Automated Multiple Eye Disease Detection via EfficientNet Model using Transfer Learning

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***Abstract*—Diabetic retinopathy, glaucoma and cataracts are some of the most widespread eye related diseases that bring about a serious problem in medical science in terms of public health on the globe. One of the keys to avoid permanent vision damage is to perform the diagnosis and interventions at an earlier stage. This study is targeted on an efficient deep learning algorithm for detection of eye diseases shown in fundus images. The EfficientNet model, a state-of-the-art CNN-based model known for efficiency and performance in image classification tasks, was utilized. An accuracy greater than 95% was achieved by the deep learning model used for eye disease detection, surpassing previous works in this field. Thus, a fast, accurate, and user-friendly solution for diagnosing eye disorders is provided by the system using deep learning algorithms, assisting patients in seeking consultation with an ophthalmologist for screening purposes.**

***Index Terms*—eye diseases, deep learning, cataract, glaucoma, diabetic retinopathy, transfer learning, efficientNet**

I. Introduction

The eye serves as a crucial organ within the human body. For individuals lacking eyesight, survival becomes exceedingly challenging. According to the World Health Organisation(WHO), almost 2.3 Billion people have vision loss or eye diseases, from this almost 1 Billion people have impaired eyesight that can be cured with the help of technology. In numerous underdeveloped regions, particularly rural areas, the scarcity of adequate treatment and ophthalmologists poses significant challenges in effectively treating eye diseases. Eye diseases can indeed be identified through the examination of retinal fundus images. Hence, a system capable of detecting eye diseases in their early stages has been developed. Early detection of eye diseases benefits both patients and doctors, facilitating easier treatment and management.

In this paper, 4 eye disease classes are primarily addressed - Cataract, Diabetic Retinopathy, Glaucoma, and Normal Eye. Fig. 1 shows all the different eye diseases. Cataracts mostly happen due to aging but may also happen from eye surgery or radiation exposure. Most cataracts develop slowly but with time cataracts can affect vision. Another disease is Diabetic Retinopathy that happens because of diabetes. According to recent data on Diabetic Retinopathy, approximately 6 million individuals with diabetes in India are affected by a severe form of Retinopathy that poses a threat to their vision. Glaucoma is a serious eye condition that damages the optic nerve and leads to vision loss. The threatening part is that Glaucoma symptoms are hidden. That's why it is crucial to get regular eye check-ups, even if you seem fine. According to the WHO, glaucoma ranks as the second most prevalent cause of blindness globally.

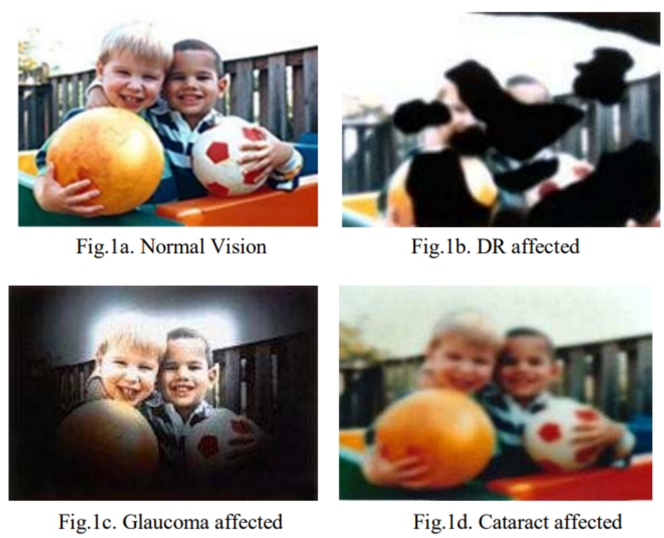

Fig.1a. Normal Vision
Fig.1b. DR affected
Fig.1c. Glaucoma affected
Fig.1d. Cataract affected

Fig. 1. Different Eye Diseases

The focus is on four major ocular diseases classification. Firstly, images were obtained from the Kaggle dataset. Then, deep neural network models were trained and the accuracy of each model was tested to identify the most optimal one.

Subsequently, a graphical user interface was developed where images could be uploaded and the accuracy of potential eye diseases in those images could be obtained.

