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# Detecting Diabetic Retinopathy Using Artificial Intelligence

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***Abstract*: Diabetic retinopathy is an eye condition that can cause vision loss and blindness in people who have diabetes. The disease affects blood vessels in the retina. More than 347 million people in this world suffer from diabetic retinopathy. The disease if left untreated will lead to blindness. Blindness can be avoided if the disease is detected in its early stages. Highly trained doctors are required to diagnose and detect the stage of the disease. This causes a limitation for the patients in the rural parts of the country. This problem can be solved with Artificial Intelligence which can detect the stage of the disease without the need of experts. This can be cost effective and the results can be shown almost immediately.**

***Keywords*: Artificial Intelligence, Blindness, Convolution Neural Networks, Diabetes, Diabetic Retinopathy detection.**

## 1. Introduction

Diabetes happen when the pancreas can't handle sufficient insulin in the patient's body. body. On the off chance that the patient doesn't take appropriate consideration, the glucose level in their body will increment and along these lines prospects of creating DR gets higher. Serious improvement of DR can harm the retina which can prompt loss of vision and in the end into visual deficiency. The World Health Organisation (WHO) made a study about DR, there are more than 347 million individuals in this world experiencing diabetic retinopathy. They anticipate that the number can reach upto 500 million individuals before the finish of 2030. Specialists and exceptionally prepared clinicians identify injury with vascular anomalies for distinguishing the degree of DR. They likewise require a parcel of types of gear and supplies to effectively arrange DR. DR is a major issue in overpopulated and immature nations like India and China. In immature nations, the primary issue is there is an absence of master clinicians and supplies. Examining and turning into a capable DR master requires time and practice too. In this way, there is a lacking. Thus, constant location for arrangement of DR is essential for the prosperity of individuals experiencing it. Diabetic retinopathy stages can be isolated into two classes which are early DR and progressed DR. Early DR is known as Non-Proliferative Diabetic Retinopathy (NPDR). Progressed DR is known as Proliferative Diabetic Retinopathy (PDR). NPDR is the point at which the patient can be relieved whenever legitimate treatment is given and if the patient controls their diabetes level and makes way of life changes. In PDR, the patient has little any expectation of getting restored from DR, if the condition turns out to be more regrettable the patient can for all time become visually impaired.

### *A. Convolution Neural Networks (CNN)*

Convolutional Neural Networks (CNN) are composed of a ton of layers. Data is passed between the layers. These layers can be isolated into 3 sections. Initial segment takes the info pictures. Second part separates the highlights from the pictures and the third and last part gains from the removed highlights of the subsequent part. For our concern of distinguishing the level of DR the yield layers returns the strength of the networks expectation of every conceivable class. For instance, the subsequent part contains layers like convolution, pooling, relu and so forth that plays out particular kinds of extractions and passes that data onto the following layer. The third part contains layers like completely associated, softmax, yield and so on which takes data created by the layers in the second part and gains from them. The actual layers accompany numerous boundaries which are called weights. The weights decide how the layers carry on when information is gone through them. The upsides of these weights are controlled via preparing the network on known information. Along these lines, the conduct of the network is gained from the information. The networks can have a similar engineering however act contrastingly on the off chance that they were trained utilising diverse informational collection. In any case, if two networks have diverse engineering however are trained utilising the equivalent dataset the networks will learn in an alternate manner. In a way, the two networks resemble two people. The two people learns same things in their own specific manner.

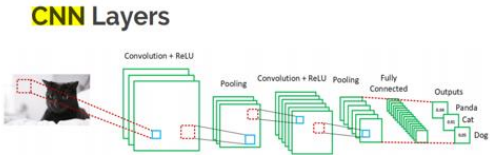


Fig. 1. CNN layers

### *B. Image Preprocessing*

Image Resized since the images of the retina in the dataset are in different sizes. The dataset is obtained from "APTOS 2019 Blindness Detection" competition on Kaggle, which was hosted by Asia Pacific Tele-Ophthalmology Society (APTOS).

