Classification of Severity of Diabetic Retinopathy stages using Keras

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Abstract- Diabetic Retinopathy (DR) is caused because of abnormal growth of blood vessels in the eye which cannot be visible to naked eye and we need to use funduscope which captures the fundus images for screening. There are some physical tests available but the problem with the physical tests is they consume more time therefore affects patients and may lead to complete blindness. It is very difficult to identify through the tests during the early stage of the test. DR occurs because of swollen blood vessels because of high level of diabetes. The physical test for DR is very time consuming as it involves capturing of eye by fundus camera. To accelerate this process some, form of computer processing is required.

Our project uses a Convolutional Neural Network (ConvNet) based approach to detect and classify the grades of DR. CNN is preferred because it handles all the pre-processing of images and normalization by itself. It uses the concept of filter to extract the necessary features to classify the DR. CNN with help of keras [12] provides greater flexibility in terms of image handling and processing and we are using a lightweight Python web framework called Flask for user interaction and classifies the severity of DR into stages namely Level 0, Level 1, Level 2, Level 3, Level 4.

Key Words: - Diabetic Retinopathy (DR), Funduscope, Convolutional Neural Network (CNN), Fundus Image, Image Classification, Flask, Keras.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a common disease caused by diabetes. In early stages, DR doesn't show any symptoms but if it is not treated. It may result in vision loss. Many physical tests are used to detect DR like

- Visual acuity test
- Pupil dilation test
- Tonometry test

The problem with these tests is they consume more time therefore affects patients and may lead to complete blindness it is very difficult to identify through the tests during the early stage of the test. DR occurs because of swollen blood vessels because of high level of diabetes. The physical test for DR is very time consuming as it involves capturing of eye by fundus camera. To accelerate this process some, form of computer processing is required.

Diabetic Retinopathy is mainly classified into two types:

1. Non-proliferative (NPDR)
2. Proliferative (PDR)

1. Non-proliferative DR (NPDR)

NPDR includes micro aneurysms, cotton wool spots and hemorrhages. NPDR is the milder form and mostly symptomless.

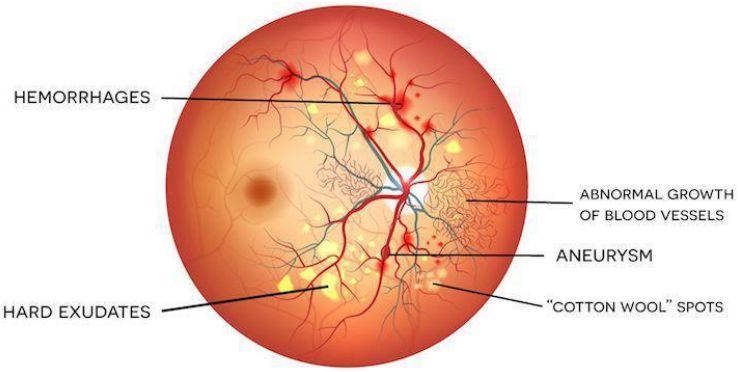

Fig: 1 Features of Non-Proliferative DR Eye

2. Proliferative DR (PDR)

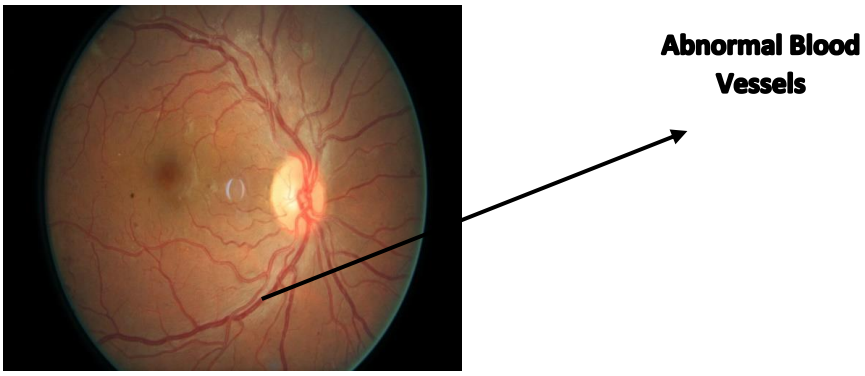

Fig: 2 an Example of Proliferative DR Eye

The PDR include abnormal growth of blood vessels. Iris or retinal neovascularization defines PDR. These features are examined by ophthalmoscopy or fundus images, and it can be graded in clinical terms as

