library is used to unsharp masking and highboost filtering of the image. In this function the images are blurred and smoothened then the smoothened image is subtracted from the original image making it unsharp masking. This mask is then added to the original image enhancing the high frequency components. Fig. 3 exhibit the Original input image and Fig. 4 exhibit the input image after pre-processing and enhancement.

C. Architecture

In our project we proposed a Convolutional Neural Network model which is a type of neural network model. The model is trained using Convolutional Neural Network architecture. The core building block of Convolutional Neural Network is Convolutional layer. Implemented different layers of CNN such as Convolutional layer, Pooling layer and fully-connected layer which has Rectified Linear Units (ReLU) correction layer.

D. Training

The model is trained with total of 3600 high resolution retinal images. The model is trained separately. The images are randomly split into 30% of total images as testing image and remaining as training image. Further the dataset is again randomly split into 40% of total images as validation testing images and remaining as validation training images. Fig.5 shows the model accuracy graph for 40 epoch having label as accuracy and epoch. We can see the validation accuracy increases as epoch increases.

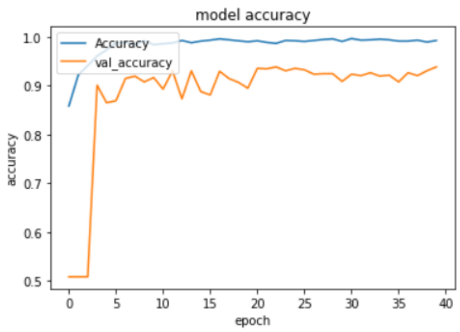

Fig. 5. Model accuracy graph

E. Testing

The trained model is saved and connected to web interface. Web based interface is created for easy interaction with the user. The web page will accept the high-resolution retinal image as input. This retinal image is pre-processed. In pre-processing the images are cropped, resized and blurred using Gaussian - blur filter and converted to gray scale. Then the images are enhanced by CLAHE filter which improve the contrast of the image. The model then predicts the result as 0 or 1. The predicted result is sent back and the classification result is displayed in web page as No DR or with DR.

F. WEB Application

The Web based interface is created for easy interaction with the model. The web page is created using the FLASK web frame work which is written using Python. The first page gives the details or knowledge about the Diabetic Retinopathy. In second page user can upload the image to check for the result. After a few seconds the web page displays the result as No DR or with DR, classifying the retinal image.

4. Result

In our project we proposed a deep learning model in detection of Diabetic Retinopathy using Convolutional Neural Network. The model is trained with Convolutional Neural Network architecture. The web-based interface is created which connects the model for better interaction. High resolution images are given as input from the web page which then given input to the model. The input image is pre-processed and enhanced. The model then predicts the result as 0 or 1. The classification is then displayed in the web page as No DR or with DR.

The model predicts the 99% of accuracy and 93% validation accuracy. The testing model predicts 91% of accuracy. The model has the f1-score of 91% and precision of 96%.

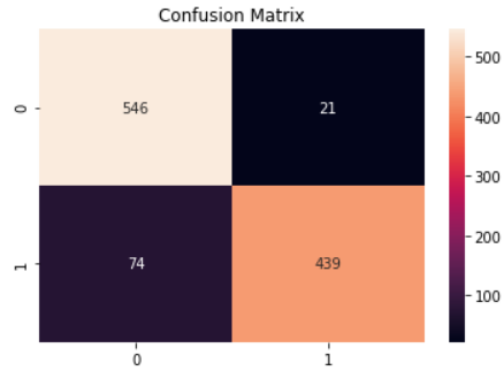

Fig. 6. Confusion Matrix

True Positive (TP) is the condition where the images are with DR and are predicted as with DR. True negative (TN) is the condition where the images are No DR and are predicted as No DR. False positive (FP) is the case where retinal images are No DR and got predicted as with DR. False negative (FN) is the case where retinal images are with DR and got predicted as No DR. Fig. 6 shows the confusion matrix which summarizing the performance of a classification algorithm. Confusion matrix will summarize the True positive, True Negative, False Positive and False Negative of the trained model.

The model has the sensitivity of 86%, specificity of 96%. Sensitivity is the measurement of True positive rate which means it predicts very few negative results or False positive rates. Sensitivity formula can be defined as Sensitivity = TP / (TP + FN). Specificity is the measurement of True negative rate which means it predicts very few negative results or False negative rates. Specificity formula can be defined as Specificity = TN / (TN + FP).

5. Conclusion

In our paper we have created a Binary Classification of Diabetic Retinopathy Detection using web interface for easy interaction. In this project we have considered the Convolutional Neural Network architecture to train the model. Web based interface is used for accepting the input image and for predicting the result. The given input images are pre-processed, enhanced and predicted as 0 or 1. The web page displays the predicted result as No DR or with DR. The model shows 99% of training accuracy and 93% of validation accuracy. And gives the testing accuracy of 91%. The model has the sensitivity and specificity of 86% and 96% respectively.

Future work may include in improving the performance of the model and increasing the accuracy of the model. Training the model with real dataset from the hospitals. Training the model with equal number of datasets of each classification. Using high resolution retinal images for training and testing the model. Classifying the model with different types of Diabetic Retinopathy such as mild, moderate, severe, proliferative. Using the equal number of datasets containing high resolution of the retinal images to train the model.

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