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Early Detection of Eye Disease Using CNN

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Abstract: The eyes perform an essential part of life. The eye is one of the organs that assist humans learn about their natural environments and collect information from them. Almost everywhere in the world, the frequency of eye disease has increased, needing a serious response. Immediate eye detection will be invaluable assistance in offering further treatment to prevent blindness. In this study, a Convolution Neural Network model is used for identifying eye diseases. This research aims to categorize human eyes into four categories: trachoma, conjunctivitis, cataract, and healthy. The investigation got an accuracy of 88.36%, while the CNN model evaluation provided Precision of 89.25%, Recall of 88.75%, and F1 Score of 88.5%. Based on the accuracy and evaluation results, this system can be used for the early detection of multiple eye diseases. Several random samples were also used for testing in this investigation. The test results indicate that this system is functional.
Keywords: CNN, Eye Disease, Deep Learning, Confusion Matrix, Gradio

I. INTRODUCTION

Deep Learning has wide-ranging uses across numerous disciplines, such as agriculture, medicine, robotics, etc[1]. Deep Learning's algorithm is able to classify classes based on the input that has been provided. Deep learning networks can accelerate classification with extremely accurate results[2].

Eye disease is one of the most common diseases of the modern era[3]. According to data from the WHO (World Health Organization), the disease will have a total of 2,2 billion people, shortly requiring comprehensive therapy to mitigate its effects[4][5][6]. Various eye diseases require intensive treatment before bringing blindness[3]. With faster treatment, blindness can be avoided and the disease's effects can be minimized.

Ophthalmologists perform an essential role in the treatment of this eye disease[5]. Therefore, AI (artificial intelligence) assistance is required in the initial phase because it can detect quickly and efficiently[7]. Deep Learning CNN (Convolution Neural Network), an AI component, was used in the case. Using AI, detection can be performed automatically. CNN Model is utilized for real-time disease classification. The results of the CNN model are evaluated for accuracy, precision, recall, and f1-score, which are essential parameters that determine the efficacy of the system being developed[7].

II. RELATED WORK

Ali Serener et al. [8] proposed a system to detect glaucoma in its advanced stages. This study employs ResNet-50 and GoogLeNet to classify glaucoma. The dataset utilized contains 1544 images. The number of datasets increased to 5,430 images after Augmentation. This trial includes three classes: early glaucoma, advanced glaucoma, and no glaucoma. The average accuracy of ResNet-50 was 79%, while the average accuracy of GoogleNet was 83%. Experiments using GoogLeNet generate more precise results than ResNet-50.

Avigyan Sinha et al. [9] proposed a method for detecting melanocytic tumors of the iris. Models of the Miles Eye Camera 24MP and the CRCS-FH4 Premium Professional Chinrest/Camera are used in this experiment. The utilized images are in RGB format, so the conversion to a two-dimensional form requires the use of grayscale. In the investigation, LeNet produced 98% accuracy with normal images and 95% accuracy with abnormal images.

Md. Rajib Hossain et al. [5] proposed a Deep Convolution Neural Network (DCNN)-based system. A total of 5 718 fundus images are utilized by this system. This algorithm is used for cataract and non-cataract detection. The experimental results yield a precision of 96.25%, a sensitivity of 94.43%, and a specificity of 98.07%. This system can be utilized as a cataract detector because it generates excellent parameters.

Xiong Luo et al. proposed [7] a method for diagnosing cataracts, glaucoma, and age-related macular degeneration (AMD). In this investigation, a total of 5,000 fundus images from OIA-ODIR were utilized. CNN and Adam serve as optimizers in this work. CLAHE (Contrast Limited Adaptive Histogram Equalization) was utilized as the enhancement method. In the experiment, AMD had the highest accuracy at 90.08%, Cataract at 99.45%, and Glaucoma at 84.7%.

