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Automated Detection of Eye Disease using Transfer Learning

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Abstract—*The eye is an extremely effective organ for humans. The primary aim of the eye is to collect information from the environment, which is then transmitted to the brain so that humans can identify their environment. Thus, eye blindness is a very serious issue today. Many eye illnesses currently cause blindness. People constantly have cataracts, trachoma, and conjunctivitis. Detection and treatment during an early stage can prevent young blindness through early identification. The CNN model, which is part of deep learning, is utilized in this experiment. VGG-16 and Inception-V3 are the transfer learning algorithms used. Using 653 datasets collected from a variety of sources, the fine-tuned model demonstrates a remarkable 98% accuracy with VGG-16. However, transfer learning yields an accuracy of 88%. The best fine-tuning evaluation results were obtained by the VGG16 model with 98% precision, 98% recall, and 98% F1-Score. The best VGG-16 results were achieved on a desktop environment to improve disease diagnosis using Flask.*

Keywords: *Transfer Learning, VGG16, Inception-V3, Flask, Image Processing.*

INTRODUCTION

Based on data from the Vision Atlas, in 2020, there will be 1.1 billion people who have lost their sight around the world. There are 90 children and adolescents and 2.1 million blind people in the world. This number will increase with the projection that there will be 1.76 billion blind people in 2050, of which an estimated 40 percent will be children and adolescents. Early detection and treatment can prevent the loss of vision [3][14][17]. By utilizing early detection, it will be possible to reduce children blindness [16].

Currently, several people live in urban and semi-urban areas, so they face problems in self-detection because of the lack of metropolitan ophthalmologists [13]. Among the many eye diseases are cataract, trachoma, and conjunctivitis. There are numerous techniques for detecting eye diseases, such as deep learning and image processing [18].

This paper addresses the use of transfer learning, a deep learning subfield, to detect eye diseases. There are two models, VGG-16 and Inception-V3, that are used to classify eye diseases with high accuracy. The results of the two models are compared to find out several evaluation parameters, namely accuracy, precision, recall, and F1-score.

RELATED WORK

Xiangyu Chen *et al.* [18] proposed an algorithm that utilizes a deep convolutional neural network to detect glaucoma. Normalization layers and overlapping-pooling layers are used to minimize overfitting. Had used dropout and data augmentation, to raise the accuracy program.

To identify cataracts, Linglin Zhanga *et al.* [11] proposed a Deep Convolutional Neural Network algorithm and a grading task. The G-Filter improves the accuracy of the system for detecting cataracts. The accuracy of the detection task is 93.52% compared to the accuracy of the grading task, which is 86.69%.

Suresh Limkar *et al.* [3] proposed using Python's OpenCV library and Region of Interest (ROI) feature. The proposed system for recognizing eye diseases includes retinal diseases such as CNV, DME, and Drusen, as well as cataracts and glaucoma. All types of eye diseases can be predicted with a 95% accuracy rate using the proposed models.

Ayesha Kazi *et al.* [6] proposed a system that implements the Keras and TensorFlow development tools. The classification of retinal diseases utilizes three convolutional layers. This system's average accuracy is 90.69 percent.

Arun Govindaiah *et al.* [2] proposed a system that employs the algorithm of a Deep Convolutional Neural Network. This system detects age-related macular degeneration (AMD). Age-Related Eye Disease Study (AREDS) dataset containing 150,000 images is used. VGG-16 is the algorithm used, and its accuracy is 92.5%.

Amit Asish Bhadra *et al.* [1] proposed a system to detect cataracts using the average grayscale value (AGV) method and conjunctivitis using the average red mean. As a tool for image processing, the OpenCV library and RGB color space are utilized. The accuracy of the experiments was 92% for cataracts and 83% for conjunctivitis.

Mrunalini Manchalwar *et al.* [13] proposed applying HOG to diagnose eye disease through detecting pupils and processing sclera portions. This algorithm is used to treat chalazion, styles, and subconjunctival hemorrhage.