II. Literature Review

Several research studies have explored the application of convolutional network techniques in segregating fundus images of the eye, focusing on the significant advancements in detecting eye diseases, facilitated by technologies like Convolutional Neural Networks (CNN). These studies have particularly emphasized labeling various eye conditions, aiming to enhance the accuracy of eye diagnosis and improve management strategies.

In paper[1], Dr R Dhanasekaran and Mahendran Gandhi suggested a disguise methodology, starting from capturing image, preprocessing and then different structural mathematical operations like dilations and erosion were implemented on the pre-processed image. Identification of exudates location was done using this process. To identify the image degree abnormality is normal or high risk, the segmented images were given into a SVM classifier. In paper[2], various mathematical activities are used by researchers to get pixel values of images. Various instances of network are integrated for the training, thus avoiding rule based classic techniques for programming. In paper[3], microaneurysm detection from digital eye image of patients was proposed by Dr S Vasuki and A. Alaimahal. Ophthalmologists could precisely detect symptoms in less time. Predictive value and sensitivity of the model was given 98.89%. Using the ResNet50 model in paper[4], Rafi and Farzia aimed to classify fundus images of eye diseases. Initially achieving 51 percent accuracy, significant improvement was made through modifications and fine-tuning. The updated model achieved an impressive 95 percent accuracy on testing datasets. Preprocessing techniques like horizontal and vertical flips, and rotation range contributed to enhanced performance. In paper[5], the focus was on the grouping of macular retinal diagnostics using OCT images of retina and the MobileNet and EfficientNet CNN architecture. Training accuracy obtained was 95.67%, with validation accuracy at 92.04%. The researchers gave a timely and efficient detection technique for pathology classification in different categories including drusen, Diabetic Macular Edema (DME), Choroidal Neovascularization (CNV), and normal conditions.

Overall, all the studies exhibited the value of sophisticated technologies and deep neural network based models in accomplishing better efficiency, increased accuracy, and high speed optical disorder detection. Diagnostic abilities of healthcare professionals can be improved using deep neural networks and artificial intelligence, helping in early disease assessment and customized healthcare solutions, thus enhancing patient results in the ophthalmology field.

III. Proposed System

In this system, eye disease detection is done using deep neural networks. Three layers are generally used - Convolution Layer, Pooling layer and fully linked layer. DNN requires extensive datasets to get high accuracy in its prediction. Transfer learning is used to get better weights for the model using computationally less resources. In this, a pre-trained model is utilized, and various different layers are added according to the requirement to enhance the accuracy of the model. Thus, this model classifies any fundus image into one of four classes. This whole model is demonstrated using a human-friendly graphical interface. It classifies the image into the above 4 categories along with confidence percentage for that disease. The graphical representation of the complete flow of the process is shown in Fig. 2. Hence, early stage detection of critical eye diseases can be easily done. The model had an increase in accuracy compared to other models, surpassing 95%.

IV. Materials and Methodology

Eye disease detection is done in 2 stages. First stage includes training and testing of the model. Second stage is the development of a graphical user interface for real-time disease detection.

A. Training and testing of Model

The organization and saving of image datasets on disk for training and testing deep learning models must be done in conformity with the accepted protocols, which can also help to achieve better loading times. This may be achieved using tools such as an Image Data Generator in the Keras package used in deep learning that helps to upload images automatically into separate train, test, and validation sets after formatting. In this way, it ensures efficient dataset photos are incrementally loaded onto memory so that even large-scale image datasets running into hundreds of millions could be processed by any system whose size would otherwise hinder its loading at once.

