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Glaucoma Detection Using CNN

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Abstract

The word "glaucoma" refers to both the progressive loss of retinal cells within optic nerve, and the gradual loss of vision caused by optic neuropathy. A condition that affects eye vision is called glaucoma. This condition is thought to be permanent and causes visual impairment. There are no early warning signs of this glaucoma in them. The effect is so subtle that we could not even observe that your vision has changed. Today, several models have been created to accurately detect glaucoma. Thus, we describe an architecture built on deep learning and convolutional neural network for enhanced glaucoma detection. CNN can be used to differentiate among the patterns created for glaucoma and non-glaucoma. This Glaucoma Detection Web Application, patients' retinal pictures are given and it detects the glaucoma significance and provide the results.

Keywords: Glaucoma, Retinal cells, Deep learning, Optic neuropathy, Visual deterioration, Convolutional Neural Network.

INTRODUCTION

Vision is a major aspect of human perception, contributing significantly to the overall quality of life. However, certain ocular conditions, such as glaucoma, pose a substantial threat to vision health. Glaucoma, characterized by the progressive loss of retinal cells within the optic nerve, is a relentless and permanent disease that outcomes in a gradual deterioration of vision. Unfortunately, the challenges related with this disease is the nonappearance of early warning signs, making timely detection crucial for effective intervention. In recent years, the medical imaging field has witnessed remarkable advancements, particularly in the application of different techniques in deep learning for disease diagnosis. This project focuses on addressing the imperative need for accurate and early recognition of glaucoma by the utilization of Convolutional Neural Network (CNN). A CNN offers a robust framework for analysing complex patterns within medical images, allowing for the discrimination among glaucomatous and non-glaucomatous conditions. This research aims to present an innovative architecture designed for improved glaucoma detection, leveraging the hierarchical structure provided by CNN. From training the model to recognize subtle patterns indicative of glaucoma, we seek to advance the effectiveness and precision of diagnosis, enabling prompt medical intervention and vision preservation. The proposed methodology holds the potential to revolutionize glaucoma detection by providing a reliable tool for healthcare professionals to assess whether a patient is affected by glaucoma at an early stage when intervention can be most effective.

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RELATED WORKS

In [1] Methods are divided into 2 categories as experimental and deep learning hand crafted features for the vertical optic disk ratio segmentation such methods achieving the end-to-end testing and training most of those lack of sufficient training data accuracy of the 5 experts from tier 2 is 88.4%, 87.7%, 90.0%, 87.0% and 92.7%, accuracy by 0.9% and 0.2%, with and without the pathological area localization subnet [1] the LAG database can be achieved from the Chinese glaucoma study alliance (CGSA).