RESEARCH METHODOLOGY

This experiment consists of two stages: the proposal of a transfer learning model and the flask-based testing of the model in real-time. The proposed model employs the VGG-16 and Inception-V3 algorithms. Figure 1 shows the flowchart for the proposed model employing transfer learning. Figure 2 shows testing the model in real-time using Flask. Adam and the RMS Prop Optimizer were used to establish the model with a learning rate of 0.0001. The use of Adam Optimizer and RMSProp is intended to reduce the error rate model. To produce a model with a small error.

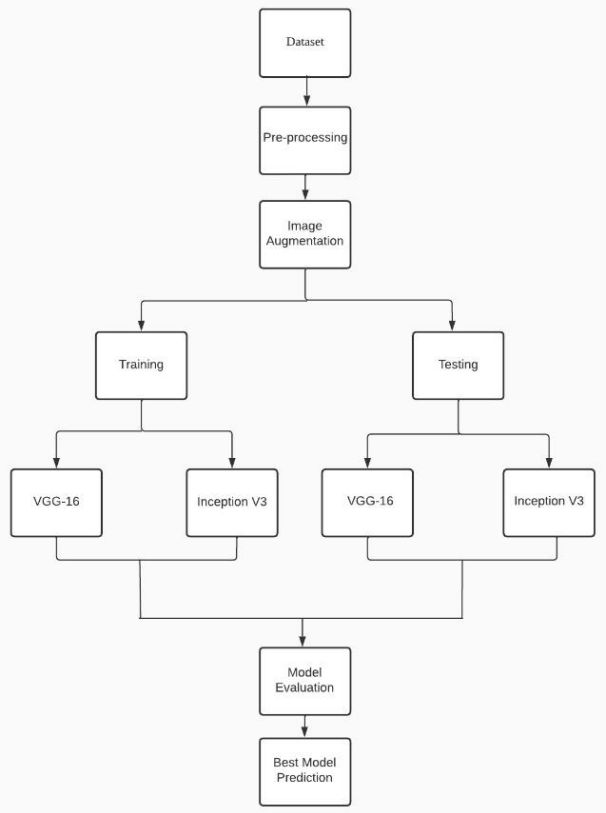

Figure 1: Proposed Model

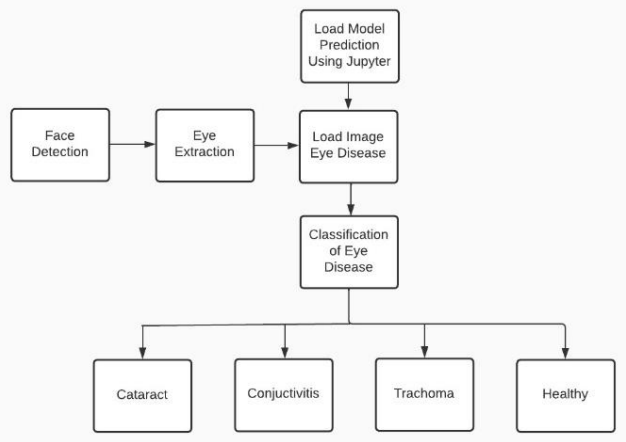

Figure 2: Real-time Classification of Eye Disease

DATASET

Eye disease images are collected from an assortment of open-access websites, such as Kaggle, the International Center for Eye Health, the National Library of Medicine, the American Academy of Ophthalmology, the University of Iowa, and others. The data set is prepared for training, validation, and model testing.

The dataset consists of 199 cataract images, 170 conjunctivitis images, 119 trachoma images, and 165 healthy eye images. Figure 3 shows the distribution of each total eye disease.

