Multiple eye disease detection using Deep Neural Network

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***Abstract*—India has a blind population of approximately 15 million, and the sad reality is that 75% of these cases are curable. The doctor-patient ratio in India is 1:10,000. Studies have found that Diabetic Retinopathy(DR) and Glaucoma are the leading causes of blindness in India. Diabetic retinopathy is caused mainly due to enduring diabetes in a person and is found to be the principal cause of blindness among the working-age population in developed and developing nations. Glaucoma causes damages to the optic nerve, thereby leads to blindness. Early stages of both diseases are asymptomatic, making its detection difficult, and if left untreated, this can cause irreversible damages to vision. The proposed deep neural network model helps to detect the presence of diabetic retinopathy and glaucoma at its early stages. It can alert the patients to consult an ophthalmologist on a screening standpoint. The developed model is less complicated and resulted in an accuracy of 80%.**

***Index Terms*—Diabetic Retinopathy, Glaucoma, Deep Learning, Convolution Neural Network**

I. Introduction

Diabetic retinopathy (DR) is a condition of the human eye caused due to diabetes. It is caused due to damage of blood vessels in light-sensitive tissues in the retina of the eye, which eventually leads to blindness. Based on studies, it is known that the Western Pacific Region has a higher prevalence of diabetes (152.2 million), and South East Asia has a count of 78.3 million. In India, 69.2 million people are affected by diabetes, and almost 36 million people remain undiagnosed. The number of diabetes cases is expected to rise to 109 million in 2035, which could result in an increased risk of eye diseases and blindness in the near future. Current statistics on Diabetic retinopathy points to the fact that 6 million diabetes patients in India have a sight-threatening form of retinopathy [1].

Abnormalities like microaneurysms, exudates, neovascularization, cotton wool spots, hemorrhages, or vitreous hemorrhages are commonly seen in the fundus image of suspected patients. It can also be related to other diseases, including cardiovascular risks. This particular disease is mostly asymptomatic. Highly trained medical professionals are required to detect the disease accurately, and also current diagnostic methods are time-consuming and costly. Early detection of the disease can potentially reduce the risk of vision loss. Owing to the asymptomatic nature of the disease, this is not possible. The disease has mainly four stages of severity levels namely Mild Non-Proliferative DR (NPDR), Moderate NPDR, Severe NPDR, and Proliferative DR [1] [2].

Glaucoma if left undetected and untreated can cause irreversible damage to the optic nerve. According to the world health Organization, Glaucoma is the second leading cause of blindness in the world. In India, it is estimated that the number of persons aged 40 years and older affected by glaucoma and is approximately 11.2 million. Glaucoma is of two types: Open-Angle and Angle Closure Glaucoma. It is estimated that Primary open-angle glaucoma affects 6.48 million persons. The number of people with primary angle-closure glaucoma is estimated to be 2.54 million. Those with any form of the primary angle-closure disease could comprise of approximately 27.6 million persons. Most of those with the disease are not diagnosed properly. Also, there exist major challenges in detecting and treating those with the disease. Glaucoma results in the loss of peripheral or side vision initially, which affects ones ability to move about safely. Over time, glaucoma can damage the central vision of the eye.

The manual diagnosis process of both diseases is very tedious as the ophthalmologist has to go through many tests to find the microaneurysms and other related features responsible for the disease, which can make them weary and therefore lead to misdiagnosis. Many works have been carried out in this domain. There have been studies involving the detection of both DR and Glaucoma using various classification methods using different models and methods which includes the direct identification of patterns in the fundus, but those studies resulted in lower accuracy rates. However, they can be

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automatically diagnosed using Convolution Neural Network (CNN) whose architectures commonly assume to work with bi-dimensional data (typically images) as an input of the networks. Our system is trained using the datasets received from Kaggle [3] and Medimrg [4], and after training, the system can identify the disease with higher accuracy at less amount of time. The paper aims to give an insight into the neural architecture of the proposed system which involves the use of various layers that can further extract the features thereby improving its prediction capability and hence improving the accuracy rate.