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The images provided in the dataset are not consistent and hence the stage of image preprocessing is very important. Images will be resized to a standard size of 200 X 200. Since the number of images for training is very less, we have to use image augmentation to increase the size of the dataset.

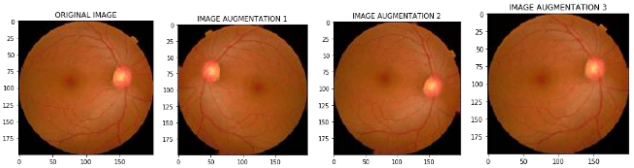


Fig. 2. Applying Image Augmentation

### *C. Gaussian Blur*

A Gaussian filter is a linear filter. It's usually used to blur the image or to reduce noise. Since it is difficult to see the blood vessels in the normal picture of the retina, we use this filter. The Gaussian filter alone will blur edges and reduce contrast. After applying Gaussian filter on the images if the retina we obtain the following image

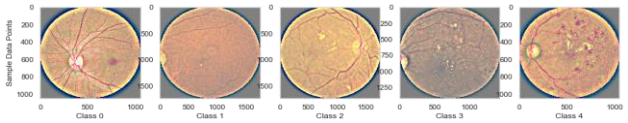


Fig. 3. Applying Gaussian Blur

As we can see from the above images the blood vessels are clearly seen as compared to the normal image of the retina. The hemorrhage in the eye in the image of the class 4 image is prominent.

## 2. Methodology

The images from the dataset are resized, augmented and Gaussian Blur filter is then applied to it. The images are split in 70-30 where 70% of the images taken at random are used for training and rest are used for validation purposes. As you can see the images are very inconsistent as the images of class 0 are much more than images of class 1, 2 and 3.


Fig. 4. Classification of Training Data

We then use ResNet50. The ResNet-50 model consists of 5 stages each with a convolution and Identity block. Each convolution block has 3 convolution layers, and each identity block also has 3 convolution layers. The ResNet-50 has over 23 million trainable parameters. Originally, we set the epochs to 40 and used the early stopping method. The training was done in 17 epochs and the results were plotted on a graph as shown.

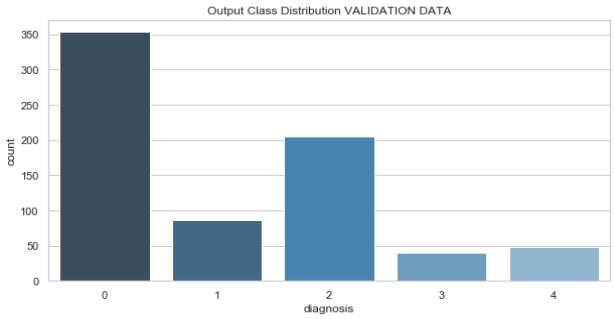


Fig. 5. Classification of Validation Data

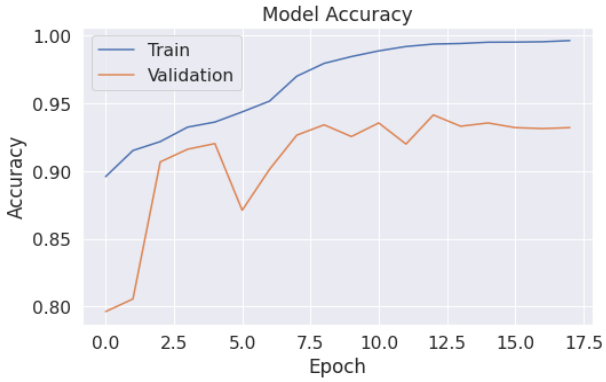


Fig. 6. Accuracy vs. Epoch graph

As you can see from the graph, after 17 epochs the accuracy of the training phase is 98.9% and after validation, we get a final accuracy of 94.1%. The confusion matrix which is a statistical model to see the performance of the model is also shown.