Rahul Krishnan et al. [10] proposed a glaucoma detection system. Calculating the Cup-to-Disc Diameter Ratio is a technique used to diagnose glaucoma. The utilized dataset consists of 101 images, with 50 training images and 51 testing images. The investigation applied an SVM model with an RBF kernel. The results of the investigation yielded an F1 score of 86%.
Using Faster R-CNN and DenseNet Regression, Manar Algeria et al. [4] propose a system. This model is intended to detect glaucoma. RIGA contains 750 images, MESSIDOR contains 460 images, and Magrabi contains 94 images. MAE of the proposed model is 0.095. The experimental results demonstrate a precision of 100% for MESSIDOR and 98% for the Magrabi datasets.
Biswarup Ganguly et al. [2] proposed a melanoma detection system. The used dataset consists of 170 images, with 60% for training and 40% for assessment. The system utilized is 8-layer CNN. In the experiment, Stochastic Gradient Descent and learning rate were used, and the outcomes were an accuracy of 91.76 percent, a specificity of 95%, and a sensitivity of 90%.
Amit Asish Bhadra et al. [11] proposed a system to detect cataracts and conjunctivitis using an algorithm. This system employs the OpenCV library to implement the developed model. The classification method employs the Average Grayscale Value (AGV) in the pupil to identify cataracts and the Average Red Mean in the sclera to identify conjunctivitis. The used dataset consisted of 100 images with an accuracy of 92% for cataracts and 83% for conjunctivitis. The created algorithm integrates pattern recognition with BGR.
Laurine A. Ashame et al. [12] proposed a system for detecting eye abnormalities using optical disc segments in the fundus image. Adaptive Otsu's Threshold, Hough transform, and Kirsch's template filtering are incorporated into the proposed model. The experimental results demonstrate a high degree of sensitivity. This experiment employs the software MatLab. DIARETDB0 contained 619 images, DIARETDB1 contained 69 images, and STARE contained 397 images. This dataset is used to generate results that can distinguish between normal and abnormal fundus images.
Diabetic Retinopathy (DR) detection system proposed by Sugasri et al. [13] The created model can detect multiple stages of DR disease, including exudates, hemorrhages, and microaneurysms. This algorithm for disease detection employs a Support Vector Machine (SVM) Classifier with a linear kernel. The calcification yield is 97%, allowing this system to be used as a detector for all stages of DR disease.

III. METHODOLOGY RESEARCH

This experiment employs a pre-trained CNN (Convolution Neural Network) model. This model is a Deep Learning part. In experiments applying this model with nine layers, additional layers were included. In this model, augmentation was implemented to improve the accuracy of the model's results[6]. Cataracts, conjunctivitis, trachoma, and healthy are classified using the proposed model. After the design is complete, a test will be conducted using random input to determine whether the model can accurately detect the disease. This research's flowchart is shown in Figure 1.