The organisation of the rest of the paper is as follows. The previously conducted study on the topic is first discussed in section II. The proposed system model is explained in section III. The simulation results were presented in section IV. Lastly, the work is concluded and some possible future researches are presented.

II. LITERATURE SURVEY

There have been related works done in the past to detect eye diseases using machine learning and deep learning.

Igi Ardiyanto et al [2] created a compact deep learning algorithm named Deep-DR-Net that is aimed at fitting on a small embedded board. By adopting the residual network on a encoder-classifier manner, they have successfully created a deep learning network which is small enough to be fitted on a small embedded system. It opens up the future possibility of establishing an integrated DR system with strong capability and better differentiation of grading the severity at a low-cost. The survey showed us that better results were obtained when deep learning was used in the detection process and so we decided to use deep learning towards the cause.

Mahendran Gandhi and Dr R Dhanasekaran [5] proposed a screening methodology,starting from image acquisition preprocessing and then mathematical morphological operations like erosion and dilations were applied on the pre-processed image to identify the exudates location. Then segmented images are fed into an SVM classifier to assess the degree of abnormality of an image as moderate or severe risk.

Karan Bhatia et.al. [6] gave a brief insight into how a system works with machine learning. This paper focuses on various machine learning classifiers such as Logistic Regression, Neural Network and SVM. The work focuses on decision about the presence of disease by applying ensemble of machine learning classifying algorithms on features extracted from output of different retinal image processing algorithms, like diameter of optic disk, lesion specific (microaneurysms, exudates), image level (pre-screening, AM/FM, quality assessment). Decision making for predicting the presence of diabetic retinopathy was performed using alternating decision tree, adaBoost, Naive Bayes, Random Forest and SVM. The one that showed more accurate results were used to identify DR and non-DR categories.

Darshit Doshi et al [7] suggested the design and implementation of GPU accelerated Deep convolution neural networks which can automatically diagnose and classify the retinal Images into 5 stages of severity. The research in diagnosing diabetic retinopathy has been based on explicit extraction of features like microaneurysms and lesions through which the classification is performed. The work was implemented using image ImageMagick and python library, OpenCV. The results were evaluated using a quadraticweighted kappa matric. The kappa matric varies from 0 to 1. The accuracy obtained was 38.6

A. Alaimahal, Dr S Vasuki [8] proposed work which concentrates on microaneurysm detection from a patients digital image. This will help ophthalmologists to detect symptoms faster without any doubt. Sensitivity and predictive value was proposed to be 98.89% and 89.70% respectively. Their proposed algorithms could detect microaneurysms from very poor-quality images.

Baida Al Bander et al [9] neural network (CNN) is developed to distinguish between normal and glaucomatous patterns for diagnostic decisions. Unlike traditional methods where the optic disc features are handcrafted, the features are extracted automatically from the raw images by CNN and fed to the SVM classifier to classify the images into normal or abnormal.

Guangzhou An et al [10] used a hybrid feature extraction process which involves the use of classifiers like SVM Naive Bayes, Neural Network, Gradient Boosted Decision tree(GBDT). 91 parameters were identified from the eye image and then and a hybrid feature selection method that combines minimum redundancy maximum relevance and genetic-algorithm-based feature selection was applied to find the most valid and relevant features for NN, NB, and SVM. A comparison of all the outputs showed that NB method gave maximum accuracy with 87.8

Our contributions include:

- The system will produce accurate results which is achieved by using less complex a 5-layer network. But more accuracy can be obtained by adding dropout layers and dense layers along with the conv2D layers. These layers improve the system capability of reducing over fitting and improving its feature extraction property respectively.
- The result can be used as a referral trigger i.e. it enables the user to know if there is a need to consult a doctor at a screening stand point.
- A user friendly web page was developed to enable the user to test with live image samples and to get instant results with the occurrence confidence level.