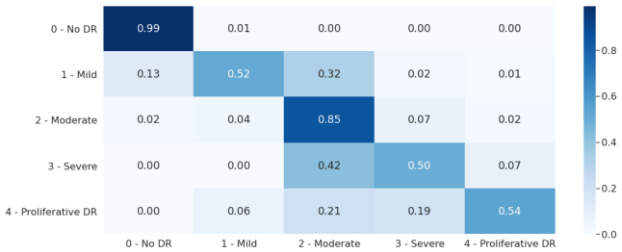


Fig. 7. Confusion Matrix

As you can see, the model did well for Class 0 and Class 2 DR, it performed poorly for the rest of the classes. This was due to less number of images for Class1,3 and 4 DR. The quality of the images is also a limitation. The image quality varies because the dataset had some images taken from different devices.

## 3. Final System

The model trained above was saved with a .h5 extension. This model was then used in the web app. Since it's a prototype we use Django as a backend as it's a framework in python. Django is a high-level Python Web framework that encourages rapid development and clean, systematic design. With Django we can easily implement the model. Features such as user authentication are added so that the reports can be viewed by a

registered person. When a registered user login, the tabs for uploading images and the reports section are unlocked. For uploading the images, we have to fill out the form where we can store the images of the right and the left eye. The name, age of the patient is also to be entered. For demonstration we enter the following details shown below.

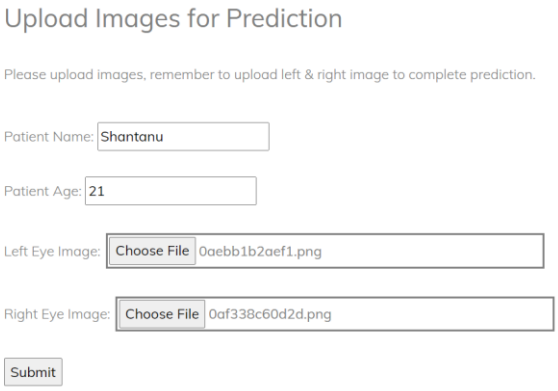


Fig. 8. Form to enter Patient Details

We pass the image of the left eye with moderate DR and the image for the right eye with proliferate DR.


Fig. 9. Generated Medical Report

The predictions are correct. The medical report is generated as shown above. This is a clear medical report which can be read easily and understood by a layman. The report of each eye is shown with their respective prediction score. Further the report section has a table containing information of all the patients. For each patient we included an option to show the results, updating the results and deleting the data. The report section is shown below.

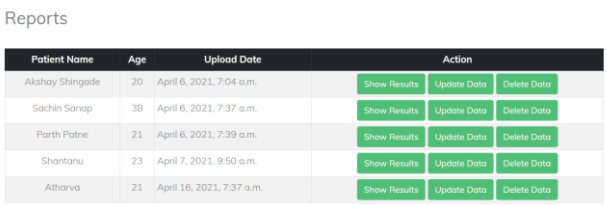


Fig. 10. Report Section

## 4. Conclusion

Consequently, identifying the degree of DR in a patient's eye is a crucial task, particularly in nations where the pace of diabetes is high among the population and in places where the necessary identifying hardware or experts are not promptly available. There are many existing models out there that identifies the degree of DR from retinal pictures of the patient with remarkable exactness. For most of the examination paper given in the reference area it tends to be seen that a great deal of capable personalities dealt with them onto building neural organization that can effectively recognize and characterize the degree of DR. A few scientists utilized exchange learning and contrasted them and CNN's that were worked without any preparation. By chipping away at this undertaking and from the experience we gained in the course of recent months we can particularly say that we have developed significantly more appreciation for AI and AI. The force that this device has is enormous and whenever used appropriately a great deal of the issues in this day and age can be improved.

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