1) Dataset: The dataset comprises four classes: diabetic retinopathy, glaucoma, cataract, and normal eye, sourced from various contributors on Kaggle. Source [17] dataset is utilized, containing the above four classes, but encountering technical issues in the Glaucoma dataset. Hence, data for this disease is gathered from different available datasets. Similar observations are noted in other research papers, as cited in reference [13]. Consequently, the final total number of images amounts to 3721, encompassing eye diseases and normal eye images with a specified distribution.Data is partitioned in ratio of 80-10-10 for the following three processes:

   a) Training Dataset: It is the fundamental data which is used for training the model. Maximum percentage of the overall dataset is used for training purposes. The content of supervised learning is an output variable for one or multiple input variables.

   b) Validation Dataset: A small percentage of dataset is used for validation purposes in DNN models. Once the model is trained and the model is ready for prediction, validation data is used to evaluate the model performance on unfamiliar data. Thus, cross-validation

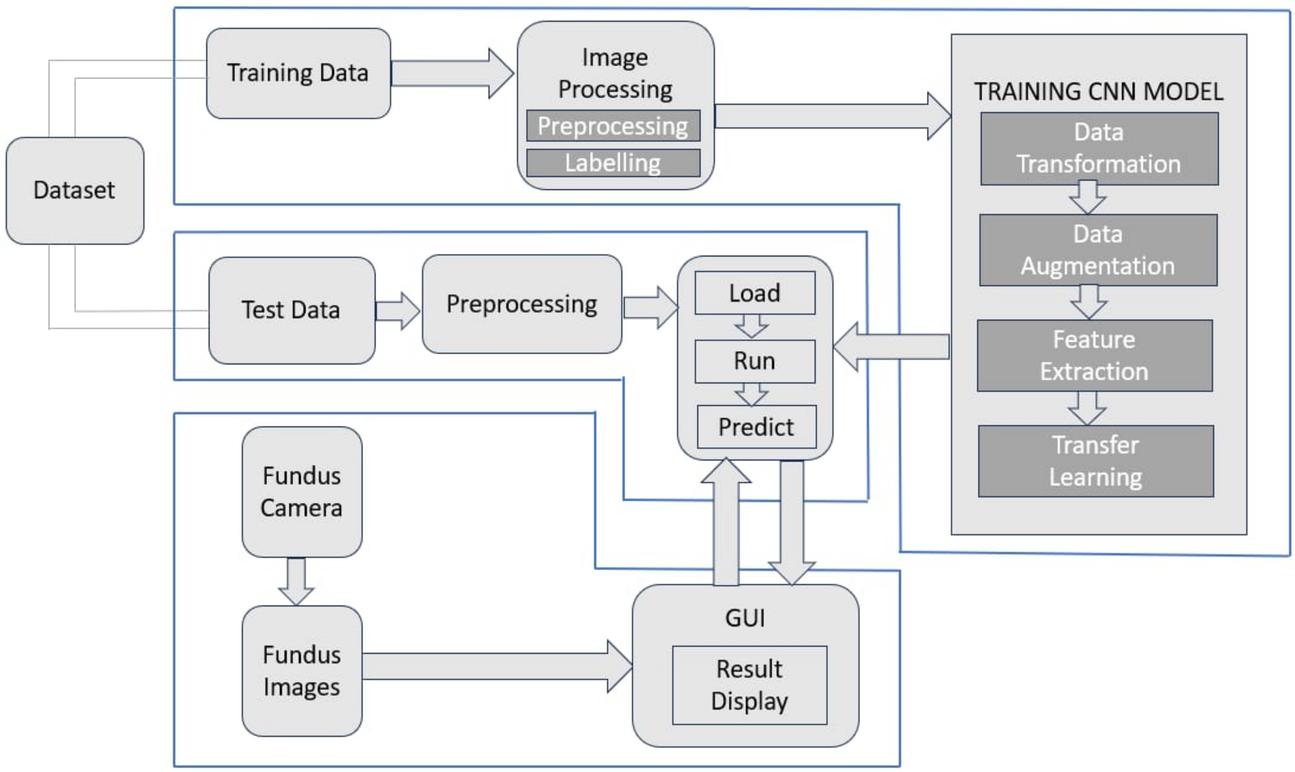

Fig. 2. Proposed Model Workflow

is performed to check the accuracy of the model on unseen data.

c) Test Dataset: The test dataset has a similar distribution to the validation dataset and is utilized for final model testing. Overfitting occurs when the training accuracy significantly exceeds the testing accuracy, indicating inaccuracy for new data. Therefore, the model is trained to improve test accuracy.

