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# Deep Learning Approaches for Glaucoma Diagnosis: A Focus on Convolutional Neural Networks

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**Abstract**
Glaucoma refers to the progressive loss of retinal cells in the optic nerve, leading to gradual vision impairment caused by optic neuropathy. It's a condition affecting eye vision, often resulting in permanent visual impairment without early warning signs. Detecting glaucoma accurately has been a challenge, but various models, including deep learning and convolutional neural networks (CNN), have been developed for this purpose. This architecture utilizes CNN to differentiate between patterns indicative of glaucoma and those that aren't. Through the Glaucoma Detection Web Application, patients' retinal images are analyzed to ascertain the presence of glaucoma.
Keywords: Glaucoma, Retinal cells, Deep learning, Optic neuropathy, Visual deterioration, Convolutional Neural Network.

## 1. Introduction

Vision plays a vital role in human perception, significantly impacting overall well-being. However, certain eye conditions, such as glaucoma, pose serious threats to vision health. Glaucoma, characterized by the gradual loss of retinal cells in the optic nerve, is a relentless and irreversible disease resulting in a gradual decline in vision. One of the significant challenges of this condition is the lack of early warning signs, underscoring the importance of timely detection for effective treatment. Recent years have seen notable progress in medical imaging, particularly in employing various deep learning techniques for disease diagnosis. This project aims to address the critical need for precise and early identification of glaucoma using Convolutional Neural Network (CNN) technology. CNNs provide a robust framework for analyzing intricate patterns in medical images, facilitating the differentiation between glaucomatous and non-glaucomatous conditions.

This study endeavors to introduce a novel architectural approach tailored for enhanced glaucoma detection, capitalizing on the hierarchical organization inherent in Convolutional Neural Networks (CNNs). Through training the model to identify nuanced patterns associated with glaucoma, our objective is to enhance diagnostic precision and efficiency, facilitating timely medical intervention and preservation of vision. The proposed methodology carries the promise of transforming glaucoma detection by furnishing healthcare practitioners with a dependable tool to ascertain the presence of glaucoma in patients during the early stages when interventions are most impactful.

### 1.1. Glaucoma detection techniques

The condition called glaucoma damages the eye and causes permanent blindness in the affected area. Given how complicated this situation is thought to be, accurate detection is essential. If this issue is identified at an early stage, it may be treated; otherwise, vision loss may result. A single examination is insufficient to detect glaucoma symptoms, according to the previous assessment. Frequent ocular examinations may reveal glaucoma signs, and additional care and testing may be recommended. The medical diagnoses that are examined to determine whether glaucoma is approved are listed below.

1) **Ophthalmoscopy**: During this examination, the optic nerve is carefully scrutinized. This assessment is pivotal because glaucoma significantly impacts the optic nerve. To identify signs of nerve cell loss associated with the disease, eye drops are administered to dilate the patient's pupil, enabling a clearer observation of the optic nerve.[15].

2) **Optical Coherence Tomography**: Optical Coherence Tomography (OCT) is an essential scan used in diagnosing glaucoma. It plays a crucial role in detecting changes in the retinal nerve fiber layers surrounding the optic nerve, serving as an early indicator of glaucoma damage.

## 2. Literature Survey

[1] These methods can be categorized into two groups: heuristic and deep learning. Heuristic methods involve handcrafted features for segmenting the vertical optic disk ratio. While some of these methods aim for end-to-end training and testing, many lack sufficient training data. The accuracy of five experts from tier 2 is recorded as 88.4%, 87.7%, 90.0%, 87.0%, and 92.7%, with variations of 0.9% and 0.2% when considering the inclusion or exclusion of the pathological area localization subnet. The LAG database, sourced from the Chinese Glaucoma Study Alliance (CGSA), provides valuable data for these evaluations. Attention maps can be refined and subsequently utilized in deep learning models for the detection of glaucoma.

[2] In this work no preprocessing, and no augmentation of data was done. A publicly available huge data set is 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**.**

[3] Presented a system based on deep learning algorithm. The final output image was then 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 increase the number of fundus photographs. The drawback of this system is, it is expensive and time-consuming and may be utilized for early detection only.

[4] This paper described web-applicable computer-aided analysis of glaucoma by deep learning. The revival of convolutional neural networks (CNNs) and the public availability of large-scale datasets like ImageNet have led to significant performance improvements in computer vision. CNN-based predictive models have shown to be highly successful in medical image analysis. The authors developed a model for computer assisted diagnosis of glaucoma, including CNNs and Grad-Class Activation Mapping. This model has been implemented by using a small-sized fundus dataset image.

