International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 10, October-2020

Iris - Diabetic Retinopathy Detection Software

Noel J Philip[*1], Romi Roji[*2], Rosme Jose[*3], Rehna Cherian[*4], Dr. Arun K.S[**5]

[*]UG Students,

[**]Associate Professor

Department of Computer Science and Engineering

Amal Jyothi College of Engineering, Kottayam, Kerala, India

***Abstract*—Diabetic retinopathy is a main cause of blindness among adults. Early detection of this condition is critical for good prognosis.In the experiments conducted on a large scale of retina image dataset, we show that the proposed CNN model can achieve high performance on DR detection. In this paper, we demonstrate the use of convolutional neural networks (CNNs) on color fundus images to diagnose diabetic retinopathy staging. Our network models achieved test metric performance comparable to baseline literature results, with validation sensitivity of 95 . We discovered that preprocessing with contrast limited adaptive histogram equalization and ensuring dataset fidelity by expert verification of class labels improves recognition of subtle features. Transfer learning on pretrained GoogLeNet and AlexNet models from ImageNet improved peak test set accuracies.**

***Index Terms*—Exudates; Micro aneurysm; Haemorages**

I. INTRODUCTION

Diabetes is a widespread disease in the world. A large number of people are suffering from this disease. So, it is high time to find a remedial measure. Diabetic retinopathy (DR) is an eye disease caused by the prolonged diabetes. Basically, DR affects blood vessels in the light-sensitive tissue called retina. It cause vision impairment and blindness for working- age adults in the world today. The main challenge for DR is that it has no early warning sign. Thus, it is highly desired that DR can be detected in time. Unfortunately, in practice the current DR detection solution is nearly infeasible to meet this requirement.

DR can be classified into normal, NPDR and PDR. Diabetic retinopathy is of two type's namely non proliferative i.e., NRDR and proliferative type i.e., PDR. Non proliferative is the early stage of the disease characterized by the presence of micro aneurysms. As the disease progresses the retina is deprived of oxygen and new blood vessels are formed leads to clouding vision. There are also three categories that are mild NPDR, moderate NPDR and severe NPDR. In mild NPDR, micro aneurysms are small areas of balloon-like swellings in the retina's tiny blood vessels.

Fig. 1: Normal Vision

Fig. 2: Vision with DR

II. BACKGROUND AND RELATED WORK

Diagnosis of pathological diseases in fundoscopy, is a med- ical technique to view the retina, depends on a complex range of features and localizations within the image. The diagnosis is very difficult for patients with early stage diabetic retinopathy as this relies on discerning the presence of microaneursyms, small saccular outpouching of capillaries, retinal hemorrhages, ruptured blood vessels— among other features—on the fundo- scopic images. Prototypical retinal disease stages. Computer- aided diagnosis of diabetic retinopathy has been explored in the past.This was done to reduce the burden on opthamolo- gists and mitigate diagnostic inconsistencies between manual readers 16 . Automated methods to detect microaneursyms and reliably grade fundoscopic images of diabetic retinopathy patients have been active areas of research 19. The first artificial neural networks demonstrated the ability to classify patches of normal retina without blood vessels, normal retinas with blood vessels, pathologic retinas with exudates.

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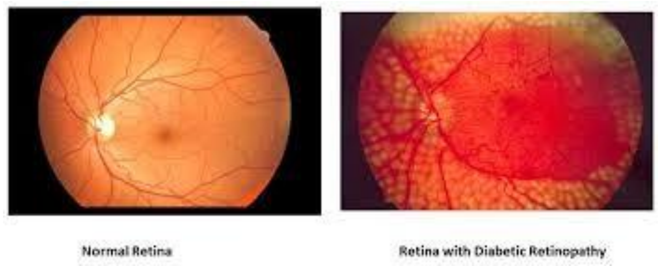

Fig. 3: Eye Images

Fig. 5: New Patient

III. METHODOLOGY

A. Dataset

We used two fundoscope image datasets to train an automated classifier in our study. Diabetic retinopathy images were acquired from a Kaggle dataset of 35,000 images with 4-class labels (normal, mild, moderate, severe).

B. User Interface

The visual component of our proposed system is the user interface. The user/client can access the functionalities in the system through user interface. It is mainly designed using HTML5, CSS, JavaScript technologies. The user can register their clinic using the signup functionality, add a new patient using 'add patient', upload the patient's image stored on the computer using the browse and upload functionality.