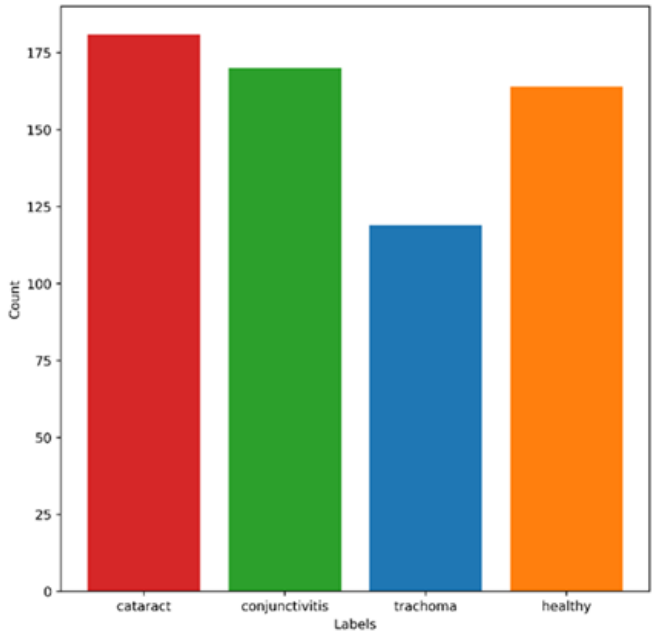

Figure 3: Distribution Dataset of Eye Disease

DATA PRE-PROCESSING

Image pre-processing is the preliminary stage in algorithm model building [1]. The process of deep learning requires increasing the number, which can be achieved through geometric modifications. Images are rotated, resized, and translated as part of the geometric alternation process [9]. In this experiment, the image enhancement method was implemented by performing a width shift range of 0.1, a height shift range of 0.1, a brightness range of (0.3, 1.0), as well as a horizontal and vertical flip. Figure 4 illustrates the outcomes of pre-processing [9].

Additionally, all utilized images are RGB, possibly requiring conversion to a two-dimensional format. This conversion uses a grayscale based on average brightness and luminosity [8].

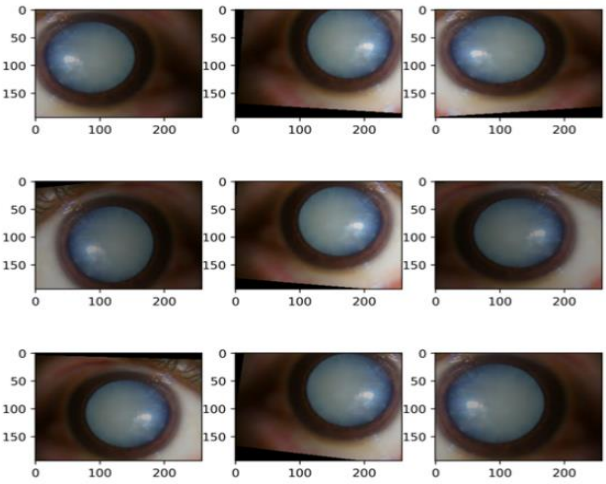

Figure 4: Result of Image Augmentation

MODEL THEORY

Transfer learning is a portion of deep learning, and models employing larger datasets are used to generate feature images [4][7]. Transfer learning can result in multiple problems [2]. There are two proposed models in Transfer Learning. VGG-16 and Inception-V3 are used for classification of eye disease.

VGG-16

The Visual Geometry Group created the VGG-16 convolutional neural network. Simonyan and Zisserman from the University of Oxford proposed VGG-16 [19]. This model employs sixteen pre-trained network filters. The image size used for VGG-16 is 150 pixels by 150 pixels with three channels (RGB Channel) [4].

The image will pass through five block convolution layers, with each block receiving a 3x3 filter to increase its value. Separate block maximum pooling layers are utilized. All the while, three fully connected layers follow five layers of block convolution [15]. The final layer is softmax, which captures the output model using categorical cross-entropy for the number of classes. Figure 5 of depicts the structure of the VGG-16, which consists of three additional screens.