[5] Presented an artificially intelligent glaucoma expert system that divides the optic disc and optic cup into separate segments. CNN is used as the central component of a Deep Learning architecture that automates glaucoma detection. The suggested method segments the optic cup and disc using two neural networks cooperating with each other. There are three fundamental 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 red channel images blue channel images green channel images.

[6] A methodology has been proposed to enhance the explainability in a hybrid convolutional and traditional neural network for better detection of glaucoma. This methodology is characterized by the collection of data from fundus images in clinical settings, primarily to address the high false positive rates and low precision commonly encountered. Researchers noted that retinal structures exhibit static properties, which contribute to improved performance in the combined model. Additionally, dynamic changes in retinal specificity and sensitivity were observed, with models achieving a range between 85% to 95% when utilizing transfer-trained models.

[7] This paper suggested an image segmentation and transfer learning based diagnostic tool for glaucoma identification. In this study, this model consists of two subsystems:

(1) Segmentation Subsystem using U-Net in which images from two datasets are split individually into training and testing datasets.

(2) The Direct Classification Subsystem consists of a light-weighted network MobileNet v2 that has been pre-trained with ImageNet and an extra classifier network. Compared to the results generated by the heavier networks for individual datasets, the suggested light-weighted method performed well for mixed datasets

[8] The study presented a model aimed at enhancing the interpretability of population labeling and training effects on glaucoma detection. Deep learning-based approaches were found to effectively utilize complex visual cues in fundus images, resulting in high accuracy even on unseen datasets. Glaucoma labeling was conducted by three expert graders who assessed fundus photographs along with additional clinical information. The diagnostic accuracy for detecting glaucoma was higher in eyes with high myopia compared to those without, likely due to the more severe glaucoma in eyes with high myopia. Weaknesses of the study include differences in glaucoma definitions and labeling among various datasets, particularly between the DIGS /ADAGES, MCRH/Iinan, and ACRIMA datasets. An additional performance metric and race-stratified sensitivity were suggested for all datasets.

[9] This methodology introduces an advanced attention-guided 3D-CNN structure for the discovery of glaucoma and the association between structural and functional aspects. Volumetric image analysis techniques are employed to assess the significance of glaucoma, with the visual field test (VFT) serving as a functional test to evaluate vision loss attributed to glaucoma and other optic nerve diseases. The dataset comprising 3782 OCT volumes is partitioned into training and testing subsets. The model is trained using the Adam optimizer, and to mitigate biased training caused by class size imbalances in the data, biased cross-information loss is utilized.

Training is conducted with a batch size of 12 over 100 epochs.

[10] The researchers presented a deep convolution neural network-based technique for the early identification of Glaucoma. Preprocessing and post-processing steps are avoided to decrease the computational rate of the system. There are no more images in the considered dataset, so augmenting the data with rotations ranging from 0 to 360 degrees is done, and brightness is increased and decreased to counter the contrast issue. This model resulted in a higher dice value for optical cup segmentation, which is difficult because of the blood vessels' presence. However, it can also train with fewer epochs and few. The limitation of this model is that the dice value on the DRISHTI dataset is comparatively less than others

[11] A novel two-phase Optic Disk Localization and Glaucoma Diagnosis Network (ODGNet) is proposed. In the first phase, a visual saliency map, integrated with a shallow CNN, effectively localizes the optic disk (OD) from fundus images. In the second phase, transfer learning-based pre-trained models, such as AlexNet, ResNet, and VGGNet, are employed for glaucoma diagnosis. These models, along with saliency maps, are evaluated on five public retinal datasets to differentiate between normal and glaucomatous images. A sliding window approach is utilized to train the shallow CNN model by selecting patches with or without the OD, while the saliency map targets the next salient region in case of a non-OD region. The proposed approach achieves an accuracy of 95.75%, which can aid ophthalmologists in alleviating the burden of mass screening.

[12] Presented a glaucoma detection method using a 2d tensor empirical wavelet transform. Using a pre-processed images for quality enhancement to eliminate unnecessary variations, and decomposition is performed with 2D-T-EWT. Decomposed images extract texture-based features, and robust features are selected. A multi-class LS-SVM was used for the image classification as normal, early, and advanced stages of Glaucoma. Using tenfold cross-validation, this model is 93.65 accurate with just 12 characteristics. However, this model does not work well when tested on multiple data sets.