III. PROPOSED SYSTEM MODEL

The detection of eye disease is carried out in 2 phases. Phase 1 includes the training phase and the testing phase, and Phase 2 contains the development of GUI for real-time detection. The dataset for DR was procured from Kaggle, and the datasets for Glaucoma was procured from Medimrg.

A. Phase One: Training and Testing of Model

This phase involves the training and testing of the model using the acquired datasets. The datasets were divided into training and testing set in the ratio 8:2. Training set consists

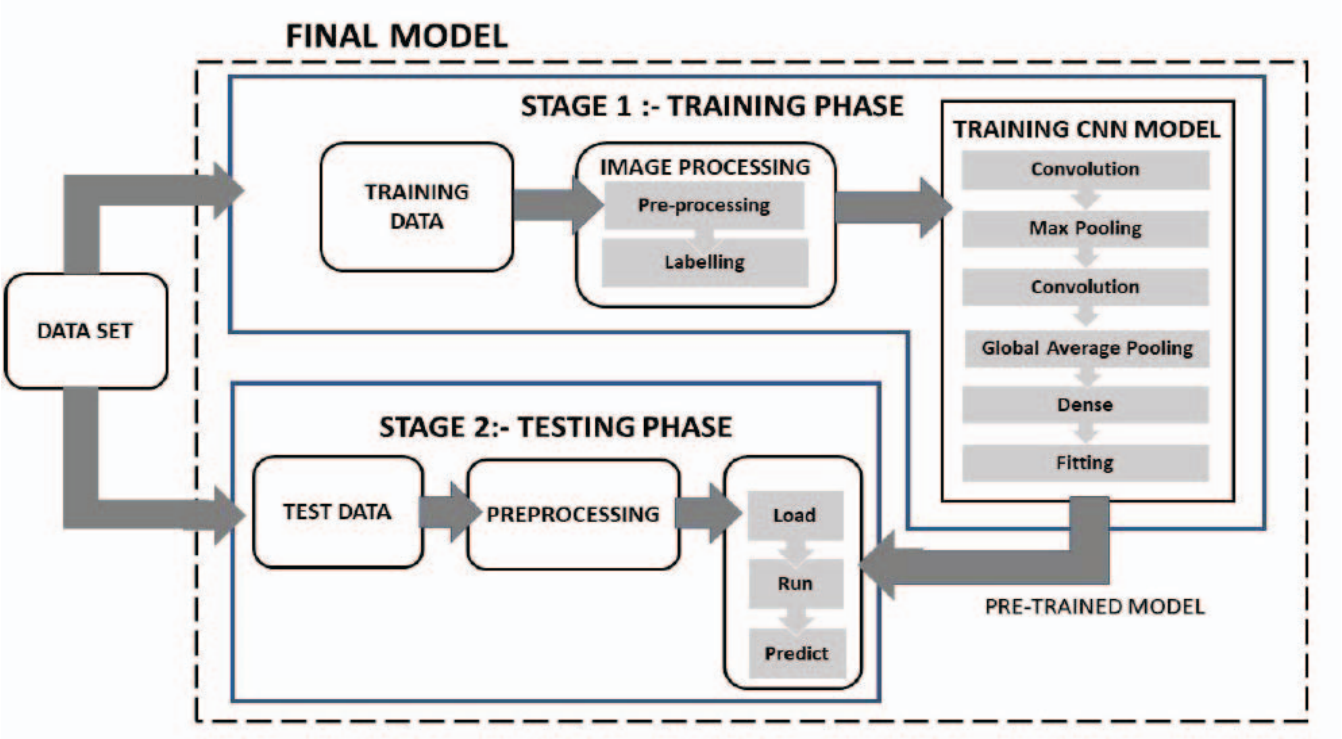


Fig. 1: Phase 1: Training and testing phase

of labeled images were label '0' indicates a healthy eye, and '1' indicates an affected eye. Each image in the dataset was preprocessed, which includes operations like rescaling. The operations involved in this phase is illustrated in figure 1.