1. Normal - Level 0
2. Mild - Level 1
3. Moderate - Level 2
4. Severe - Level 3
5. Proliferative - Level 4

II. RELATED WORK

There are some models developed to detect and classify the severity of diabetic retinopathy and these models have their own advantages and disadvantages and some of them are discussed here.

Manoj Kumar Behera et al. [7] defined a support vector machine and in their research they used two feature extraction techniques called scale-invariant feature transform (SIFT) and speeded up

robust features (SURF) to capture the Exudates regions in the fundus images. They used feature matrix to store exudates of each image and used support vector machine (SVM) classifier to predict DR. They used 100 test images and got an average sensitivity of 94%.

Jahiruzzaman et al. [3] defined a k-means color compression technique for dividing different parts of fundus image by reducing color dimension. They segmented the fundus images using region properties attributes and recognized DR using fuzzy inference system (FIS) by this they got accuracy of 92.3%.

Manjula et al. [4] proposed a Micro aneurisms (MA) detection based on Eigen value analysis using hessian matrix in fundus images. They used 89 images and got true positive rate of 91%.

Ahmad Taher et al. [2] developed an automatic algorithm and applied 100 retinal images. By using the minimum distance classifier they got a classification rate for microaneurysms(MAs) ,haemorrhages ,exudates and cotton wool spots was 60%, 94%, 95% and 86% respectively.

Imran Qureshi et al. [1] proposed a [Acive Deep Learning CNN] ADL-CNN based on a CNN architecture using expected gradient length (EGL). They implemented it on 54,000 retinal images, and their model achieved a Sensitivity of 92.20%, Specificity of 95.10%.

Supriya Mishra et al. [6] used APTOS dataset and compared two pre-trained models i.e. VGG16 and DenseNet121 and got an accuracy of 96.11 for DenseNet model.

Shital N. Firke et al. [8] proposed a CNN model using APTOS dataset which achieved an accuracy of 96.15%.

Optic disc segmentation [9] is one of the important retinal image segmentation method used in DR classification.

Rahul M.S.P et al. [10] used CLAHE preprocessing technique along with canny edge detection and they got a good results on extracting the vascular pattern when compared to other edge detection tecniques.

Satwik Ramchandre et al. [11] use transfer learning models like SEResNeXt32x4d and EfficientNetb3 and got a training accuracy of 91%.

III. METHODOLOGY

A. Specifications of our Proposed Model

We used a Convolution Neural Network based approach to classify the Severity of DR stages because as this project involves image classification and Convolution Neural Network using keras [12] provides some preprocessing techniques like Image Normalization, Image Augmentation.
Convolution Neural Network provides a kernel or a filter concept which plays an important role in extracting the features from the images for classifying the DR Stages.
Each stage of our model consists of the following operations:

- Convolution
- Non-Linearity
- Max Pooling

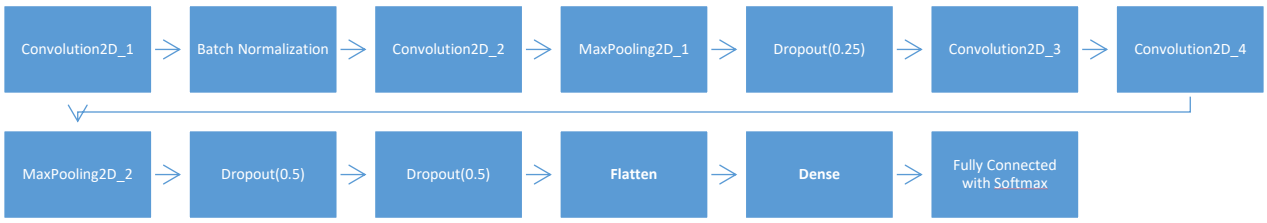

Fig: 3 Proposed Model Network Architecture

As shown in the Fig: 3 each layer consisting of a Convolution layer with "Relu" as Activation function and our CNN model consists of two Dropout layers with 0.5 and 0.5 respectively to overcome the Overfitting problems and a Flatten layer followed by a Dense layer with 512 units and with "Relu" as it's Activation function and finally a Fully connected layer for a 5-class classification with Softmax as its activation function. We used "categorical_crossentropy" as validation loss function with Adam optimizer with learning rate of 0.00001 and for callbacks we used EarlyStopping with patience of 5 epochs where if the validation loss does not improve for 5 continuous epochs then the model training will be stopped and ModelCheckpoint to save the best model.

- **Convolution:** This layer is basically used to extract the features from the given input. It uses filters, filter Size or also called as Kernal Size which slides over the input image and it performs a Dot product between the image pixels and filter and generates a convolution matrix. This process is continued throughout the image and finally forms another image which is an input to other layer.
- **Non-Linearity:** In this layer each and every negative value from the resulted matrix of previous layer is removed to avoid all the values summing up to zero. "ReLu" Layer is used as an activation function which replaces negative values to 0. The ReLu function activates the node only if the input is above some value. If input is below zero then the output is zero.
- **Max Pooling:** In this layer it down samples the input layer by replacing maximum value from the input matrix. It consists of a pool size which slides over the input.

B. Preprocessing

Because we are using a small dataset consisting of 3662 images the preprocessing step places an important role in feature extraction. The preprocessing technique which was proposed by [10] i.e CLAHE which is an Adaptive histogram equalization for improving the visibility level of foggy fundus image which is shown in fig: 4, where we can see the blood vessels more clearly in fundus image and we cropped the images to 256x256. We used image augmentation provided by keras ImageDataGenerator.

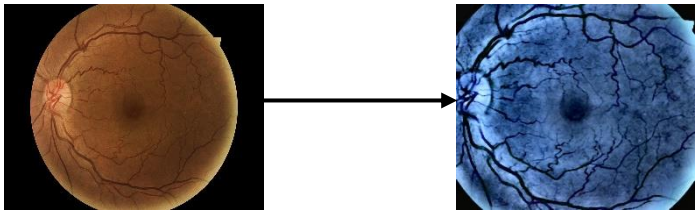

Fig: 4 preprocessing of fundus image

We can clearly see the blood vessels and because we reduced the images to lower resolution the training speed will gradually increases. Since we are using Max pooling in our proposed model it captures the minute details in the fundus images.

C. Advantages of Proposed model

It usually takes about 1 week - 2 weeks in regular screening methods to detect DR taken into consideration of the screening of the eye and consulting from an ophthalmologist. Since we use end-user CNN model to detect and classify it takes around 2-5 minutes depending on the resolution of the fundus image. However, the person should first take a pre-screening and undergoes a regular fundoscopy test at the clinc, after which our propose CNN model may be used to detect DR. This greatly reduces the screening and consulting time to approximately an hour and helps in quicker diagnosis of Diabetic Retinopathy.

IV. IMPLEMENTATION

A. Datasets

A total of 3662 images from APTOS Blindness Detection in Kaggle [13] are used which were later resized to 256x256 for efficient training. The distribution of these images to their respective lasses is given in the fig.3. In our model around 3000 images were used for training and validation, i.e. 20% of those images were assigned for data validation. Fig: 5 shows us how the data is distributed among different classes.