In [2] This model has no preprocessing, and augmentation of data was done. A publicly available huge data set used for training model. The system was able to producing auto-cropping images used by the DCGAN model and classified labels are associated with images. In [3] Presented a system on deep learning algorithm. The final output image was categorized using ResNet and GoogleNet neural networks and fine-tuned using transfer learning after being pre-processed into three separate channels (red, green, and blue). Data augmentation is used to improve the number of fundus photographs. The drawback of this system is, it is expensive and time-consuming and may be utilized for only premature identification. In [4] described web-applicable computer-aided analysis of glaucoma by deep learning. The authors established a system for computer assisted diagnosis of glaucoma, including CNNs and Grad-Class Activation Mapping. This system has applied using a small-sized fundus dataset image. In [5] Presented an intelligent artificial glaucoma adept system that divides the optic cup and optic disc into separate segments. CNN is used as the central component of a deep Learning model. The suggested method segments the optic disc and cup using two neural networks cooperating with each other. The important steps in the CAD system: Pre-processing Segmentation Classification U-net modified Optical disc and cup segmentation G-Net model trained and validated on RGB images. In [6] Proposed a methodology that advances the explainable in mutual convolutional and regular neural network. They observed that retinal structures are static in nature and are reasoning for improved performance on the combined model dynamic changes on the retinal specificity and sensitivity of these models range between 85 to 95% [11]. In [7] they suggested a photo segmentation and transfer learning based diagnostic tool for glaucoma identification. This model has two subsystems, Segmentation Subsystem using U-Net and the Direct Classification Subsystem consists of a light-weighted network MobileNet v2. Compared to the results generated by the heavier networks for individual datasets, the suggested light-weighted method performed well for mixed datasets. In [8] they presented a model that advances the explainable effects of study population labelling and training on glaucoma detection. The differences between the glaucoma definitions and labelling employed in numerous datasets, particularly between the DIGS/ADAGES, MCRH/Iinan, and ACRIMA datasets, are the study's weaknesses an additional performance metric and race-stratified sensitivity for all datasets. In [9] the methodology that advances the attention guided 3D-CNN structure for glaucoma discovery and structural functional association. Volumetric images methods are utilized to determine the significance of glaucoma. VFT used to evaluate vision loss due to glaucoma and other optic nerve diseases. The researchers also use biased cross information loss to avoid biased training by the class size imbalance in the data. Training is performed with a batch of size 12 through 100 epochs. In [10] researchers presented a deep convolution neural network-based technique for the early identification of Glaucoma. This model resulted in a higher dice value for optical cup segmentation, which is difficult because of the blood vessels' presence. The limitation of this model is that the dice value on the DRISHTI dataset is comparatively less than others [12].

METHODOLOGY

Most of the proposed models used ground truths and modified ground truths for the significance of glaucoma. Some researchers have used UNet for Image Segmentation, which slows down the middle covers of the model. Nearly of the existing methods used imbalanced data where, imbalance data caused disturbance in the results or final detection. So, balancing should be applied. Very few researchers used many parameters, it'll definitely effect the evaluation of the model. It is also liable on the dataset they have taken. In our proposed model, consisting of a combined dataset of ACRIMA, DRISTI and RIMONE. The proposed methodology uses an image data generator for data augmentation. The original images features have increased due to augmentation and a large dataset is virtually prepared. The dataset is split into 80:10:10 for training data, testing and validation data. Later, the augmented images have been sent for selection of feature by CNN. The images are classified using binary classification as it has two outcomes, positive and negative. This ideal can predict the glaucomatous eye accurately (Figure 1).