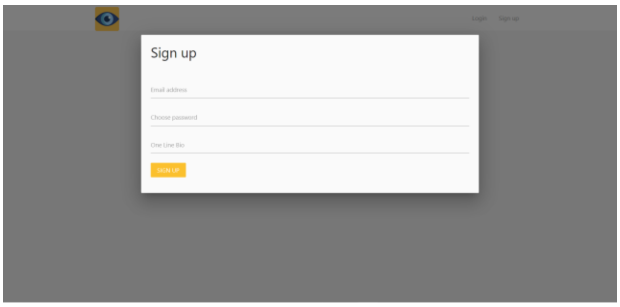

Fig. 4: Signup

C. Firebase

Firestore is a cloud based storage facility. It is provided by Google firebase. We will use the storage functionality and cloud functions provided by firebase for the development of the backend . Firebase storage can handle real time updates made by users from different clinics. The cloud functions are used to query the data in the firestore database as well as sending the stored image to the API server and receiving the result back from the API. The output is sent back to users.

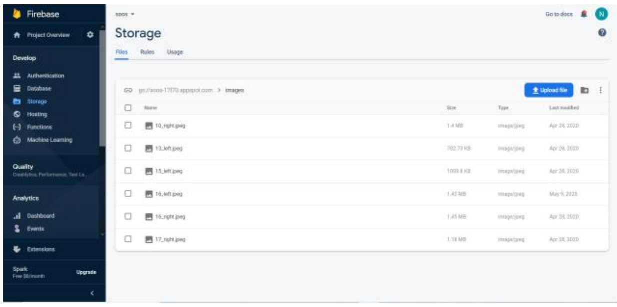

Fig. 6: Firestore

D. DR Detection API

An ML model is developed by training a Convolutional Neural Network (pre-trained model) on Diabetic Retinopathy Dataset provided by Kaggle competitions. The model is cross validated to find the best weights for the network and provide the highest accuracy using AUC curve. The model is tested and found to be working well. The model is then converted into an API and hosted on a public server so that it can be accessed by anyone from anywhere.

E. Image Processing

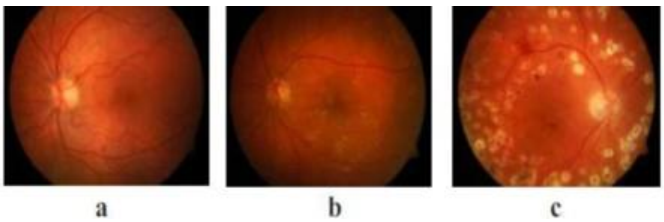

Fig. 7: Different types of DR

The image must be pre processed before training the model. This helps to ensure that all the images will be devoid of any noisy or unwanted information.

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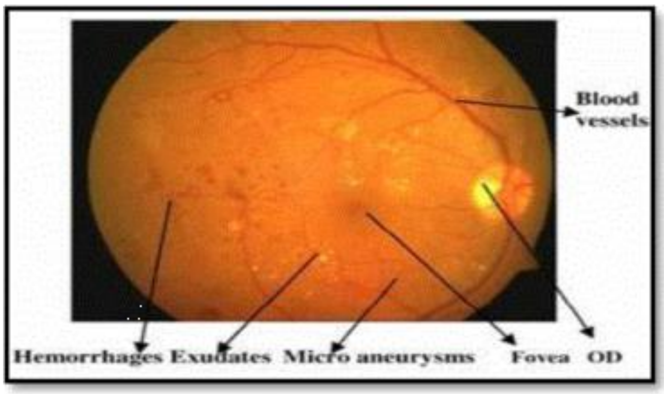

Fig 2: Diabetes Features In Defected Human Eye

F. Normalisation

Data normalization is a very important step which ensures that each input parameter (pixel, in this case) has a similar data distribution. This makes the process of convergence faster while training the network. Data normalization can be calculated by subtracting the mean from each pixel and then dividing the result by the standard deviation.

G. Feature extraction from CNN

The combination of convolutional and pooling layers help to extract features from the image. This information is used from classification.

IV. RESULTS AND DISCUSSIONS

The outcome of the project is a web application. The application can be used to know the severity of the disease (Diabetic Retinopathy) the patient has. Also, the application will classify the uploaded retinal images of the patient in one of the following groups.

No DR - Level
0 Mild DR -
Level 1
Moderate -
Level 2 Severe
- Level 3
Proliferative DR - Level 4

This will be very helpful for the clinic/doctors to identify and select potential patients from a group of eye tests which can be sent for further processing.

V. CONCLUSION

The automated software to screen and diagnose DR, by using the combination of digital image processing techniques has been developed. This software yields the good accuracy for the detection of DR from fundus photographs. It can be used as an alternative tool for DR screening, especially in the remote area where ophthalmologist is not available or in the rural area where ophthalmologist has many task overloads. However, the software yields good accuracy for classifying the severity of this disease. This study helps in the detection of retinopathy at an early stage; timely treatment of this disease will prevent permanent vision impairment. In this paper, we have discussed experiments done by authors for the detection of diabetic retinopathy. This work can be very useful for technical persons and researchers who need to use the ongoing research in this area.

VI. FUTURE WORKS

This paper have provided an insight into the research work on the detection of the diabetic retinopathy disease in the human eyes which could be detected using novel pre- processing segmentation techniques. The paper could act as a ready reckoner for those who want to pursue their research in this area.

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