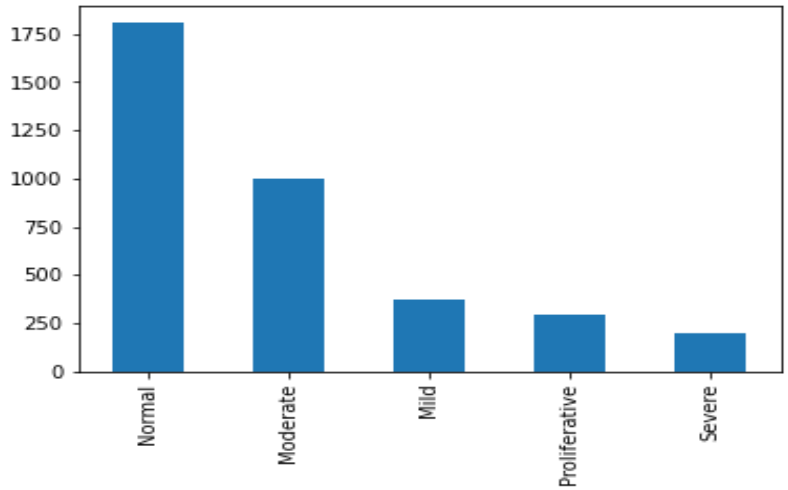

Fig: 5 Distribution of fundus images over 5 classes

B. Model flow for classification

After preprocessing, the image is used as input fundus image for implementation of the model which is shown in fig: 6. Then the image with dimensions of 256x256x3 will be passed through first convolution layer which consists of 32 filters of size 5x5 with "ReLu" as it's activation function and with BatchNormalization. The image is processed to second convolution layer having 32 filters of size 5x5 with "ReLu" as it's activation function with Max Pooling Layer of pool size 2x2 and a Dropout layer of value 0.5 then the images pass through third convolutional layer with 64 filters of size 5x5. Then the images pass through fourth convolutional layer with 64 filters of size 5x5 with a Max Pooling Layer of pool size 2x2 Two Dense layers are defined with Dropout of 0.25 and 0.5. Each Dense layer consists of 512 and 5 respectively. The learning rate used is 0.0001. The last Dense layer is added with activation function "SoftMax" and the loss function used is "categorical_crossentropy". The optimizer which we used here is "Adam".