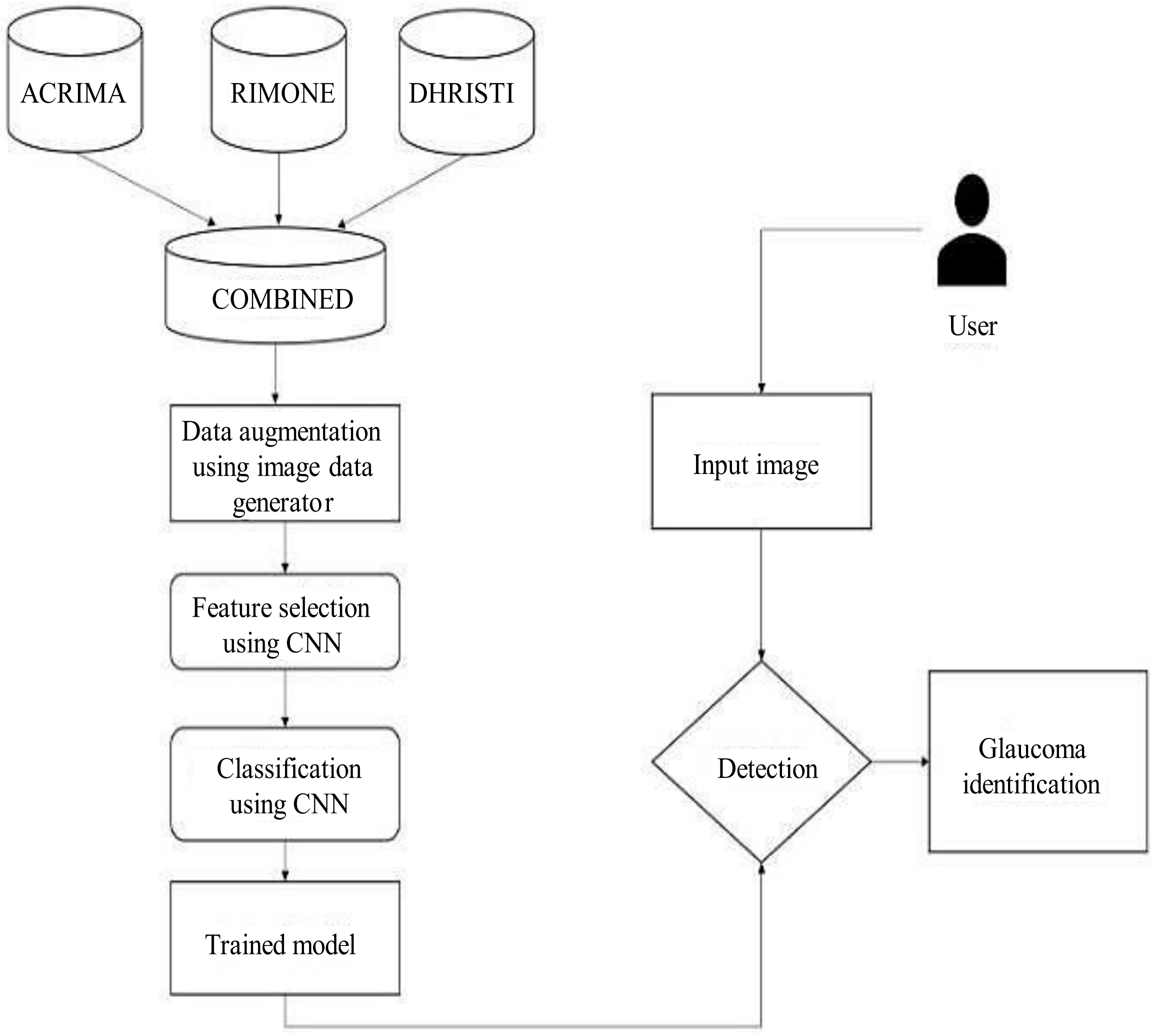

Figure 1. System Design.

The datasets that are used in this model are RIMONE, DHRISTI and ACRIMA. We have taken 3 different datasets to increase the model to train and improve the detection algorithm accuracy.

DRISTHI: Acquired with a retinal fundus camera, the dataset includes 101 retinal fundus images, of which 31 are normal and 70 are glaucomatous. The “normal/abnormal” labels and soft segmented maps of “disc/cup” produced by IIIT Hyderabad researchers in collaboration with Aravind Eye Hospital in Madurai, India, serve as the truth for comparing the applied techniques. Moreover, the photographs in the data repository were taken under various brilliance and difference conditions while patients of different ages were visiting the hospital.

RIMONE: This dataset contains 313 healthy images and and 172 glaucoma images. These images were captured in three Spanish hospitals: Hospital Universitario de Canarias (HUC), in Tenerife, Hospital Univ ersitario Miguel Servet (HUMS), in Zaragoza, and Hospital Clínico Universitario San Carlos (HCSC), in Madrid. This dataset has been seperated into test and training sets, with two variants:

- Partitioned randomly: the training and test sets are built randomly from all the images of the dataset.

- Partitioned by hospital: the images taken in the HUC are used for the training set, while the images taken in the HUMS and HCSC are used for testing [13–16].

ACRIMA This database consists of 705 retinal images (where as 396 glaucoma affected images and 309 healthy images). These were collected at the FISABIO Oftalmología Médica in Valencia, Spain, from glaucoma affected patients and normal patients. All images from this database were annotated by glaucoma experts with several experience.