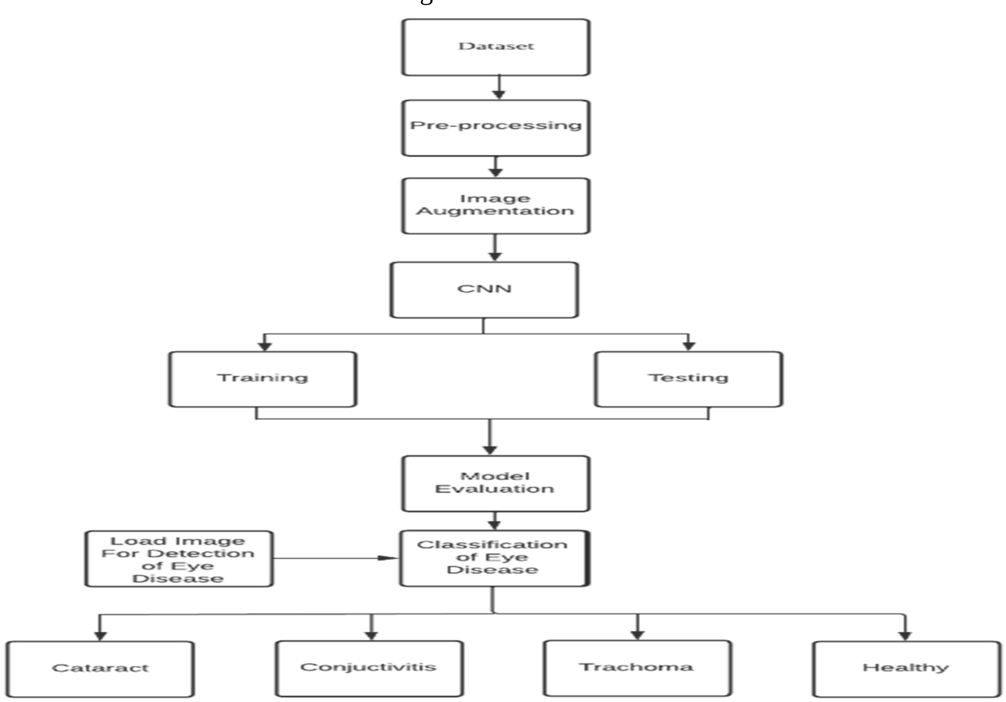

Fig. 1 Proposed Model

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A. Dataset

This experiment's dataset consists of photographs obtained from multiple reputable open sources. This is an open dataset in which image data is collected from multiple websites and images are resized independently.

The compiled data set contains a total of 653 images, which are divided into four categories and described in Table 1 below.

Table 1. Dataset

No	Type of Class	Total Image
1	Cataract	199
2	Conjuctivitis	170
3	Trachoma	119
4	Healthy	165

B. Pre-Processing Image

The acquired dataset will be separated into three categories based on their respective functions. There are three categories of obtained images: training, which will be used to train the created model, validation, which will be used to validate training results during training, and testing, which will be used to evaluate the results of the created model. As a benchmark, three categories are used to designate data in images. With these three designations, the images from the dataset will be categorized.

All created images are in RGB format, necessitating additional processing, including grey conversion to convert images into two dimensions [9][14]. Figure 2, below depicts the outcomes of the RGB image distribution for one of the images.

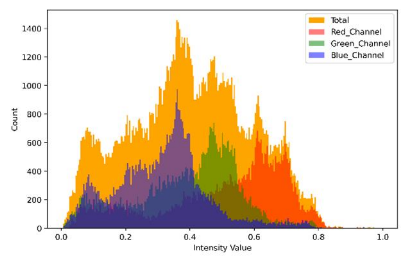

Fig. 2 Sample of Intensity Value of RGB

C. Architecture of CNN

CNN is an evolution of the Multilayer Perceptron (MLP), a data-processing algorithm designed for two-dimensional data. CNN is categorized as a Deep Neural Network due to its high network depth and widespread application to image data. Kunihiko Fukushima, a researcher at the NHK Broadcasting Science Research Laboratories in Kinuta, Setagaya, Tokyo, Japan, created CNN under the name NeoCognitron[15]. The proposed CNN Model's architecture is depicted in Figure 3.

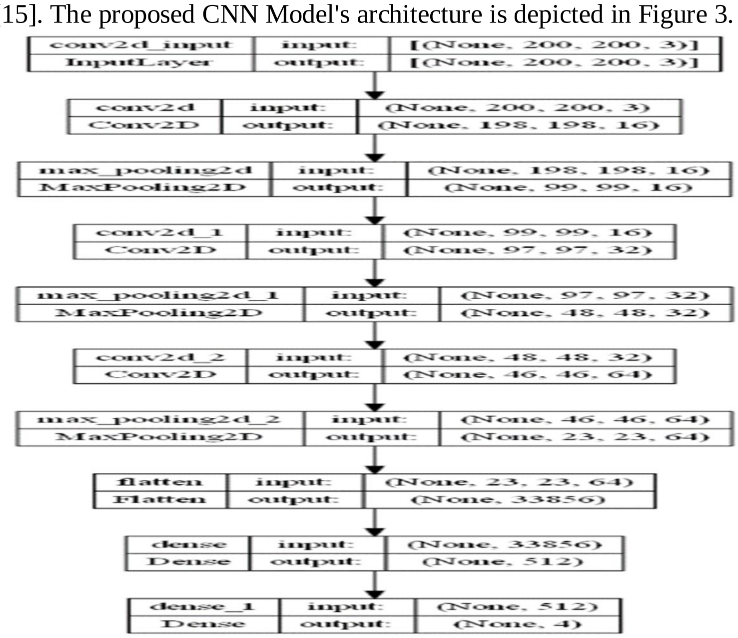

Fig. 3 CNN Architecture

This is how the CNN layer can be described:

1) *Input Layers:* The images used have been processed with a 200 x 200-pixel resolution.
2) *Convolution Layers:* Image input through a 2D convolution layer process that is executed in three phases with 16, 32, and 64 filters that are alternately executed with MaxPooling. This layer is used to derive salient features and information from images displayed on each screen[2].
3) *Max Pooling Layer:* This layer uses MaxPooling with a 2x2 dimension. The purpose of this MaxPooling Layer is to reduce the neighboring values in the resulting convolution layer. This operation is performed concurrently with the Convolution Layer and is repeated three times with the same dimension[2].
4) *Rectified linear unit layer (ReLU):* The model is constructed with ReLU activation, which serves as activation for the convolution layer[2].
5) *Flattens:* This layer is completed after Convolution and MaxPooling have been completed. Flatten is used to convert the value of a two-dimensional matrix to a one-dimensional MaxPooling vector. The results of Flatten will be applied to Dense to classify the created model's classes[2].
6) *Dense:* In this layer, the classification of the model is performed. In the constructed model, there are four proposed class categories.

D. Performance Matrix

The confusion matrix is a map that describes the performance of the model in detail. In the confusion matrix, there are four categories: TP (True Positive), which denotes a true positive prediction; TN (True Negative), which denotes a true negative prediction; FN (False Positive), which denotes a false negative prediction; and FN (False Negative), which denotes a false negative prediction. The results of the confusion matrix are used to determine the accuracy, recall, precision, and specificity values, as well as the F1 score.

1) *Accuracy:* Accuracy is one of the evaluation criteria for classification models. Using the following formula, accuracy can be attained[16][17]:

$$\text{Accuracy} = \frac{TP}{TP+FP+FN+TN} x100\% \quad (1)$$

2) *Recall:* Recall is a parameter used to determine the quantity. Typically, recall is referred to as the "true positive rate" or sensitivity [16][17]. Using the following formula, recall can be determined.

$$\text{Reall} = \frac{TP}{TP+FN} x100\% \quad (2)$$

3) *Precision:* Precision is a parameter used to determine quality [16][17]. Using the given equations, being can obtain precision:

$$\text{Precision} = \frac{TP}{TP+FP} x100\% \quad (3)$$

4) *F-1 Score:* The F1 score is a method for determining the recall and accuracy of a model [16][17]. The computation is as follows:

$$\text{F1 Score} = 2\, x \frac{\text{Precision x Recall}}{\text{Precision+Recall}} x100\% \quad (4)$$

IV. RESULT AND DISCUSSION

The CNN model was used as the pre-trained model in this study. The experiment's objective was to identify four classes: cataract, conjunctivitis, trachoma, and healthy. During the model-building phase of this experiment, 653 images were divided into three categories: validation, training, and testing.

In this investigation, the baseline model and the fine-tuning model were used in two training sessions. Epoch 20 is used with an early stopping callback (patience=3) in the baseline model. In the model with a baseline model using the Adam Optimizer with a learning rate of 10^{-3}. Figure 4 and Figure 5 show demonstrate the experimental outcomes for the baseline model.

