



Detection of Diabetic Retinopathy using Convolutional Neural Network

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Abstract: Autoimmune diseases are the kind of diseases in which immune system mistakenly attacks human body instead of foreign agents and Diabetic retinopathy is one of them. Early detection of these diseases is difficult because they can be easily misdiagnosed as other common ailments. Due to this, they are diagnosed at critical stage where most often treatment does not work. The solution is to come up with techniques for early detection so that proper treatment can avoid manifestation of mild symptoms into chronic disease. This paper focuses on Diabetic Retinopathy and proposes few techniques to automate its detection with highest accuracy. Objective is to detect the presence, type and level of severity using Convolutional Neural Network. Retinal Fundus image dataset available on Kaggle which is authentic and universal is used.

Keywords—Machine learning, Diabetic Retinopathy, Convolutional Neural Network

I. INTRODUCTION

Diabetes is one of the most common diseases in day today's world, needs to be treated in its early stages for maintaining a good control on one's health. Diabetic retinopathy [1] is caused by high blood sugar due to diabetes. Over time, having too much sugar in your blood can damage your retina — the part of your eye that detects light and sends signals to your brain through a nerve in the back of your eye (optic nerve). Thus, there is a need to detect the level of severity of diabetic retinopathy in an individual, so as to take proper precautions for maintaining a good health. One of the main motivations for screening for diabetic retinopathy is the established efficacy in preventing visual loss. The number of people with diabetic retinopathy is growing higher day by day. An estimation shows that the number will grow from 126.6 million to 191.0 million by 2030 and the number with vision-threatening diabetic retinopathy (VTDR) will increase from 37.3 million to 56.3 million, if any proper action is not taken. Despite growing evidence documenting the effectiveness of routine DR screening and early treatment, it is frequently leads to poor visual functioning and represents the leading cause of blindness [3]. Most of the time it has been neglected in health care and in many low-income countries because of inadequate medical service. As there are insufficient ways to detect about diabetic retinopathy, there is a need to build a machine learning system which will give prediction about diabetic retinopathy. The rest of the paper is organized as follows: section II gives related work for detection of Diabetic retinopathy. Section III gives in detail of Diabetic retinopathy. In section IV, proposed methods with all steps discussed. Section V discusses the results. Finally, section VI gives future direction and concludes the work.

II. RELATED WORK

Many researchers have done work on detection of Diabetic retinopathy.

Anitha Gnanaselvi J et.al.[2] used available STARE of color fundus images was used for testing purposes and provide comparisons between both databases and algorithms like KNN, CNN and SVM. The most primary sign of diabetics is to detect exudates and detecting this in early screening is crucial in preventing vision loss. The

Publicly available STARE database of color fundus images is used to gain a sensitivity of 86 percent specificity of 89.8 percent and positive predictive value of 83.2 percent. The accuracy was found out to be 85.6 percent with processing speed of 3 seconds.

Ikawa H.et al.[4] proposed the evaluation of the classification process, CNN using centerlines extracted manually in thier study. As a result of a fourfold cross-validation with 40 retinal images, the mean classification ratio of the arteries and veins was 98%. Furthermore, CNN was tested using the centerlines of blood vessels automatically extracted using the CNN-based method for testing the fully automatic method. CNN classified 90% of blood vessels into arteries and veins in the arteriovenous ratio measurement zone. CNN had 30 trained and 10 tested retinal images. Their result may work as an important processing for abnormality detection.

Shu-I Pao et. al.[5] proposed the entropy image computed by using the green component of fundus photograph. In addition, image enhancement by unsharp masking (UM) is utilized for preprocessing before calculating the entropy images. The bichannel CNN incorporating the features of both the entropy images of the gray level and the green component preprocessed by UM is also proposed to improve the detection performance of referable DR by deep learning.

Tushar Rajiv Kumar et.al.[6] processed of medical images using Convolutional neural networks. The most cutting-edge strategies for classifying and detecting DR color fundus images using deep learning techniques have been examined and analyzed. Additionally, the color fundus retina DR datasets have been examined. From the results of the experiments, produced a precision score of 0.84.