[13] This model suggested a methodology that improves the explainability of quasi bivariate mode decomposition from fundus images for the automatic detection of glaucoma. The three components of this methodology are genetics, structural alterations in the eye, and eye exams. It is now simple to identify glaucoma. Imaging techniques that are frequently used to detect glaucoma include Heidelberg retina tomography, optical coherence tomography, and scanning laser ophthalmoscopes. A value of 100 has been shown to be appropriate, with the β parameter ranging from 10 to 1000. limitations, non-adaptive methods such as OHAWT, CWT, WPD, and DWT is not particularly appropriate for image decomposition. The same frequency range was used by the model to generate different SBIs. For the next step of breakdown in the upper degree of decomposition, only low-frequency SBI is used.

[14] This technique suggested a way to categorize the thirty microcalcification clusters seen in mammograms. It is frequently linked to increased intraocular pressure, wherein the optic nerve is gradually damaged over an extended period. This work primarily focuses on the diagnosis of glaucoma in patients through the use of multiple modalities such as the K Means clustering method, the Gabor wavelet modification of the colour fundus camera image, and the simple linear iterative clustering (SLIC) technique to provide precise border delineation. This method's accuracy surpasses that of the IOP measurement, aberrant visual field, and the earlier CNN based on GLCM. categorization techniques for glaucoma detection

## 3.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 layers of the model. Some 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 depending 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. The model can predict the glaucomatous eye accurately.

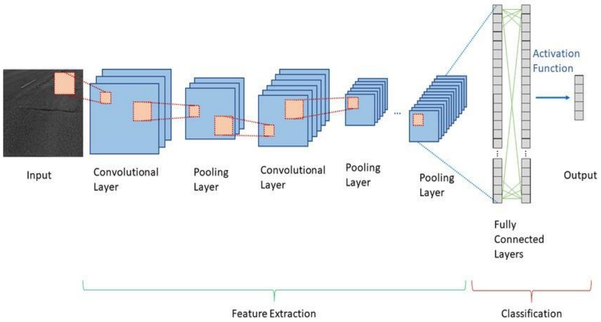

**Figure.1 CNN Architecture**

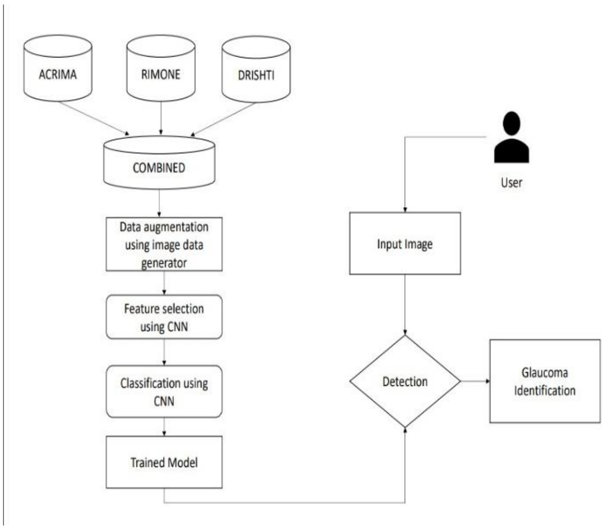


**Figure.2 System Design**

## 3.1. Datasets

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

**DRISTHI**: The dataset comprises 101 retinal fundus images captured with a retinal fundus camera. Among these, 31 images are classified as normal, while 70 are identified as glaucomatous. Ground truth labels of "normal/abnormal" and soft segmented maps of "disc/cup" were generated by IIIT Hyderabad researchers in partnership with Aravind Eye Hospital in Madurai, India, to serve as reference points for evaluating the employed techniques. Additionally, the photographs within the dataset were captured under diverse brightness and contrast conditions, with patients of varying ages visiting the hospital.

**RIMONE**: This dataset consists of 313 healthy images and 172 images depicting glaucoma. The images were obtained from three Spanish hospitals: Hospital Universitario de Canarias (HUC) in Tenerife, Hospital Universitario Miguel Servet (HUMS) in Zaragoza, and Hospital Clínico Universitario San Carlos (HCSC) in Madrid. The dataset has been divided into training and test sets, with two variants:

- Partitioned randomly: In this variant, the training and test sets are constructed randomly from all the images in the dataset.
- Partitioned by hospital: In this variant, the images captured at Hospital Universitario de Canarias (HUC) are designated for the training set, while the images obtained at Hospital Universitario Miguel Servet (HUMS) and Hospital Clínico Universitario San Carlos (HCSC) are allocated for the test set.