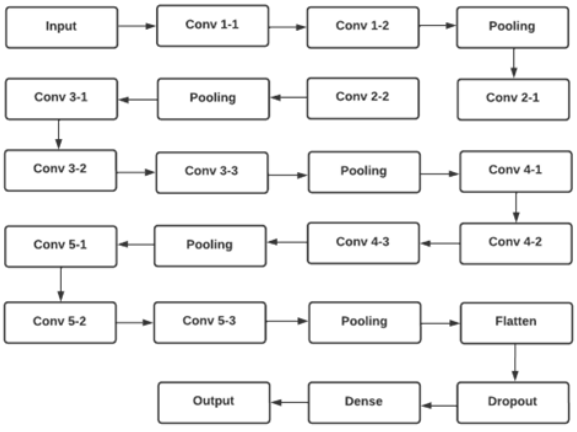

Figure 5: Structure of VGG-16

Inception-V3

Inception-V3 is a network that GoogleNet recognized with excellent results for various biomedical applications. Inception-V3 is a 48-layer convolutional neural network (CNN) trained with over one million images from the ImageNet database [5][11][15].

Inception-V3 can classify images into one thousand objects [15]. Inception-V3 is one of the most popular transfer learning models. This model permits retraining the final layer of the previous model with improved training time results. Figure 6 shows the summary structure of Inception-V3 [11].

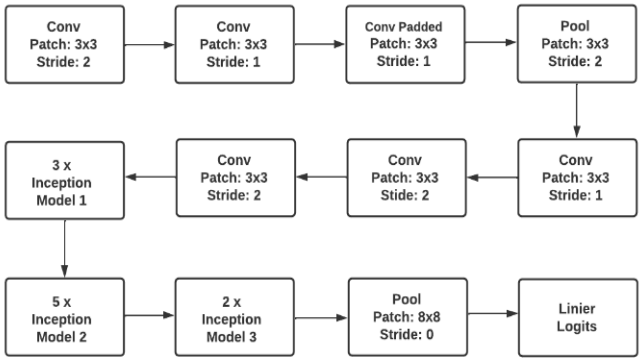

Figure 6: Structure of Inception-V3

PERFORMANCE METRICS

Several variables were used to evaluate the performance of each model in the study. The results of these variables are used as a basis for identifying the optimal model that was proposed. After recognizing the confusion matrix's value, evaluation parameters can be determined [15].

The confusion matrix is a diagram that describes in detail the model's performance [12]. There are four categories used in the confusion matrix, namely: TP (True Positive), which means positive prediction, and the prediction is true; TN (True Negative), which means negative and that is true; FN (False Positive), which means negative prediction, and that is false; and FN (False Negative), which means negative prediction, and it is false [5][15]. The confusion matrix results are utilized to determine the values of accuracy, recall, precision, and specificity, as well as the F1 score [11].

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP+FP+FN+TN}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

$$\text{F1 Score} = 2\,x\,\frac{\text{Precision x Recall}}{\text{Precision+Recall}} \quad (4)$$

RESULT AND DISCUSSION

In the experiment, VGG-16 and Inception-V3 were used as pre-trained models. The objective of this experiment is to

classify eye diseases based on the images provided. CNN's model includes four class categories: cataract, conjunctivitis, trachoma, and healthy. In the experiment, 653 images were provided as the validation and training dataset.

In the first experiment, the VGG-16 and Inception-V3 models were used to get the best performance. The VGG-16 model results in a loss accuracy is 0.25 and accuracy is 0.91, whereas the Inception-V3 model results in a loss accuracy is 0.38 and accuracy is 0.85.

In Fine Tuning, the VGG-16 model employs 10 epochs and an early stopping callback (patience of 3). As for the optimizer used only by Adam In the first experiment, a learning rate of 0.00001 was utilized. Figure 7 illustrates the results. The accuracy produced by the experiment with the pre-trained model is excellent, training accuracy is 0.98, and validation accuracy is 0.99. Accuracy shows a rising value with a value that frequently increases with increasing epoch values. The time per epoch utilized by the experiment is 187-204 seconds. The first experiment's loss can be seen in Figure 8. This result indicates that neither underfitting nor overfitting is present, as the training and validation loss values are both very good (0.03 for training and 0.06 for validation, respectively).