III. DIABETIC RETINOPATHY

Figure 1 shows the difference between a healthy eye and a diabetic eye. The retina is the inner lining at the back of each eye. The retina senses light and turns it into signals that our brain decodes, so we can see the world around us. Damaged blood vessels can harm the retina, causing a disease called diabetic retinopathy. In early diabetic retinopathy, blood vessels can weaken, bulge, or leak into the retina. This stage is called non-proliferative diabetic retinopathy.

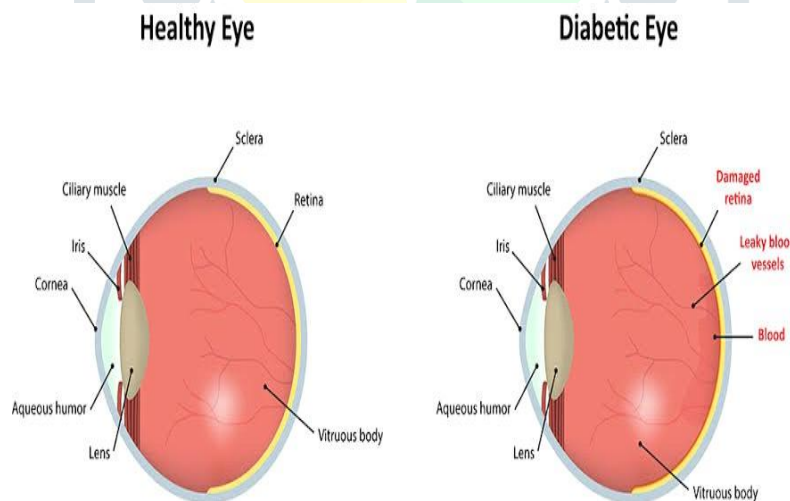


Figure 1: Difference between a healthy eye and a diabetic eye

There are four stages of diabetic retinopathy are:

Stage 1: Mild nonproliferative retinopathy — microaneurysms.

Stage 2: Moderate nonproliferative retinopathy — blocked blood vessels.

Stage 3: Severe nonproliferative retinopathy — more blocked blood vessels and a call for help.

Stage 4: Proliferative retinopathy — blood vessels grow on the retina.

Figure 2 shows the different stages of diabetic retinopathy.