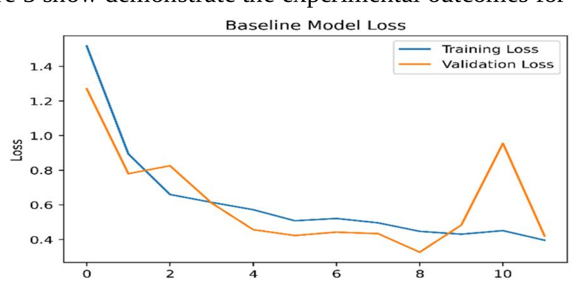

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Fig. 4 Baseline Model Loss

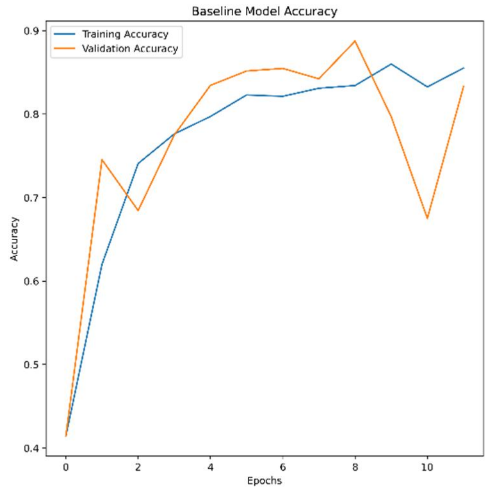

Fig. 5 Baseline Model Accuracy

Experiments utilizing the baseline model achieved a training accuracy of 85.51 % and a validation accuracy of 83.21 %. In this experiment, epoch 2 accuracy increased significantly from 41.38 percent to 62 percent. The increase in training accuracy increased linearly with the number of epochs and stopped at epoch 12. In epoch 2, the accuracy of validation increased significantly from 41.45% to 74.51%. Experimentally produced loss is 41.96 percent; therefore, accurate adjustment is required to reduce the loss value.

In the second experiment, a fine-tuning model with an epoch of 10 and an early stopping callback (patience = 5) was utilized. In this experiment, the value of the optimizer was decreased from 10^{-3} to 10^{-5}. The experimental outcomes are depicted in Figure 6 and Figure 7. The resulting training accuracy is 87.60% and the validation accuracy is 88.44%. While precise tuning results in a 32.3% loss. These results indicate that the efficacy of this model is outstanding.

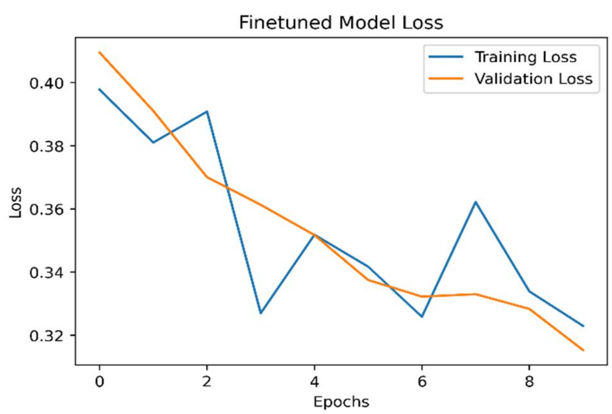

Fig. 6 Fine Tuning Model Loss

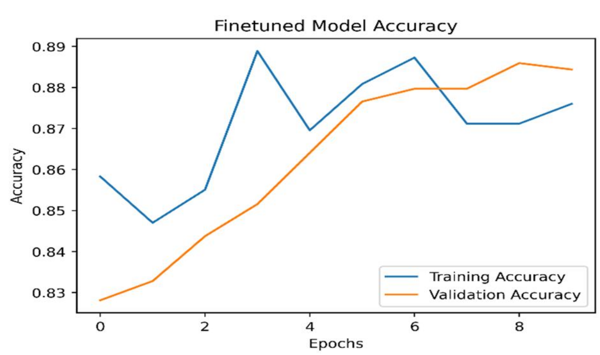

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Fig. 7 Fine Tuning Model Accuracy

After determining the accuracy value, the model is evaluated through testing. In this investigation, a confusion matrix is employed to generate a classification report with precision, recall, and f-1 scores. The confusion matrix is shown in Figure 8. The evaluation value of each category is shown in Table 2.