RESULTS

In this section, we will explain the results that we achieved from this model. Many different performance metrics that may be used to assess a model's performance. Performance is evaluated using the Specificity, Confusion Matrix, Accuracy, Recall, Precision, and F1 score. The confusion matrix represents a clear explanation of values such as False Negatives and False Positives, True Positives, True Negatives. Neural network is trained for one cycle every epoch. In a given period, we only ever use a given piece of information. A pass is when two passes are combined, one forward and one backward. One or even more batches in each epoch to train the neural network using a part of the dataset. We refer to the process of going through one batch of training samples as an “iteration.” For the model training, there are 150 epochs overall distributed across 32 batches.

We are using measures like accuracy, F1score, recall, precision. For calculating these metrics, using the confusion grid which consist of four characteristics. The model's accuracy is a measure of its performance across all classes. When each course is equally important, it helps. To calculate it, divide the total of forecasts by the whole of guesses. Be aware that the accuracy could be misleading. When data are unbalanced is one instance. Accuracy is the percentage of accurately classified items when it comes to multiclass classification.

$$\text{Accuracy } = \frac{TP+TN}{TP+FP+TN+FN} \times 100$$

TN = True negative.
TP = True positive.
FP = False positive.
FN = False negative.

Recall is intended as a fraction of Positive observations that were correctly classified as Positive in contrast to all Positive samples. When recall is higher, there are more positive samples discovered. Furthermore, if the model correctly classifies all positive data as positive, Recall equals 1.

Precision describes how precisely the model labels a random pick as positive. Whether the model makes many inaccurate Positive classifications or only a few accurate Positive classifications, the denominator rises and the precision falls. Yet, when the model makes numerous accurate Positive classifications in the initial scenario, the precision is high (maximize True Positive). This is useful in determining how accurate when it declares that an instance is true.

Sensitivity is to evaluate the model’s performance as it observes how many positive instances it was able to identify correctly. A system with more sensitivity will have a few false negatives, which resembles that it is missing some optimistic instances. Specificity measures the proportion of true negatives that are identified by the model. When sensitivity is used to evaluate model performance, compared to specificity. Specificity.

F1-score functions as a statistical instrument for performance evaluation. An F-score can range from zero to 1.0, which represents flawless recall and accuracy, and from zero to zero when neither recall nor precision are present. Common performance metric for classification, for instance when samples belonging to one class are detected in significantly more samples than samples belonging to the other class.

$$\text{F1 Score} = 2 \times = \frac{Precision\ x\ Recall}{Precision + Recall}$$

In the Figure 2, the accuracy rate of different methods with the proposed model are represented in graph. This proposed model has an accuracy of 98.47%.