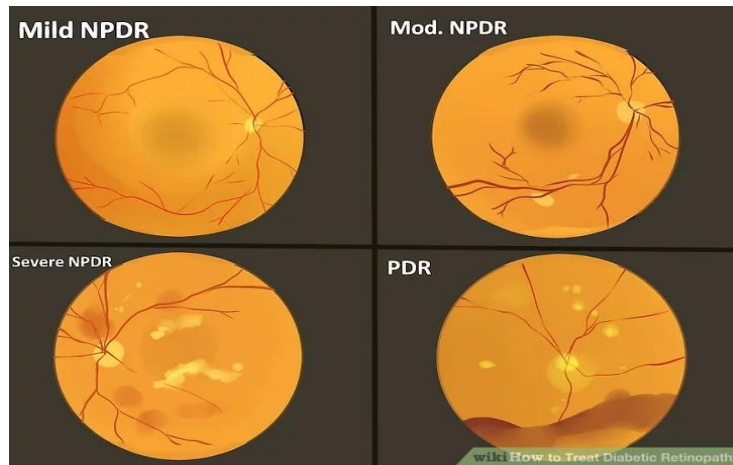


Figure 2: Stages of diabetic retinopathy

IV. PROPOSED METHODS

We have collected data set from online platform (Kaggle website). We downloaded the precaptured image file and csv file from Kaggle which allows users to explore and build models. Every image has a unique number along with the information about the placement of eye i.e. Left, Right. The csv file contains 2 columns in which the first column describes the nomenclature for the image and the second column specifies the labels, i.e the level of severity(0-4).The dataset contains features extracted from image set to predict whether an image have signs of diabetic retinopathy or not. Then features and labels of the dataset are identified. After that the dataset is divided into two sets, one for training where most of the data is used and the other one is testing. In training set four different classification algorithms has been fitted for the analysis performance of the model. The algorithms we using are Convolutional Neural Network and its successive algorithms Resnet, Vgg16. After the system has done learning from training datasets, newer data is provided without outputs. The final model generates the output using the knowledge it gained from the data on which it was trained. In final phase we get the accuracy of each algorithm and get to know which particular algorithm will give us more accurate results for the prediction of diabetic retinopathy.

We used a pre-trained VGG-16 convolutional neural network model which is fine-tuned by freezing some of the layers to avoid overfitting because our dataset is very small. VGG- 16 is a CNN model of 16 Convolutional layers proposed in 2014 by Karen Simonyan and Andrew Zisserman. The network image input shape is 224x224x3. It includes 16 Convolution layers with a fixed 3x3 filter size and 5 Max pooling layers of 2x2 size throughout the network. And at the top the 2 fully connected layers with a softmax output layer. VGG-16 Model is a large network, with approximately 138 million parameters. It's stacking many convolutional layers to build deep neural networks that improve the ability to learn hidden features. The VGG- 16 network architecture is shown in Figure 3.

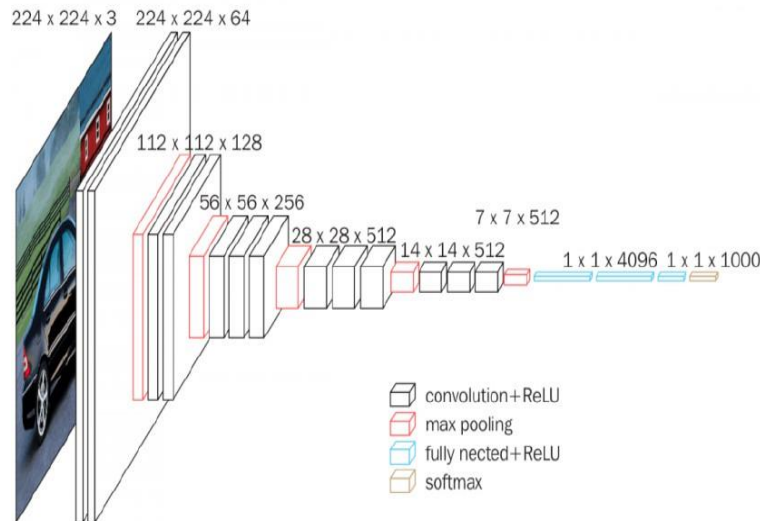


Figure 3: VGG 16

ResNet50 is a 50-layer Residual Network with 26M parameters. The residual network is a deep convolutional neural network model that is introduced by Microsoft in 2015. In Residual network rather than learning features, we learn from residuals that are subtraction of features learned from the layer’s inputs. ResNet used the skip connection to propagate information across layers. ResNet connects nth layer input directly to some (n+x)th layer which enables additional layers to be stacked and a to establish a deep network. We used a pre-trained ResNet50 model in our experiment and fine-tuned it. The Resnet Architecture is shown in Figure 4.