1) Training the model: The preprocessed images from the training set were fed into the proposed deep convolutional neural network. Features were extracted from the image through a series of convolution, pooling, ReLU layers. These layers are collectively called Hidden layers which provide a high level of abstraction to the input. The number of layers determines the feature extraction capability of the network. The proposed neural network has 5 hidden layers. As the image passes through these layers, the features are extracted one by one and pass onto the next layer. The initial size of the image is 512x512, which is convoluted, max pooled, and then it is again convoluted, and then the average pooling is done. Then there are 2 dense layers at the end. The dense layers act like a fully connected layer that classifies the images into the diseased and healthy category.

2) Neural network Architecture: Convolutional Neural Networks (CNN) represents a biologically-inspired variant of feed-forward networks, where the connectivity between neurons tend to capture the invariance of patterns to distortion or shift in the input data. Three main types of layers are used: Convolutional Layers, Pooling Layers, and Dense Layer.

- Convolutional Layers: A convolutional layer is produced by a higher-level abstraction of the input data which is, in turn, called a feature map. Units in a convolutional layer are arranged in a feature map, within which each unit is further connected to local regions in the feature maps of the previous layer and represent a convolution of the input. Each neuron represents a receptive field, which receives as input a rectangular section (a filter) of the previous layer and produces an output according to the stimuli received from this filter. Each of these convolutional neuron processes data only for its receptive field.