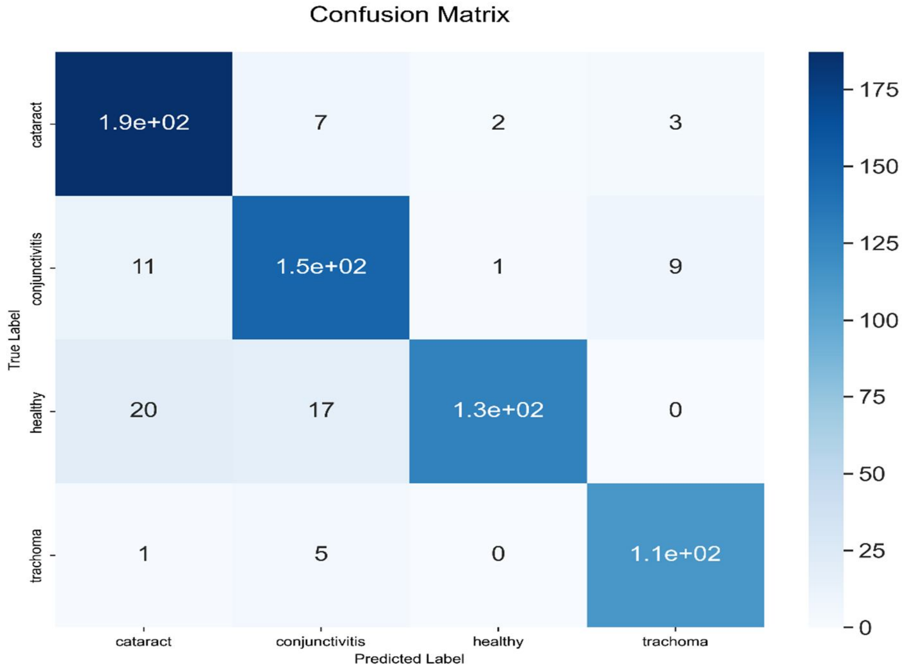

Fig. 8 Confusion Matrix

Tabel 2 Classification Report

Model		Precision	Recall	F-1 Score	Avg Accuracy
CNN	Cataract	85%	94%	89%	88%
	Conjuctivitis	84%	88%	86%	
	Trachoma	98%	78%	86%	
	Healthy	90%	95%	93%	

Using Gradio as a graphical user interface in this study and classifying image input based on the created model. The developed and evaluated model will be preserved with the extension 'h'. After saving, a Python program was generated by integrating the Gradio-created models. The Gradio display is depicted in the image that follows.

Utilizing random images from multiple sources, model, and GUI testing is performed. The outcome is depicted in Fig. 9 and Fig 10 below.