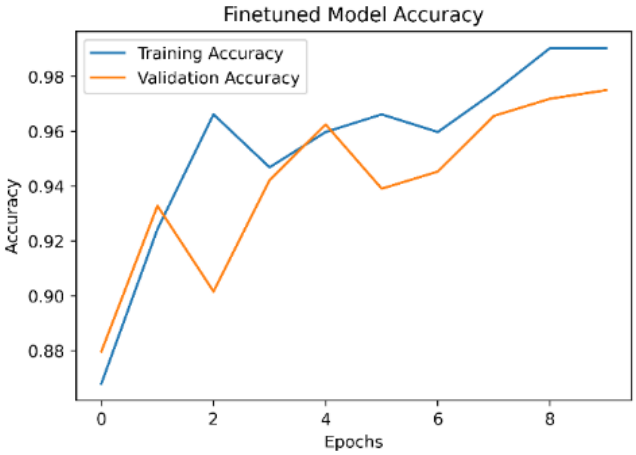

Figure 7: Training and Validation Accuracy

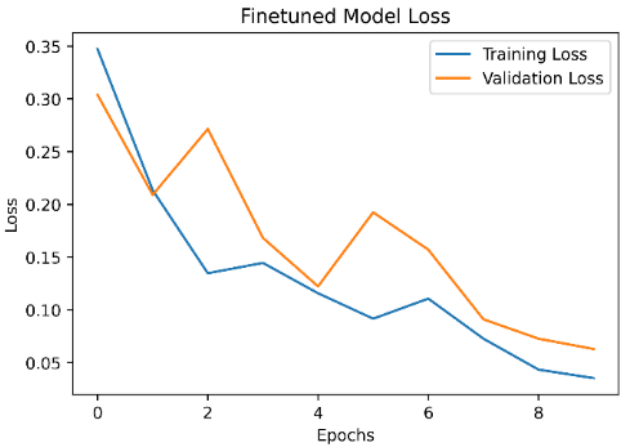

Figure 8: Training and Validation Loss

In Fine Tuning, the second preserved model employs Inception-V3 with the same number of epochs as VGG-16 (10), however, it includes a callback that stops early (patience = 3). The experiment was terminated early on the seventeenth epoch after three epochs with no change in accuracy or loss. In order to increase the accuracy value using the Adam optimizer, the first experiment in this model will employ a learning rate of 0.000001. The results are represented in Figure 9. The experimental results illustrate excellent training and validation precision. Training accuracy is approximately 0.88, while validation accuracy is 0.88. As the epoch value increases, the rise in the accuracy value also improves. The time per epoch used in the experiment is 54–74 seconds. The first experiment's loss can be seen in Figure 10. The loss for both training and validation has a poor value, 0.33 for training and 0.29 for validation.