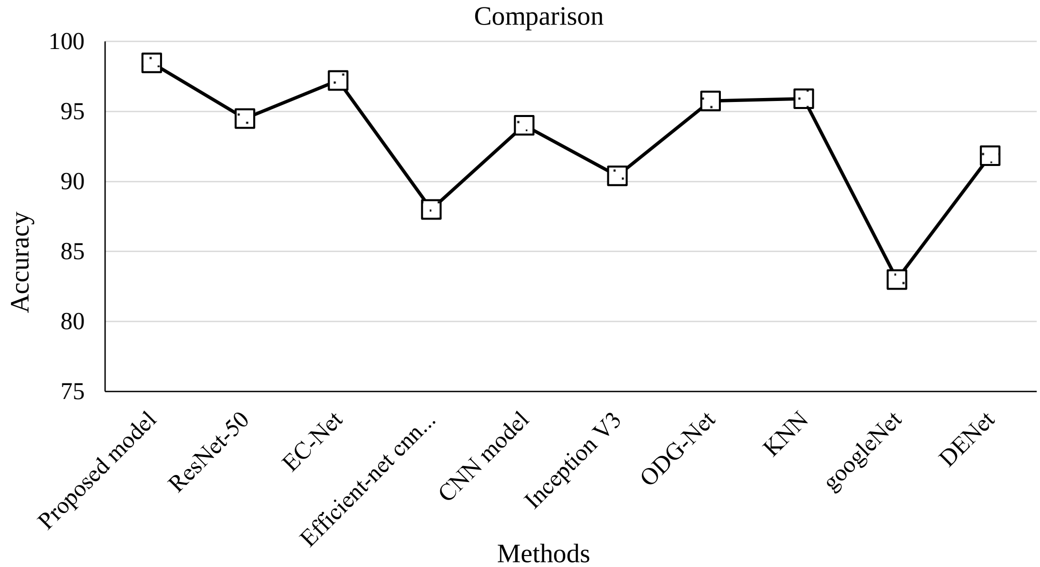

Figure 2. Accuracy comparison.

Model Accuracy

From the Figure 3, we can observe many troughs and depths in the plotted graph. Since we are having 150 epochs, the accuracy at each epoch is plotted in the graph and after 100 epochs, a sudden drop in correctness and when we increase the epochs there, we can see a steady increase in the model's accuracy. This will give us a better insight into the model's performance.

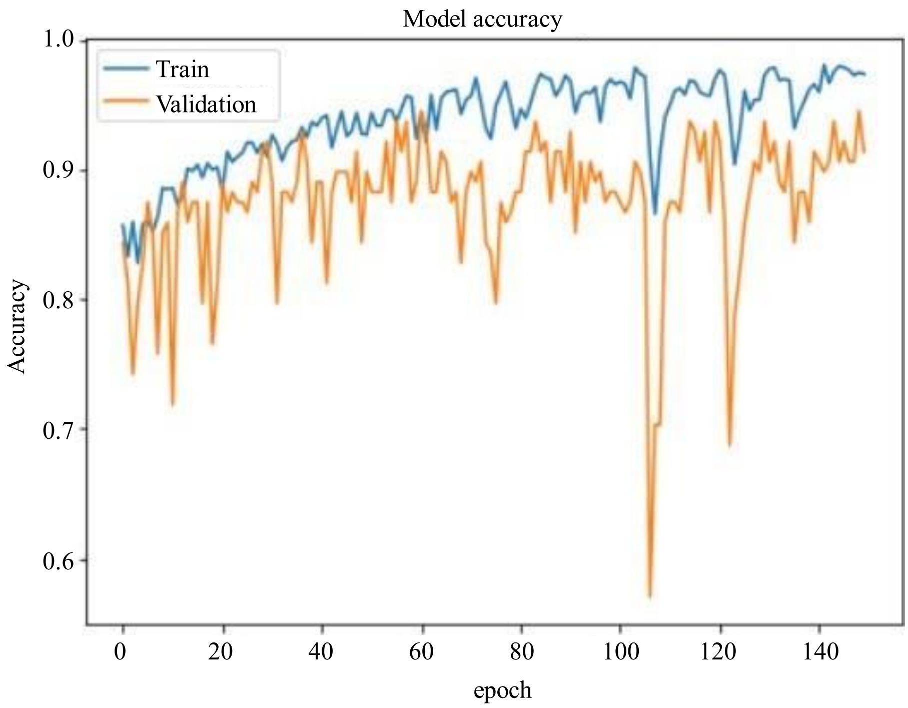

Figure 3. Model Accuracy graph.

Model Loss

Figure 4 represents the dissimilar values of loss at each epoch. As discussed earlier, there is a sudden drop in the accuracy as the loss function value is varied. This graph of degrade function helps us to forecast the issues that occur with learning. These issues can lead to underfitting or an overfitted model.