2) Methodology:
The technique used in this neural network has a precise approach for image processing and the model development. The images preprocessed from the training dataset are given to the proposed deep convolutional network model. A sequence of multiple convolution, pooling, and Rectified Linear Unit (ReLU) layers are present in this model, through which features are extracted from the images. These layers form the hidden layers, which helps in abstracting high-level features from input data. The depth of the neural network affects the training process and thus influences the feature extraction. Transfer learning techniques have been utilized to effectively increase the accuracy of the model while keeping the computational resources minimal.
The main objective of this paper is to automate multi-class eye disease detection and evaluate the outcome based on various outcomes. Transfer learning with EfficientNetB3 as the base model was employed to enhance the accuracy. Additionally, the accuracy of the model was compared with various other predefined models, including MobileNet V3 and ResNet. MobileNetV3 is an evolution from MobileNetV1 & MobileNetV2, and is particularly useful for small mobile computing devices having compact parameters and minimal latency. MobileNetV3 further used the Squeeze-and-Excitation module to further improve feature extraction and classification accuracy. ResNet is a deep CNN architecture that solves the problem of vanishing gradient using skip connections. It uses its feature of residual blocks through which it learns residual functions and trains its network. An input image of 300x300 with 3 channels is utilized in the proposed transfer learning model. EfficientNetB3 is the base model on which further layers are augmented. The base model comprises a combination of convolutional, fully connected and pooling layers. Convolutional maps are generated by convolutional layers by convolving with input pixels and ReLU activation function is utilized to generate feature maps. Diverse pooling layers, each having distinct filters, are used to identify specific features and image components. The output from tha base model is passed through various dense and dropout layers. Finally, the input image is categorized among 4 classes for disease classification.
Different regularization techniques, including L2 kernel regularization and L1 activity and bias regularization

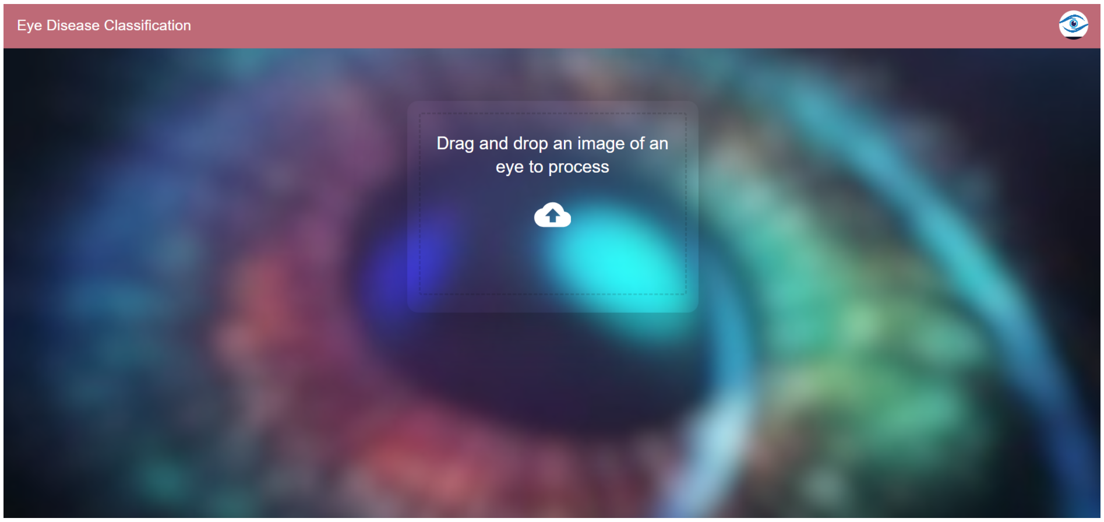

Fig. 3. GUI Home Page

are used into the dense layer to overcome overfitting and increase the generalization capability of the model. Dropout layers with a rate of 0.45 were also incorporated to further prevent overfitting by randomly dropping out some layers during the training process. Adam optimizer is used with a standard learning rate of 0.001 for model training. Model is further optimized using categorical cross-entropy loss function to compute the difference between predicted and actual class distributions.