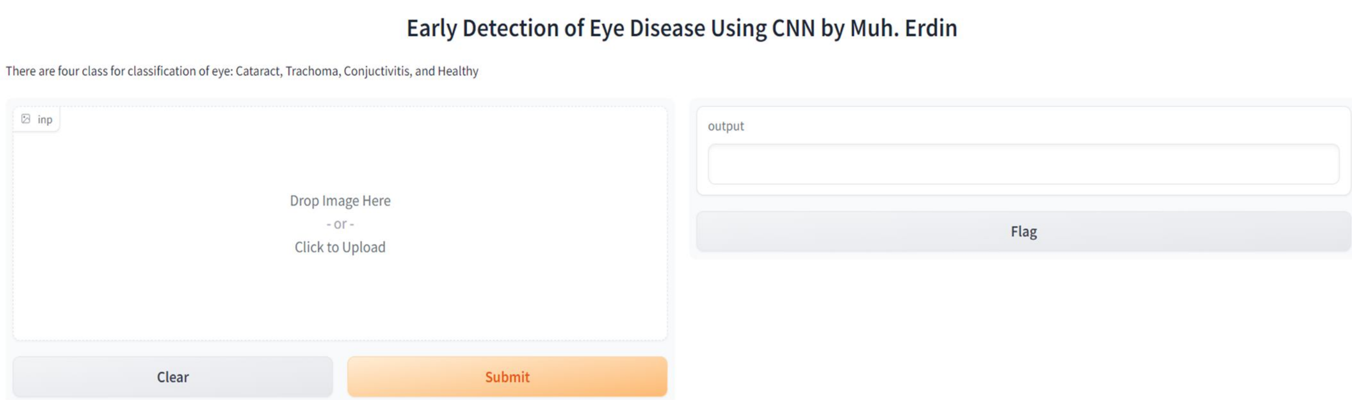

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Fig. 9 GUI of Gradio

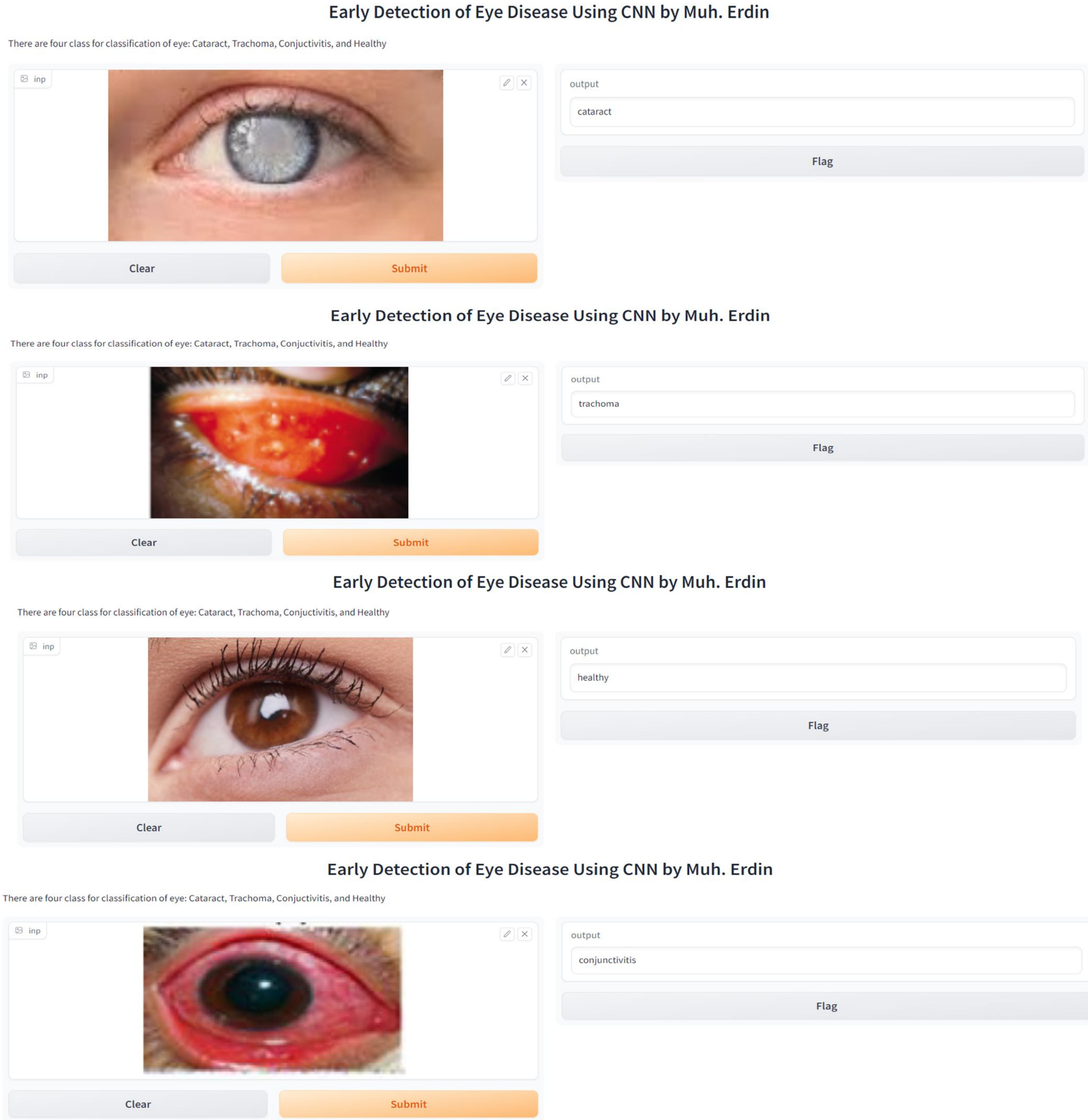

Fig. 10 Testing of Model Using GUI

V. CONCLUSIONS

In this study, the CNN model is used. The dataset consists of 653 images. This experiment incorporated the Augmentation procedure and Adam Optimizer to improve accuracy outcomes. The first experiment produced an accuracy of 85.51% whereas waiting for the baseline CNN model, which increased after Fine Tuning. Experiments on fine-tuning models have produced an average accuracy of 88% across all classes. These results indicate that Fine Tuning is required to enhance CNN model accuracy and decrease loss. Gradio was implemented as a GUI in this experiment, and this program can classify class categories based on the input provided.