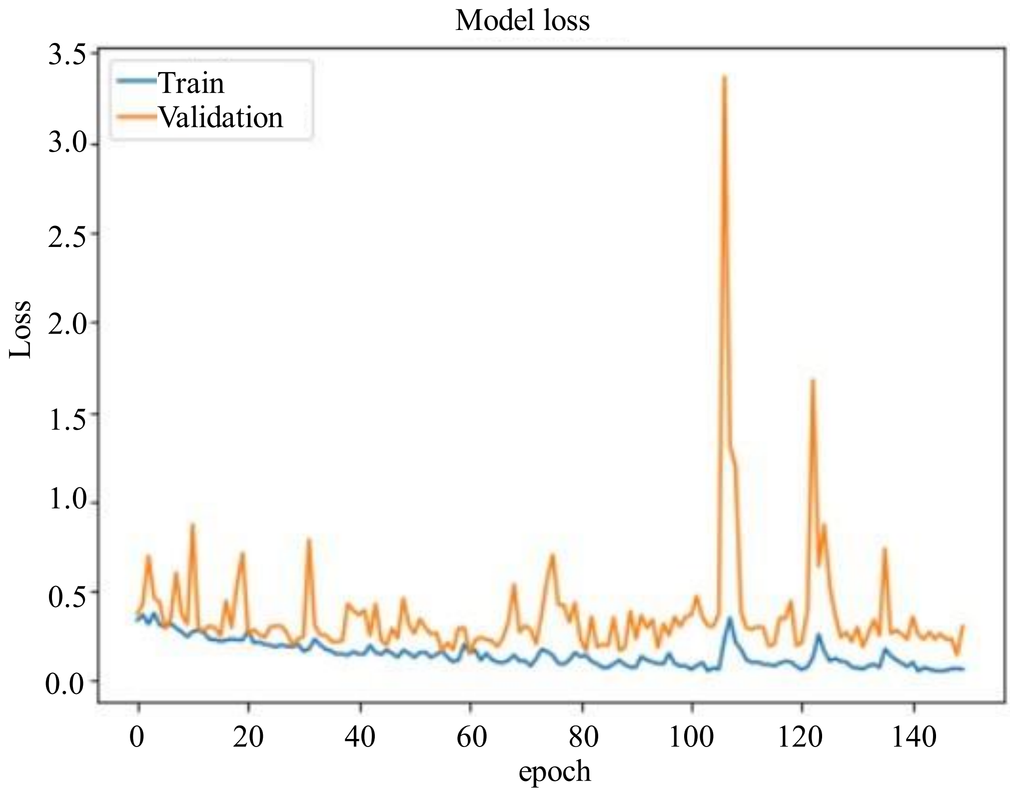

Figure 4. Model loss graph.

CLASSIFICATIONS

The classification report from Table 1, represents the achieved accuracy of 98.47% with an integrated dataset is to be noted and the existing studies have achieved the results by working on small datasets whereas the presented system has a large dataset, which is combined of three different datasets including the data augmentation and preprocessing that aids to progress the training of the model. The CNN that we implemented here can process even on low quality images. The dataset created is a balanced dataset with proportionate number of glaucoma and normal images (Table 2).

RESULTS

The output consists of the diagnosis of glaucoma, indicating whether the fundus image suggests the presence or absence of the condition (Figures 5–7).

Table 1. Classification report

	Precision	F1-Score	Support
Glaucoma	0.984	0.984	65
Normal	0.984	0.984	66
Accuracy	0.984	0.984	0.984
Macro Average	0.984	0.984	131
Weighted Average	0.984	0.984	131

Table 2. Comparison of Proposed method with Existing methods.

Model	Accuracy
Proposed model	98.47
ResNet-50	94.5
EC-Net	97.2
Efficient-net CNNs model	88
CNN model	94
Inception V3	90.4
ODG-Net	95.75
KNN	95.91
Google Net	83
DENet	91.83