In this phase, several critical parameters were determined to fine-tune the training process of a deep-learning model. The number of samples processed per iteration was regulated by using a batch size of 40 during training. Such a value affects the speed and accuracy of the training operation. By conducting the training for 30 epochs, which is the complete number of passes over the whole training dataset, the model parameters were optimized iteratively. Furthermore, a patience value of 1 was allotted, implying the number of epochs to be patient for the improvement in monitored outputs before trying to revise the learning rate. For cases in which monitored statistics do not record progress for 3 epochs, training is over to keep the model from overfitting and increasing the stop_patience value. In addition, a threshold of 0.9 was defined in order to dynamically change training by monitoring metrics dependent on the performance of the model. If the training accuracy falls below this point, the monitoring is conducted based on accuracy; otherwise, it is based on validation loss. The learning rate is reduced by 0.5 factor after reaching the patience threshold. Furthermore, training is managed through an inquiry function every 5 epochs which is designated by ask_epoch value.

However, together they do improve the training process and the model's performance. The training process of the model was properly maintained and learning rate was regularly updated at different stages by developing a custom callback function called MyCallback, which was integrated into the pipeline. This callback function keeps track of various model parameters including patience, stop_patience, threshold, factor, batches, epochs, and ask_epoch, thus making the training process much more accurate as well as time and cost efficient.

During the process, the model transforms its weights having various tasks like image transformation, augmentation, feature extraction, and transfer learning to facilitate accurate eye disease classification. Performance evaluation is done based on various parameters including accuracy, precision, recall and F1-score as shown below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

B. Real Time Implementation With GUI

A user-friendly Graphical User Interface (GUI) has been implemented for users to easily access the model without encountering any technical issues. Various development tools were utilized to make the GUI interface. FastAPI, which is known for its modern, high-performance capabilities, served as backbone for building APIs with python, alongside using TensorFlow and Keras for neural network construction, training, and testing. React was used on the frontend side, which is a javascript library for creating dynamic user interfaces and enhanced user engagement. HTML5, which is a modern web framework, was used in creating the web page interface. Fig. 3

shows a visual representation of the Home page, where users can upload images for disease prediction.

The input to this page are fundus images, captured by fundus camera, which can be seamlessly uploaded on the website. Upon upload, the images undergo pre-processing before being fed into the DNN model. Using this trained model, the system generates predictions, which are then passed on to GUI. The detected disease is displayed on the screen along with the confidence percentage corresponding to the particular disease.

	Precision	Recall	F1_score	Support
Cataract	0.96	0.98	0.97	104
Diabetic Retinopathy	0.99	1	1	110
Glaucoma	0.97	0.9	0.93	106
Normal Eye	0.89	0.94	0.91	108

Tab. 1. Performance Metrics

V. RESULTS

The product underwent evaluation by testing it with both images from the test dataset and those uploaded in real-time for the applicable diseases. In all cases, the output disease is predicted along with the confidence percentage. A sample output is shown for all the four outcomes in Fig. 5 & 6. The training of the model automatically halts when there is no significant improvement in the accuracy and loss curves, based on a callback algorithm. Thus the training process stopped after 15 epochs and achieved test accuracy of 95.3%. Performance analysis parameters are shown in Tab. 1. Training and test accuracies are shown in Fig. 4. Training and validation loss and accuracy curves are shown in Fig. 7. Fig. 8 represents the confusion matrix.

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107/107 [==============================] - 312s 3s/step - loss: 0.1385 - accuracy: 0.9988
107/107 [==============================] - 39s 321ms/step - loss: 0.3264 - accuracy: 0.9391
107/107 [==============================] - 38s 354ms/step - loss: 0.2947 - accuracy: 0.9533
Train Loss:  0.13851530849933624
Train Accuracy:  0.9988290667533875
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Validation Loss:  0.326372891664505
Validation Accuracy:  0.9391100406646729
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Test Loss:  0.29473981261253357
Test Accuracy:  0.9532710313796997
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Fig. 4. Training and Test Accuracies