Figure 4: Resnet50

ResNet-50 Model Architecture

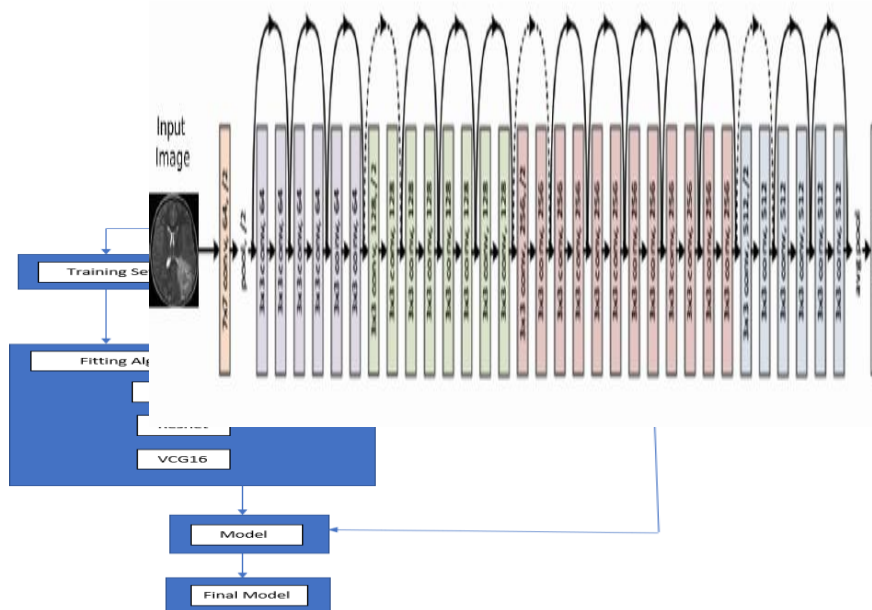


Figure 5 shows the proposed model of our system. All the steps in sequential order are given. The final model generates the output using the knowledge it gained from the data on which it was trained.

Figure 5: Proposed model

V. RESULTS & DISCUSSION

Figure 6 shows the testing part of the model and accuracy percentage for the same.

```
Epoch 1/3
82/82 [=====] - 149s 2s/step - loss: 1.4713
Epoch 2/3
82/82 [=====] - 112s 1s/step - loss: 0.9565
Epoch 3/3
82/82 [=====] - 110s 1s/step - loss: 0.9214

]: <keras.callbacks.callbacks.History at 0x16d9dafddd8>

]: scores = model.evaluate(x_test, y_test)
print(scores)

166/166 [=====] - 3s 16ms/step
0.792350064200091
```

Figure 6: Accuracy for CNN

Figure 6 shows the accuracy score for CNN model which was executed for 10 epochs with a small dataset. When the model is trained for 10 epochs and the accuracy for the CNN model is around 80 percent. The precision is highest for Level '0' images followed by level '2' and the prediction is as follows:

```
Actual Severity: 2
Predicted 02 (55.3%): *****
Predicted 04 (25.4%): **
Predicted 00 (17.4%): *
Predicted 01 (01.0%):
Predicted 03 (00.8%):
```

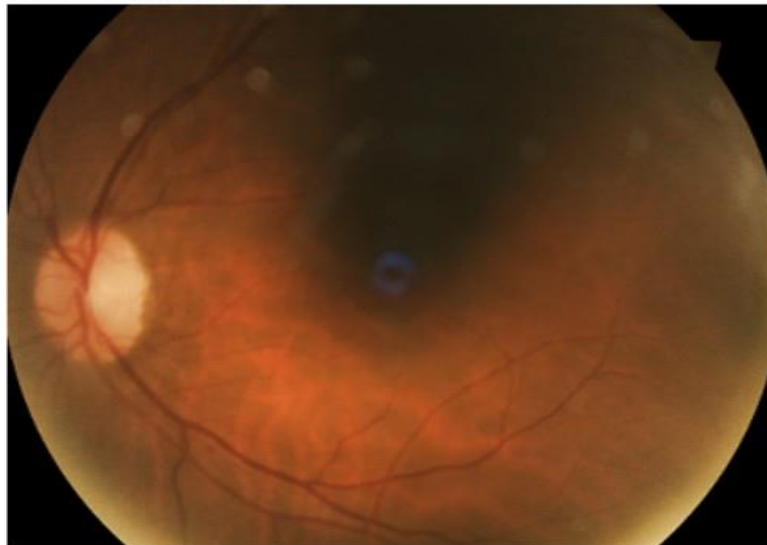


Figure 7: Prediction for level 2

Figure 7 shows the image with actual severity 2 and prediction value for level 2 severity is 55.3 percent that means the highest prediction is for level 2 which is good. Figure 8 shows the prediction for level 0 image.