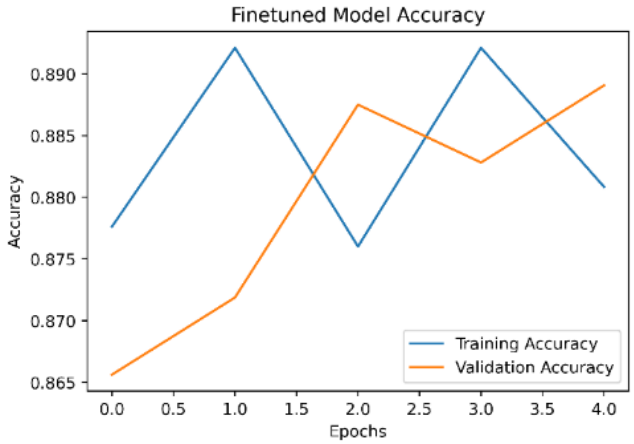

Figure 9: Training and Validation Accuracy

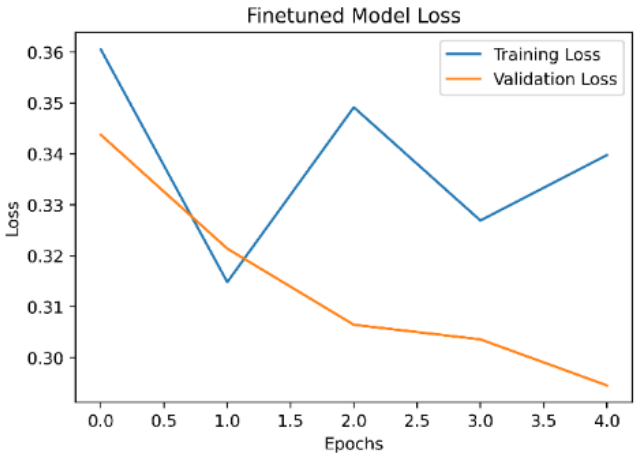

Figure 10: Training and Validation Loss

Table 1 below shows the confusion matrix for the VGG-16 and Inception-V3 models, while Figure 11 and 12 illustrates a comparison table for the performance evaluation results of the two models.

Table 1: Result in VGG-16 & Inception-V3

Model		Precision	Recall	F1-Score	Avg Accuracy
VGG-16	Cataract	97%	97%	97%	98%
	Conjunctivitis	95%	99%	97%	
	Trachoma	100%	97%	99%	
	Healthy	99%	96%	98%	
Inception-V3	Cataract	86%	92%	89%	89%
	Conjunctivitis	86%	88%	87%	
	Trachoma	88%	97%	92%	
	Healthy	97%	80%	88%	

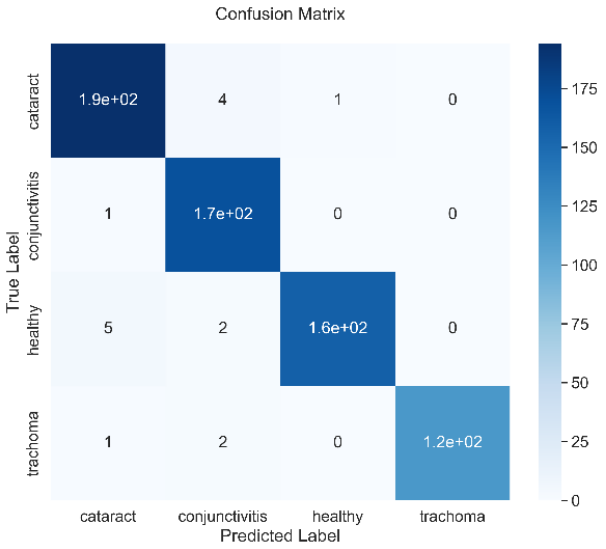

Figure 11: Confusion Matrix of VGG-16

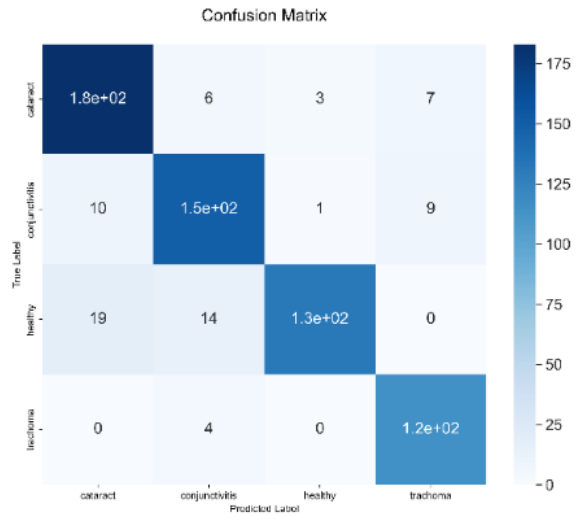

Figure 12: Confusion Matrix of Inception-V3

According to the experiment, VGG-16 produced results that were preferable to those of Inception-V3, as such VGG-16 suffered a saving model. The experiment reloaded the VGG-16 model with predictions of eye disease and flask. Figure 13 displays the experiment's GUI image.