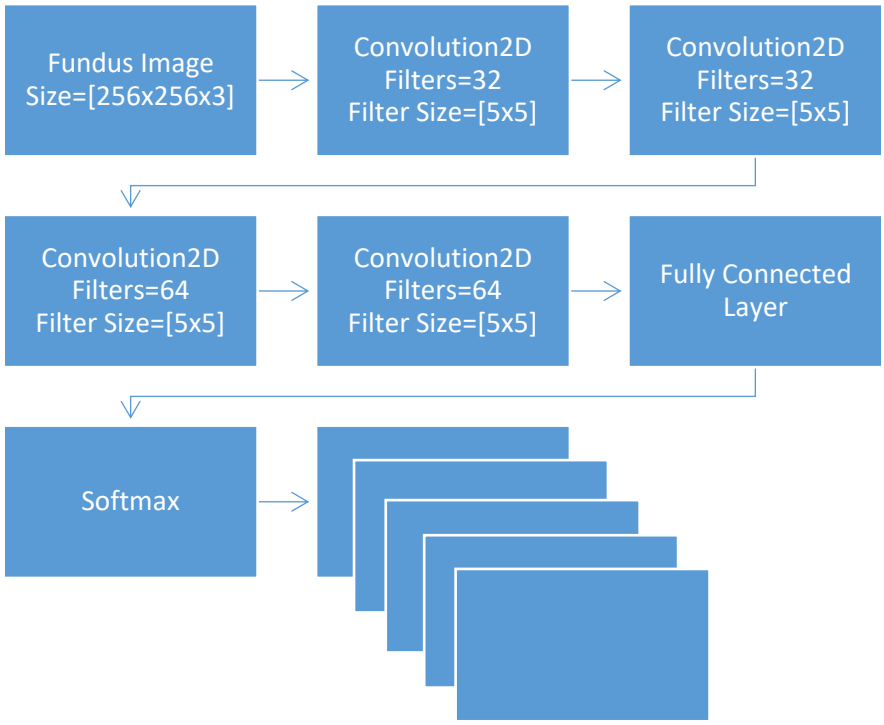

Fig: 6 Model flow

V. RESULTS

A. Model loss & Accuracy plot

Fig 8, 9 depicts how model loss and accuracy of training and testing data over the number of epochs. Our model achieved a maximum training accuracy of 98.36% and maximum testing accuracy of 81.12% which I shown in fig 7. We ran our model for 30 epochs and we got best results at 7th epoch, since we used used ModelCheckpoint we saved best only.

Training Accuracy	Validation Accuracy	Epoch
85.02%	**81.12%**	**7th**

Fig: 7 Results

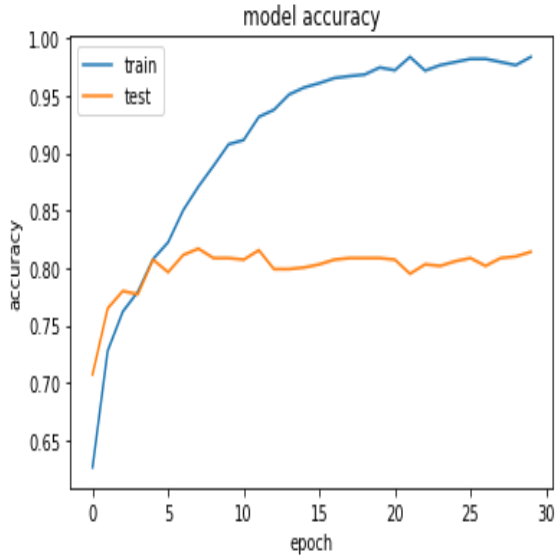

Fig: 8 Model Train/Test Accuracy Vs epochs

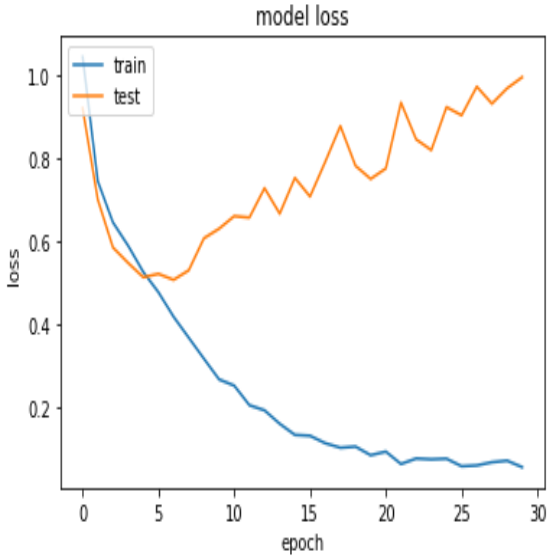

Fig: 9 Model Train/Test loss Vs epochs

VI. CONCLUSION

For a patient who came to consult a ophthalmologist need to wait 7-14 days for getting the results but using computer aided resources they can get the results within 1 day. Our proposed model also gets the results within a day where the doctor needs to upload the fundus image into the web app which we are going to provide and it gives the classification results. There are other models which outperforms our model because they used large datasets and transfer learnings. We proposed a CNN model on which if we feed it more data and using better preprocessing techniques gives better results than which we get in this model using small dataset. So there is a scope for further improvements to bring best results. Also by using Optic disc segmentation [9] we can get better results than our proposed model.

VII. REFERENCES

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