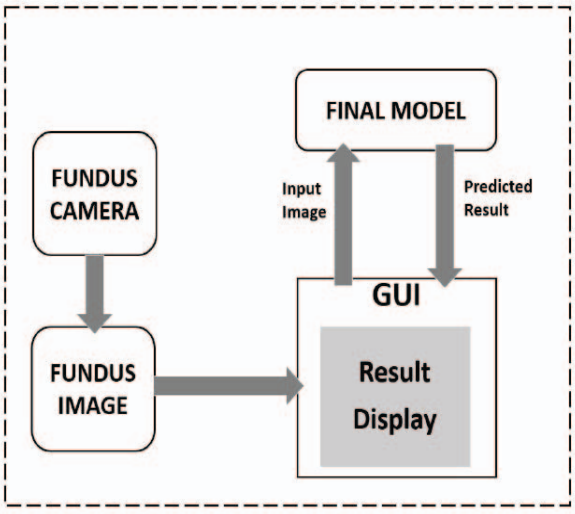


Fig. 2: Phase 2: Real time testing of final model by enabling GUI

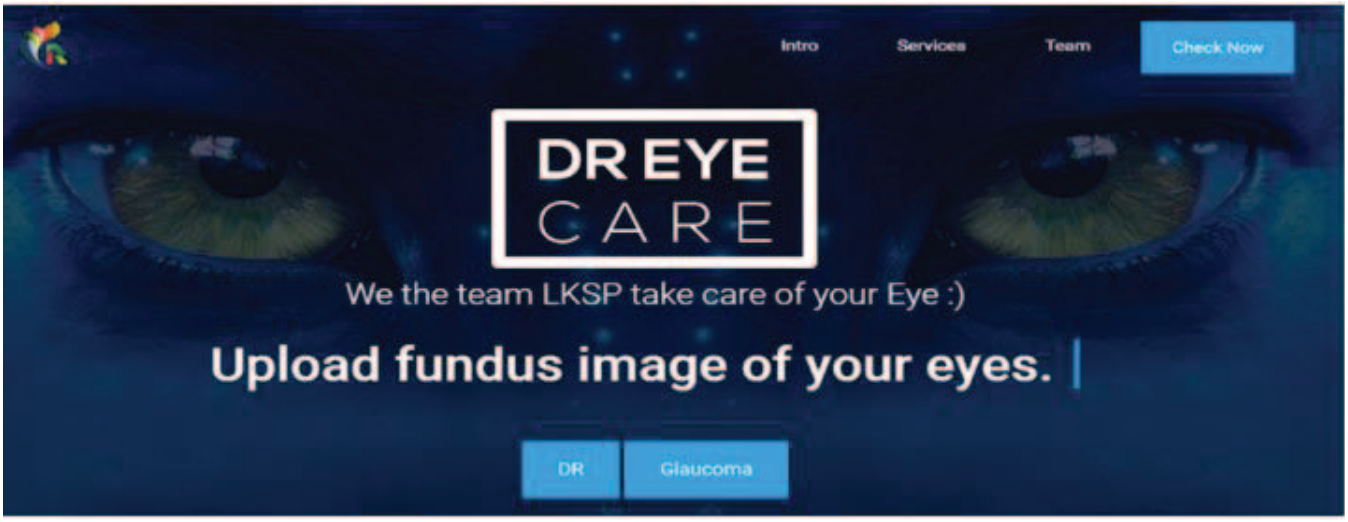


Fig. 3: Webpage

It is not practical to apply this architecture to an image, although fully connected feed-forward neural networks can be used to learn features as well as classify data. The convolution layer is used to carry out convolution on the input fundus image with the use of filter or kernel to produce a feature map.

- Pooling layer: Pooling layers merge similar features, i.e., it sub-samples the input layer, which is done to progressively reduce the spatial size of the representation and also the number of parameters and computation in the network. In the image processing domain, pooling does not affect the number of filters, and it reduces of resolution of the image, which decreases complexity. Max-pooling is one of the most common types of pooling methods. It partitions the image first into sub-region rectangles and then returns the maximum value of the inside of that particular sub-region. Pooling can be used with non-equal filters and strides to improve the efficiency of the network.
- Dense Layer: The dense layer is a linear operation in which the input is connected to every output by weight. It is responsible for classifying the features extracted by the convolution layer and downsampled by the pooling layer. It takes the number of neurons and activation function as arguments.

  In our proposed model the first layer which is the conv2d layer of size 62x62x32 i.e., this layer hold the raw pixel values of the image, in this case, an image of width 62, height 62, and with 32 color channels R, G, B. Then we have a Max pooling layer which has an image size of 31x31 with a 32 channel RGB image. Again, we have a conv2d layer of image size 29x29, 64 channel RGB image. Global average pooling layer is used to reduce overfitting by minimizing the number of parameters in the model. A dense layer is a fully connected layer in which each input node is connected to each output node as the number of layers increases the number of features that can be extracted from the fundus images also increases, which further improves the system accuracy.

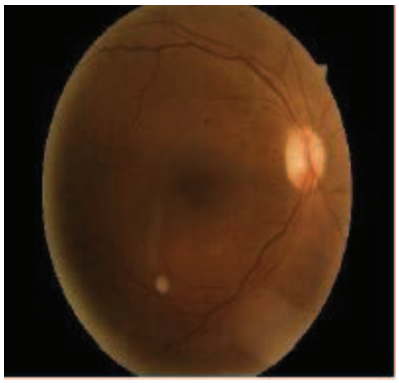
3) Testing the model: The testing phase of the model includes inputting the test data preprocessing it and running the system model. The test image goes through every layer, searching for the presence of possible features of disease affection. If found, with the acquired knowledge from the training phase, the system give an output stating the presence of DR or Glaucoma. If not then the system give an output stating No Issues detected .

B. Phase two: Real Time Implementation With GUI

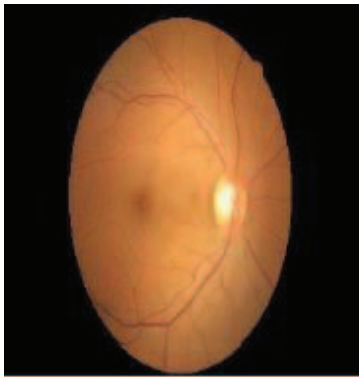
The GUI implementation presents the model in front of a common man in a much appealing way. GUI includes the development of a user-friendly website that enables the live uploading of fundus image captured using a fundus camera. This image uploading goes into the model in which it first undergoes preprocessing. Then the image goes into the CNN architecture. The system, with its acquired knowledge during the training phase, gives out the result. This result is passed on to the GUI, were displayed on the screen with the corresponding confidence percentage. This percentage indicates the system's confidence in claiming the presence or absence of disease. Figure 2 shows the process flow in phase two.