VI. ACKNOWLEDGMENT

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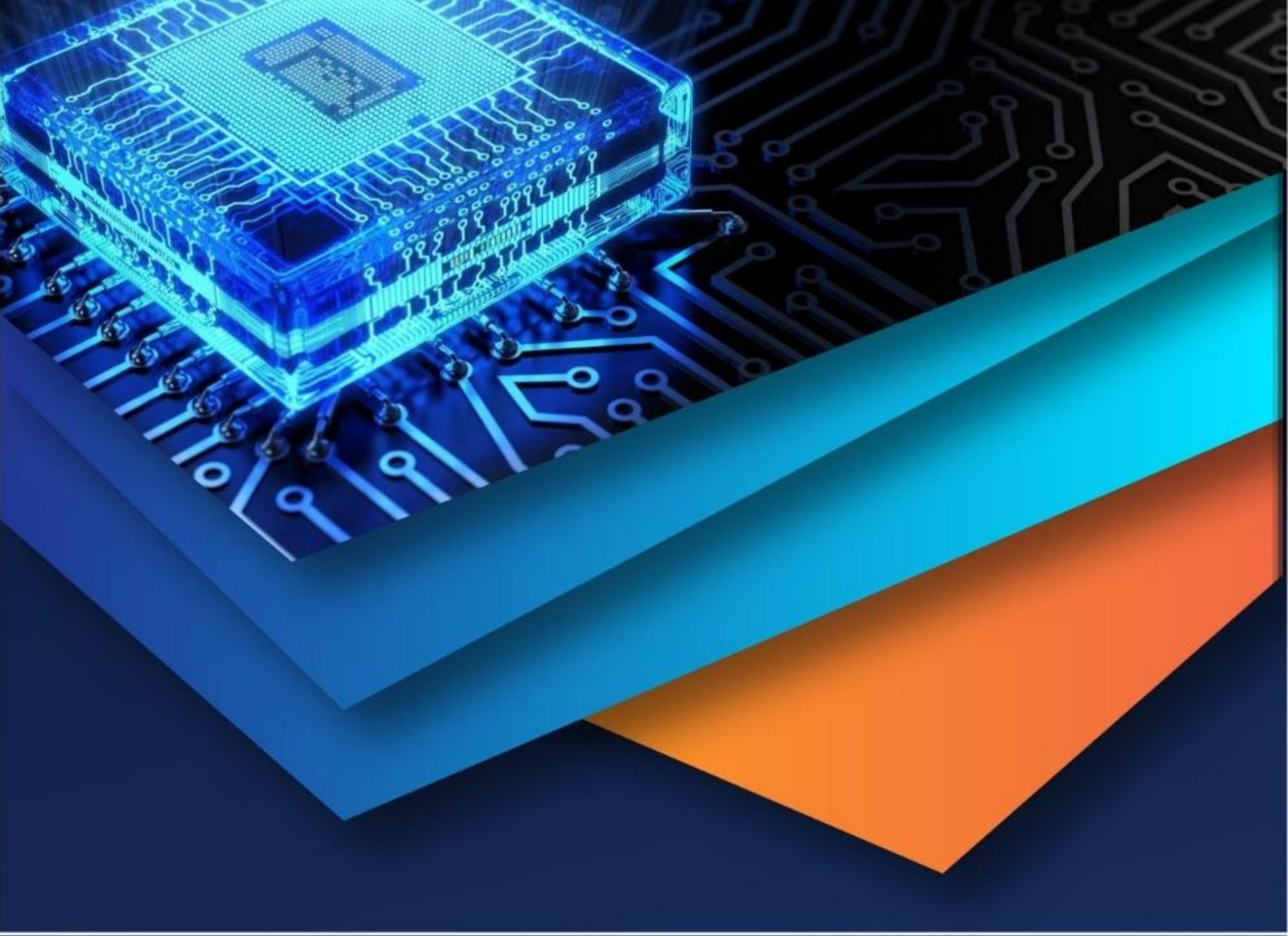

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