Actual Severity: 0
Predicted 00 (82.4%): *****
Predicted 01 (13.8%): *
Predicted 02 (03.8%):
Predicted 04 (00.0%):
Predicted 03 (00.0%):



Figure 8: Prediction for level 0

Actual Severity: 1
Predicted 03 (35.9%): ***
Predicted 02 (27.6%): **
Predicted 00 (15.0%): *
Predicted 04 (12.7%): *
Predicted 01 (08.8%):

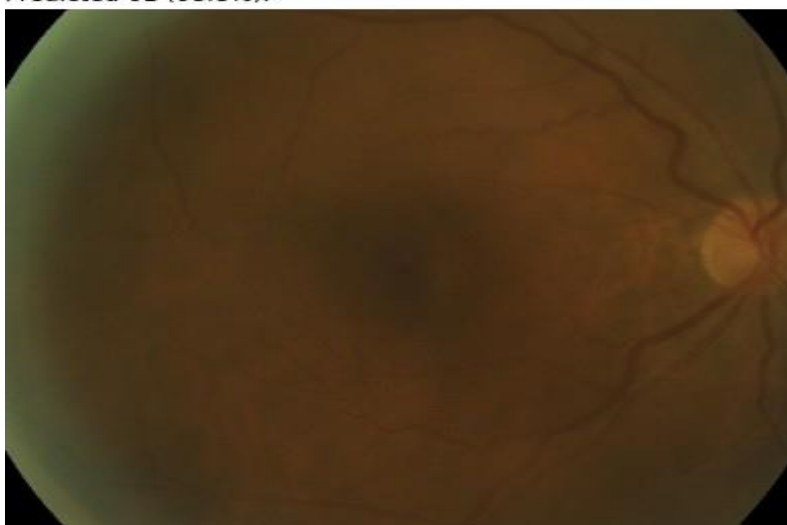


Figure 9: Prediction for level 1

Figure 9 show the prediction for level 1 image and Figure 10 the prediction for level 0 image.

Actual Severity: 0
 Predicted 00 (57.0%): *****
 Predicted 02 (22.3%): **
 Predicted 01 (14.1%): *
 Predicted 03 (04.8%):
 Predicted 04 (01.9%):

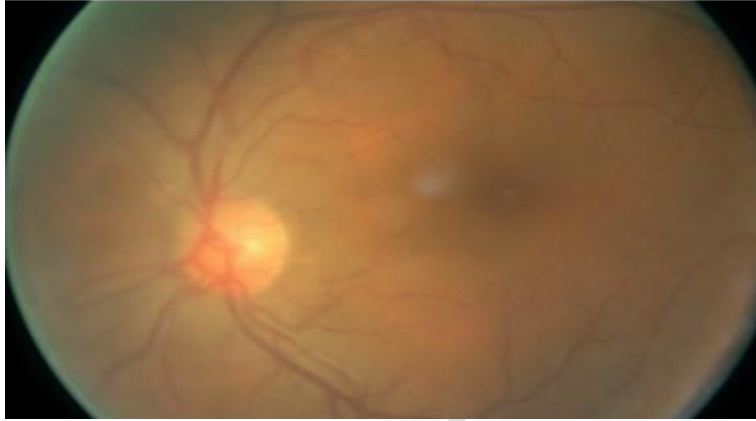


Figure 10: Prediction for level 0

VI. CONCLUSION AND FUTURE WORK

In this paper, we studied the prediction of Diabetic Retinopathy using machine learning. The detection of the disease is done by analysing the image of the retina. We also developed classification model using the features of retinal image and we have evaluated their efficiency. We got the accuracy for CNN model is around 80 %. As a future work, we plan to implement which can withstand dynamic application and changes and increase the efficiency, and also try other classification methods to reach a definitive diagnosis for Diabetic Retinopathy. In the future scope it can be used in the Healthcare institutions and organizations and also expanded for various retinal diseases diagnosis.

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