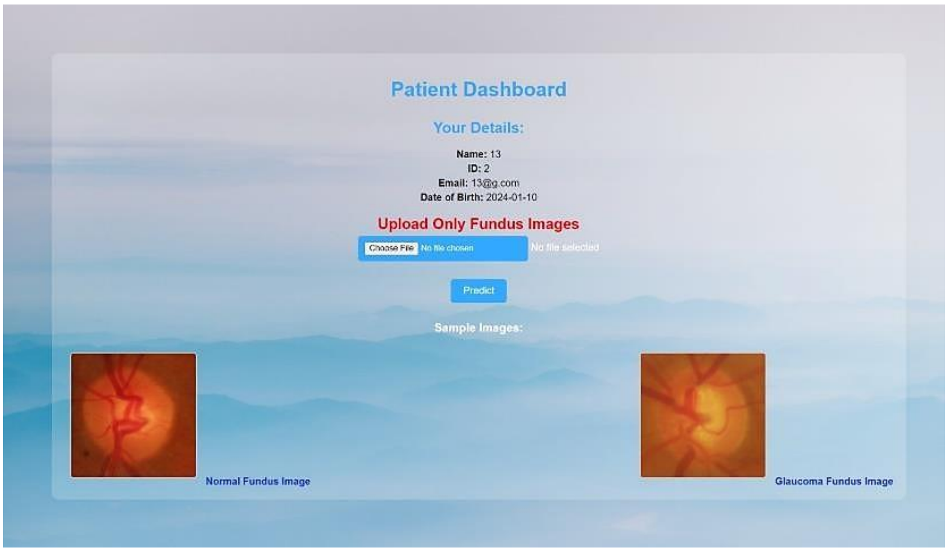

Figure 5. This is the patients dashboard.

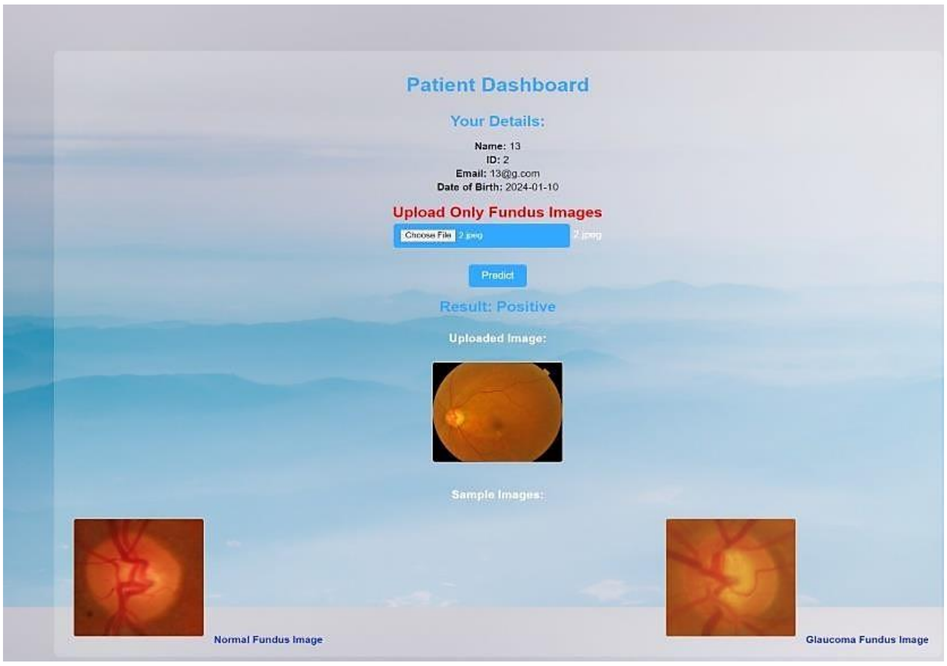

Figure 6. Image is uploaded by the user, the result is shown as positive.