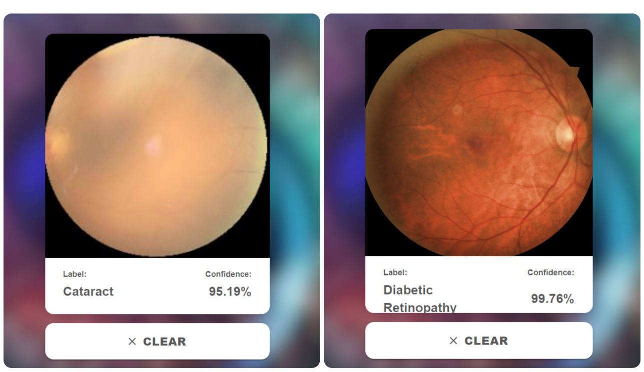

Fig. 5. GUI showing Cataract & Diabetic Retinopathy Detection

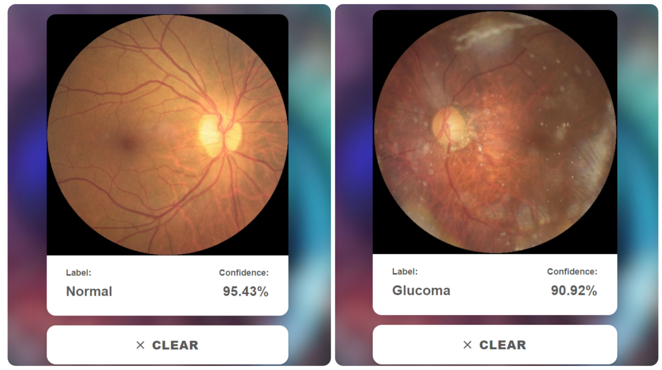

Fig. 6. GUI showing Glaucoma & Normal Eye

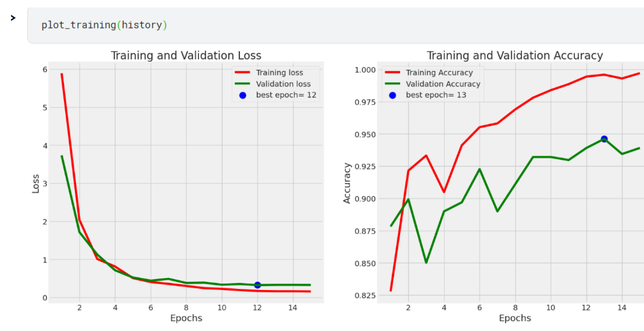

Fig. 7. Training & Validation - Loss & Accuracy Curves

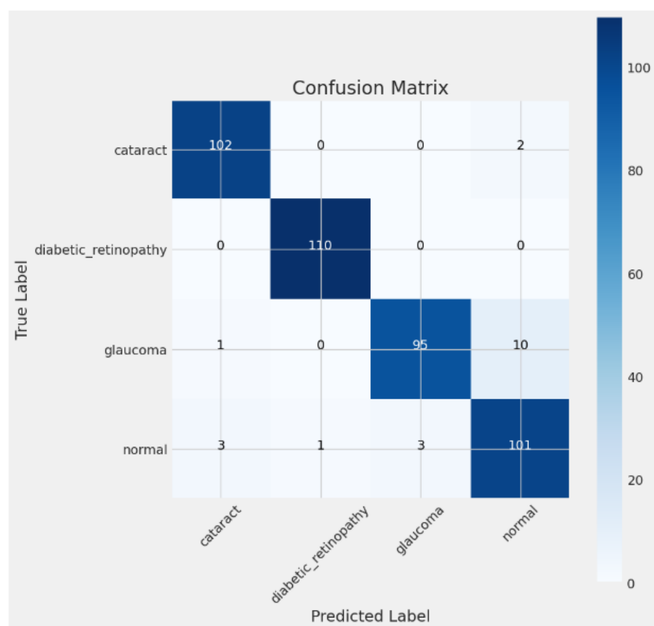

Fig. 8. Confusion Matrix

VI. Conclusion

The proposed model is utilized to effectively categorize eye images into classes such as cataract, glaucoma, diabetic retinopathy, or normal eye. This is a time saving and cost optimal alternative for early stage eye disease detection. The model used for detection has a good accuracy, greater than 95%. This technique basically acts as a referral trigger, giving the patients appropriate information about the seriousness of the disease and if they should visit a retinal doctor. The pre-trained model was evaluated with a test set and also real-time eye fundus images. The accuracy can be further improved by doing parameter tuning. The system also has a user-friendly graphical user interface for ease of the patients to predict their accurate results.

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