**ACRIMA**: This database comprises 705 retinal images, including 396 images depicting glaucoma-affected eyes and 309 images of healthy eyes. These images were gathered at the FISABIO Oftalmología Médica in Valencia, Spain, from both glaucoma-affected patients and normal patients. All images in this database were meticulously annotated by glaucoma experts with varying levels of experience.

## 3.2. Design flow

**Data pre-processing**: It involves getting the raw data ready and fitting it into a machine learning model. It is the initial and most important stage in building a machine-learning model. Pre-processing aims to improve the image data by reducing unwanted distortions and enhancing certain image attributes that are important for jobs involving additional processing and analysis. Not all of the data we encounter when developing a machine learning project is clean and well-formatted. Additionally, cleaning and formatting data is a must for any process involving it. Thus, we employ a data pre-processing task for this.

**Data augmentation** is followed by preprocessing This technique will artificially increase the training rate by creating modified copies of a dataset using existing data. It includes making minor changes to the dataset or using deep learning to generate new data points. This includes Geometric transformations like randomly flipping the images, cropping, rotating, and stretching images. Color space transformations: randomly change RGB color channels, contrast, and brightness. Kernel filters: randomly change the sharpness or blurring of the image.

**ImageDataGenerator** is used to determine the source of the data, after which it randomly alters the data and produces an output result that only contains the freshly altered data. To improve the generality of this model as a whole, augmentation of data is also brought out using the Keras picture data generator class. Image data generators are employed to produce batches of data from tensor images in the context of actual data augmentation. We can cycle through the input in batches while using Keras' picture data generator. Only the newly changed data is returned by the ImageDataGenerator after accepting the data and randomly transforming it.

**Feature selection using CNN:** The convolution neural network is stated to be a machine learning subnet. It is one of many models of artificial networks that are used for various tasks and sets of data. A particular type of neural network called CNN may be used to find important information that may existing in both time-series data and image data. This model uses linear algebraic concepts like matrix multiplication to find patterns in an image. Neural Networks CNNs have architecture resembling those of the interconnections in the human brain. The neurons in CNNs are organized differently, yet they are similar to the billions of neurons present in human brain. By overcoming the problem with standard neural network partial image processing that requires us to give them low-resolution images by this design, the full visual field is protected. CNN performs better than earlier networks when given inputs that contain both speech and/or visual signals.

**Classification using CNN:** A form of supervised machine learning method, classification involves grouping a given set of input data into classes using one or more factors. To categorise fresh observations into groups or classes, classification prediction modelling uses data or observations as training input.

After these all stages, the model is trained with the retinal image datasets (ACRIMA, RIMONE and DHRISTI), it will detect the features of the images.

The user or Ophthalmologist will register and login with their credentials to the Glaucoma detection web application and they will provide their retinal images and click proceed. Hence, this system identifies those images and provides the results to them, whether they have glaucoma or not.

## 4. Results and Discussion

There exist various performance metrics for evaluating a model's effectiveness. These include Specificity, Confusion Matrix, Accuracy, Recall, Precision, and F1 score. The Confusion Matrix offers a detailed breakdown of metrics such as False Negatives, False Positives, True Positives, and True Negatives. During training, the neural network undergoes one cycle per epoch. Within a specific timeframe, each piece of information is utilized only once. A pass consists of both a forward and a backward pass combined. In each epoch, one or more batches are employed to train the neural network using a segment of the dataset. The process of traversing through one batch of training samples is termed as an "iteration." For effective model training, there are a total of 150 epochs distributed across 32 batches.

## 4.1 Evaluation Metrics

We are using measures like accuracy, F1 score, recall, and precision. A machine will always produce an outcome and we have no idea it is the correct one or not unless someone hints that out in our model. For calculating these metrics, we can use the confusion grid which consists 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 the data are unbalanced is one instance. Accuracy is the percentage of accurately classified items when it comes to multiclass classification.

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

- TN = True Negative.
- TP = True Positive.
- FP = False Positive.
- FN = False Negative.