TThe development of the neural network model and GUI was done using various software. Anaconda (open source) which comes with python is used with TensorFlow and Keras for building the neural network, training, and testing. The development of GUI was done using Django, a Python-based free and open-source web framework. HTML5 was used to create the webpage, which is a software solution stack that defines the properties and behaviors of web page content by implementing a markup-based pattern to it.

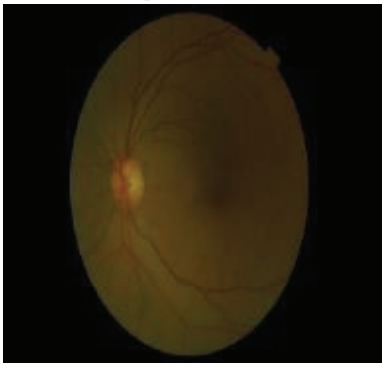
The figure 3 shows the Home HTML page where user can choose either Glaucoma or Diabetic retinopathy for the testing.



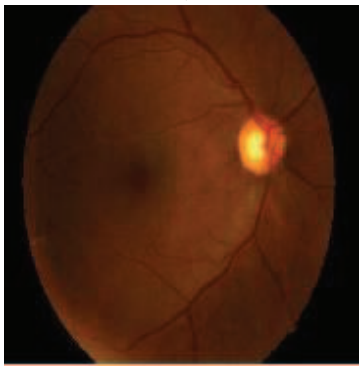
(a) Actual: DR present, Predicted:72.45%