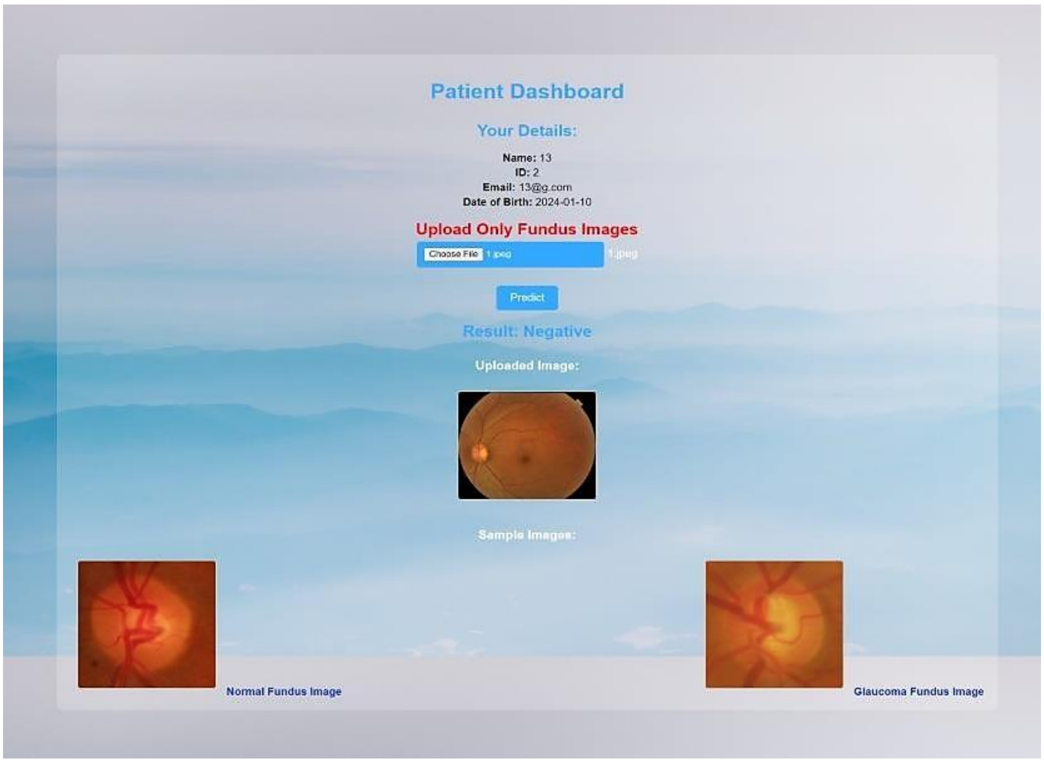

Figure 7. Image is uploaded by the user, the result is shown as negative.

CONCLUSION

Permanent blindness is brought on by the complication of glaucoma, which is connected to optic nerve damage. The computer-generated outcomes from this work will help to raise the bar for clinical judgment when it comes to glaucoma identification. There are more normal fundus photos in the dataset, this algorithm can detect the glaucomatous images accurately. The proposed methodology uses an image data generator for data augmentation. The original images have increased due to augmentation and a huge dataset is prepared. Later the augmented images have been sent for feature selection using CNN. The images are classified using binary classification as it has two outcomes depending on the input image. This model had achieved a 98.47%. Accuracy.

Advancements in image processing technology are poised to revolutionize the detection and management of various eye conditions, particularly glaucoma. This breakthrough methodology promises to significantly enhance clinical judgment in identifying glaucoma by leveraging computer-generated results. By harnessing the power of image processing, the precision and competence of glaucoma discovery are expected soar. This algorithm demonstrates remarkable proficiency in accurately identifying glaucomatous images, thus raising the standard for clinical diagnosis. Central to this method is the employment of an image data generator for augmentation, thereby expanding the primary data to facilitate comprehensive analysis. The augmented images are subsequently subjected to feature selection using advanced techniques, such as CNN. Through binary classification, wherein outcomes are categorized into two distinct possibilities, the system achieves an exceptional accuracy rate of 98%.

Building on this model, future research endeavors aim to broaden the possibility of application by improving the architecture of convolutional neural networks to sense a spectrum of eye conditions, including cataracts, retinal detachment, and diabetic retinopathy. By harnessing the potential of advanced technology and by taking the different huge datasets or with their own specific datasets of different ages, these initiatives hold the promise of revolutionizing ophthalmic diagnosis and treatment, ultimately enhancing patient outcomes and quality of life.

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