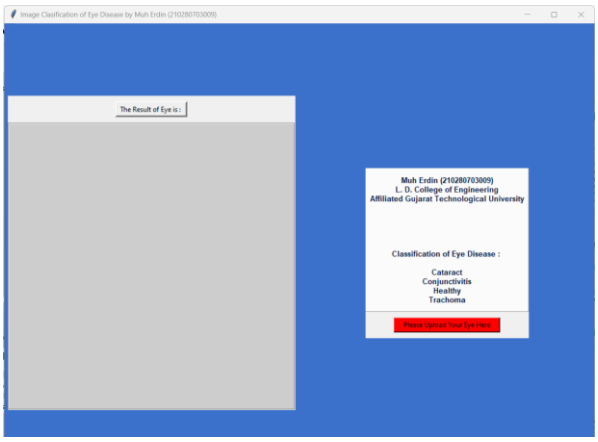

Figure 13: Desktop Classification of Eye Disease

A program is created to detect eyes live using the camera and gaze in addition to using the GUI. Gaze is used to extract the right and left of the eye so that it can be entered into the GUI program and used as input to classify diseases.

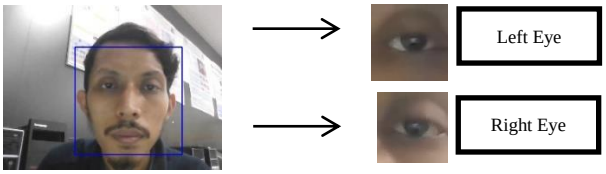

Figure 14: Live Camera and Extraction of Eye

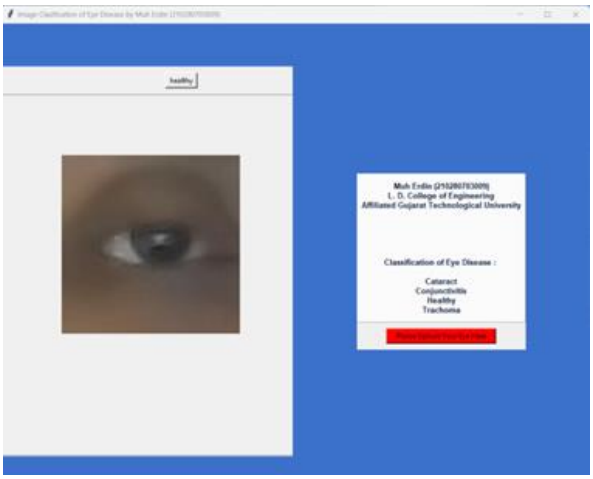

Figure 15: Testing Classification of Eye Disease

CONCLUSION

Transfer learning was utilized in the experiment to detect eye disease. Two models are utilized in the experiment: VGG-16 and Inception-V3. The used data set consists of 653 images collected from different sources. The objective of the experiment is to obtain satisfactory outcomes. Each model was performed twice, once as a baseline model and once as a fine-tuning model. Each model's precision is improved because of fine-tuning results. Adam is the optimizer utilized. The vgg-16

experimental results are 98% accurate, whereas the Inception-V3 experimental results are 89% accurate. Thus, the results of VGGG-16 are preferable to those of Inception-V3. The VGG-16 model was reprocessed to generate predictions for four classes: cataract, conjunctivitis, trachoma, and healthy. In the experiment, an eye extraction program was used to simplify the process of importing images into the developed graphical user interface. This program can run efficiently and generate accurate predictions. The accuracy of other transfer models is expected to increase in the future.

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