(b) Actual: DR Absent, Predicted:No issues

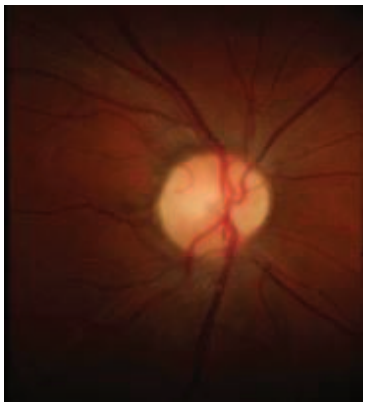


(c) Actual:DR present, Predicted:58.32%

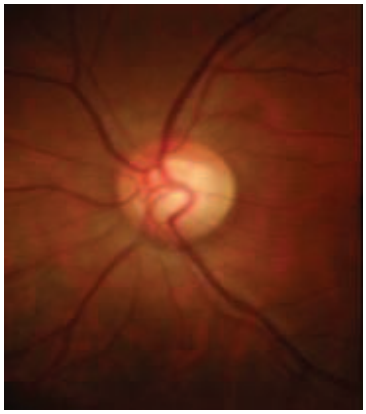


(d) Actual:DR present, Predicted:59.97%

Fig. 4: Result of test set image of diabetic retinopathy



(a) Actual: Glaucoma present, Predicted:76.44%



(b) Actual: Glaucoma present, Predicted:59.56%

Fig. 5: Result of test set image of Glaucoma

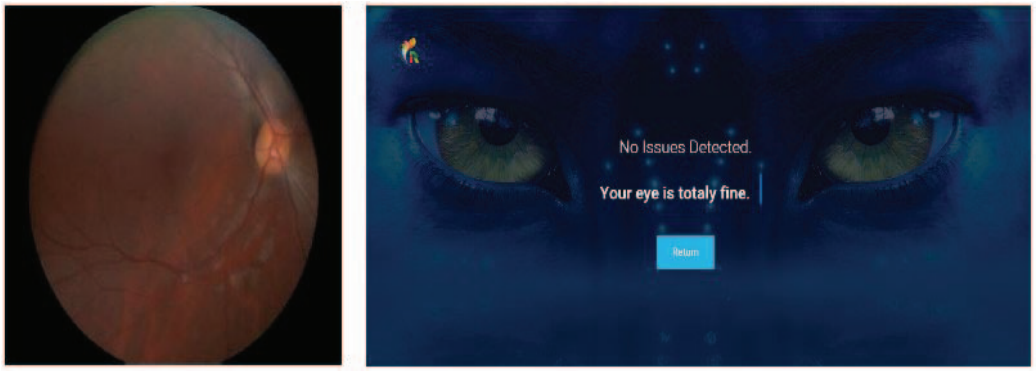
Input to this page is a fundus image that is preprocessed to the requirement of the model. It uses the model that is generated after training of the image datasets to output its prediction. There will is an individual model for DR and Glaucoma that is trained separately. The model is loaded automatically according to user selection. The predicted output will be either Not affected or Affected with a confidence percentage of xx and if any of the diseases are found, the patient is alerted to consult a doctor.

IV. Results

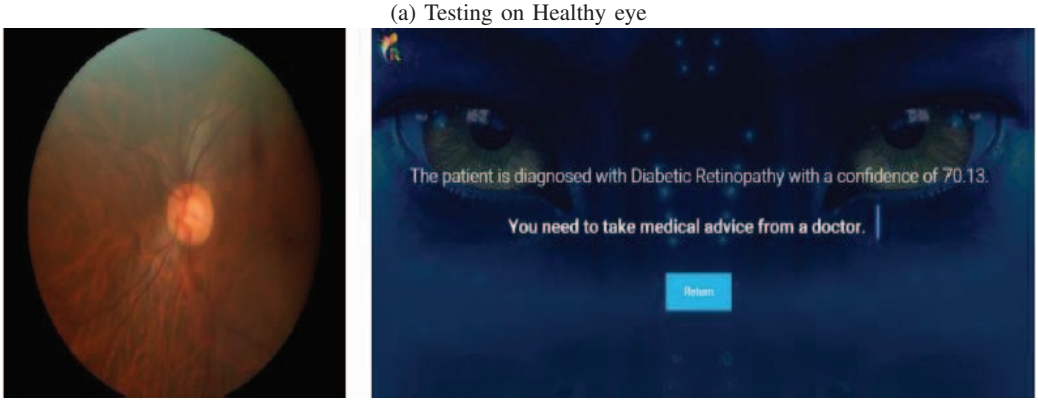
A. Results with test images of datasets

The system was tested by inputting both the test set images as well as the images taken live for both the diseases Diabetic Retinopathy and Glaucoma respectively. In both cases, the output is shown in the form of confidence percentage.

The results obtained for test images, in the case of DR is shown in figure 4. Figures 4a, 4c and 4d shows fundus images of eyes affected by various levels of DR. The predicted



(a) Testing on Healthy eye



(b) Testing on DR affected eye

Fig. 6: Display of real time results on webpage

result gives a confidence percentage of 72.45, 58.32 and 59.97 respectively which confirms the actual result.Figure 4b shows a healthy eye and the obtained result was also the same.

Figure 5 shows the fundus images of eyes affected by glaucoma at different severity levels. The corresponding predicted results also confirms it.

B. Results with live samples

Real-time detection of eyes was done by acquiring the image through a fundus camera and tested it on the pre-trained model. The results were displayed through the webpage. Figure 6 shows few examples.

V. Conclusion

The proposed system can be used for early detection of Diabetic Retinopathy and Glaucoma. This system primarily acts as a referral trigger, which advises the patient to consult a retinal expert upon positive detection. The less complicated pre-trained model is tested using a test set and real-time images. The accuracy obtained was 80%. This accuracy can be further improved by performing parameter tuning and adopting methods like cross-validation. The system has also incorporated a user-friendly and user interpretable form of GUI.

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