Recall: Recall, also known as sensitivity, is computed as the ratio of correctly classified Positive observations to all actual Positive samples. A higher recall indicates that more Positive samples are correctly identified. Recall remains unaffected by the number of incorrect classifications of other samples. Moreover, if the model accurately identifies all Positive data as Positive, Recall attains a value of 1.

Precision: Precision measures the accuracy with which the model identifies a random selection as positive. As the model makes either numerous inaccurate Positive classifications or only a few accurate Positive classifications, the denominator increases, leading to a decrease in precision. However, in the first scenario where the model makes numerous accurate Positive classifications, precision is high, maximizing True Positives. In the second scenario where the model makes fewer inaccurate Positive classifications, precision is also high, minimizing False Positives. Precision is valuable in assessing the model's accuracy when it asserts that an instance is true.

**Sensitivity**: This evaluation enables us to gauge the model's performance by assessing its ability to correctly identify positive instances. A system with higher sensitivity will exhibit fewer false negatives, indicating that it effectively captures most of the positive instances.

**Specificity**: This measures the proportion of true negatives correctly identified by the model. When evaluating model performance, specificity is often compared to sensitivity.

**F1-score**: It serves as a statistical tool for assessing performance. The F-score ranges from zero to 1.0, representing perfect recall and precision when at the maximum, and approaches zero when neither recall nor precision are present. This metric is commonly used in classification tasks, particularly when one class is significantly more prevalent than the other, to evaluate how well the model performs in detecting samples belonging to each class.

$$\textbf{F1\_Score} = 2 \times \frac{precision \times Recall}{precision + Recall}$$

## 4.2. Model accuracy

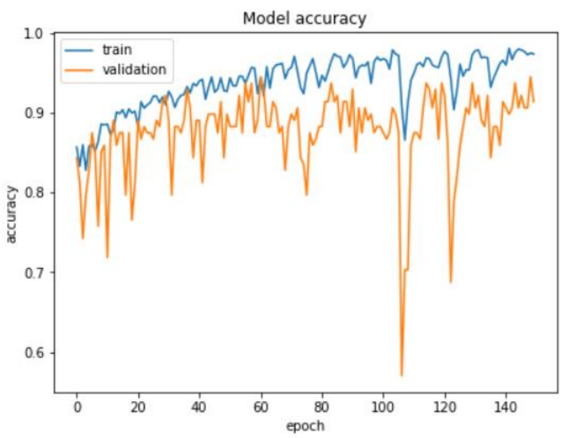


**Figure 3** Model Accuracy graph

From the **figure.2**, we can observe many troughs and depths in the plotted graph. Since we have 150 epochs, the accuracy at each epoch is plotted in the graph and we can see that after 100 epochs there is 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.

## 4.3. Model loss

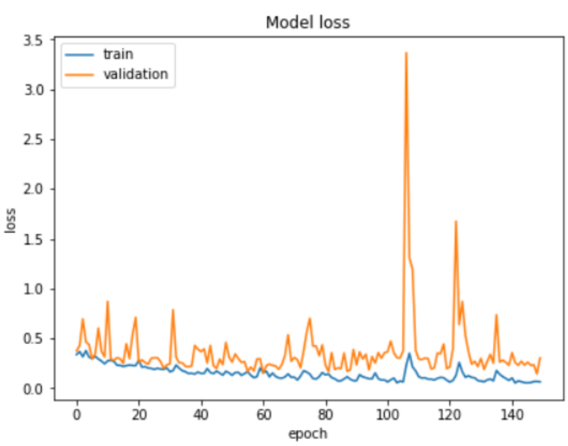


**Figure.4** Model loss graph

The **figure.3** depicts the different values of loss at each epoch. As we have discussed earlier, there will be 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.

## 4.4. Classifications

**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 |

The classification report from **Table.1**, It's noteworthy that the integrated dataset achieved an impressive cumulative accuracy of 98.47%. 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 develop 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 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 |

## 5. Conclusion and Future Enhancement

Permanent blindness is brought on by the complication of glaucoma, which is connected to optic nerve damage. The computer-generated results 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 medical 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 medical image processing, the precision and competence of glaucoma detection are expected soar. This algorithm demonstrates remarkable proficiency in accurately identifying glaucomatous images, thus raising the standard for clinical diagnosis. Central to this approach is the employment of an image data generator for augmentation, thereby expanding the original dataset to facilitate comprehensive analysis. The augmented images are subsequently subjected to feature selection using advanced techniques, such as Convolutional Neural Networks (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 endeavours 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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