# Automated Glaucoma Detection Techniques: A Literature Review

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## ABSTRACT

**Significant advances in the automated glaucoma detection techniques have been made through the employment of the Machine Learning (ML) and Deep Learning (DL) methods, an overview of which will be provided in this paper. What sets the current literature review apart is its exclusive focus on the aforementioned techniques for glaucoma detection using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines for filtering the selected papers. To achieve this, an advanced search was conducted in the Scopus database, specifically looking for research papers published in 2023, with the keywords "glaucoma detection", "machine learning", and "deep learning". Among the multiple found papers, the ones focusing on ML and DL techniques were selected. The best performance metrics obtained using ML recorded in the reviewed papers, were for the SVM, which achieved accuracies of 98.31%, 98.61%, 96.43%, 96.67%, 95.24%, and 98.60% in the ACRIMA, REFUGE, RIM-ONE, ORIGA-light, DRISHTI-GS, and sjchoi86-HRF databases, respectively, employing the REFUGE-trained model, while when deploying the ACRIMA-trained model, it attained accuracies of 98.92%, 99.06%, 98.27%, 97.10%, 96.97%, and 96.36%, in the same databases, respectively. The best performance metrics obtained utilizing DL recorded in the reviewed papers, were for the lightweight CNN, with an accuracy of 99.67% in the Diabetic Retinopathy (DR) and 96.5% in the Glaucoma (GL) databases. In the context of non-healthy screening, CNN achieved an accuracy of 99.03% when distinguishing between GL and DR cases. Finally, the best performance metrics were obtained using ensemble learning methods, which achieved an accuracy of 100%, specificity of 100%, and sensitivity of 100%. The current review offers valuable insights for clinicians and summarizes the recent techniques used by the ML and DL for glaucoma detection, including algorithms, databases, and evaluation criteria.**

***Keywords-deep learning; ensemble learning; machine learning; glaucoma detection; fundus images***

## I. INTRODUCTION

Glaucoma, a condition characterized by damage to the optic nerve due to increased intraocular pressure, is a prevalent eye disease affecting many individuals globally. The impact of glaucoma on healthcare systems is substantial, with millions of people requiring medical attention and treatment. The World Health Organization (WHO) predicts a concerning rise of glaucoma global prevalence, highlighting the growing significance of addressing this issue. For example, in developing countries, where healthcare access is limited, the burden of undiagnosed and untreated glaucoma cases is particularly high. Moreover, untreated glaucoma can cause irreversible vision loss and decreased life quality. Early detection is crucial in preventing these outcomes. Thus, raising awareness, promoting regular eye exams, and investing in research, education, and healthcare can reduce the impact of glaucoma and improve eye health worldwide [1, 2]. Glaucoma is classified into the open-angle and closed-angle forms. The open-angle glaucoma has blocked drainage, leading to an increase in the eye pressure. The closed-angle glaucoma is severe, with sudden blockage causing a pressure spike. The angle is obstructed in the open-angle glaucoma, leading to a pressure increase and optic nerve damage. The closed-angle glaucoma occurs when the angle suddenly closes, causing acute symptoms [3, 4].

The existing traditional method of diagnosis requires tests performed by eye specialists, which may consume a significant amount of time and be subjective, depending on the investigator's expertise, therefore, improved methods are required for a rapid and accurate diagnosis [5, 6]. The ML and DL techniques have demonstrated potential in diverse applications, such as predicting, recognizing emotions, education, classification, and recognition in various fields [7-15]. With the rise of the digital imaging technologies and the advances in the ML and DL techniques, automated glaucoma detection has gained significant traction in recent years. The aim is to automate the detection process through fundus image analysis, allowing early intervention and improving patient outcomes. Utilizing fundus imaging holds immense promise in this context. As a non-invasive technique, fundus imaging offers readily available accessibility and provides crucial insights into the eye's condition, particularly the optic nerve heads. These images are adept at capturing intricate details throughout the retina, including essential features, such as the neuroretinal rim, Optic Disc (OD), fovea, blood vessels, and Optic Cup (OC) [16–18]. These cutting-edge techniques offer incredible potential for a faster and more objective diagnosis, allowing healthcare professionals to provide timely interventions to patients at risk [17]. Therefore, it is crucial to focus on studying glaucoma detection deploying the ML and DL techniques. These techniques can quickly and accurately process and analyze large amounts of complex data, paving the way for researchers to develop more reliable and accurate models. The latter can then identify new patterns and trends that help in the early disease detection.

The main contribution of the current review is to gather further information from recent research focusing on ML and DL techniques for glaucoma detection that authors have not yet reviewed. Its goal is to provide readers with a detailed and up-to-date understanding of the recent advances in the ML and DL-based glaucoma detection.

## II. METHODOLOGY

Research articles published in 2023 were collected. The following keywords were used in the Scopus scientific database to search for article titles and abstracts: "glaucoma detection", "machine learning", and "deep learning". The results were restricted to computer science and engineering subjects that were in English. Moreover, this review focused on studies having a document-type article. A total of 324 articles were found. The PRISMA guidelines and their extensions for scoping reviews were followed, as shown in Figure 1.

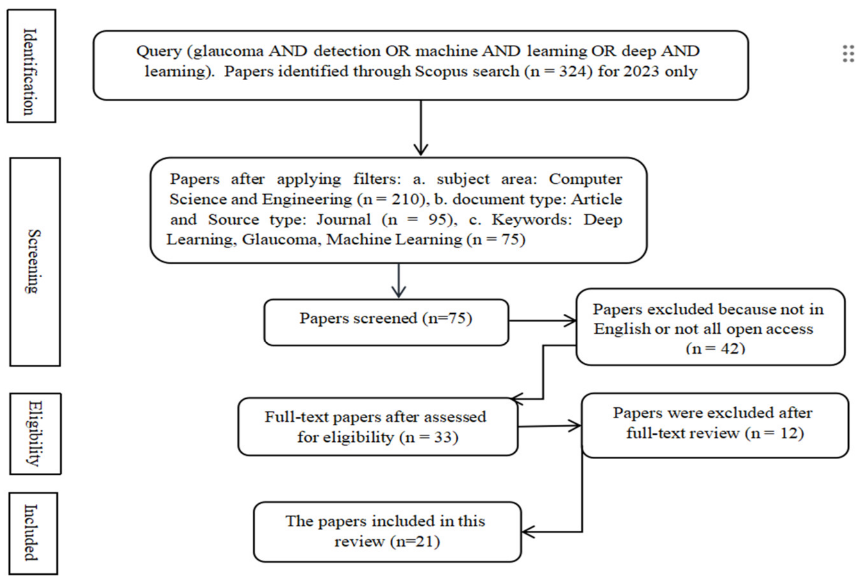


Fig. 1. PRISMA-ScR methodology utilized.

Having applied the subject area filter, 114 articles were removed, while 115 articles were removed after having implemented the document type filter and 20 articles were removed following the keyword application. Furthermore, 42 articles that were not in English and those that were not available for free were also excluded. After reading the titles and abstracts of the remaining articles, 12 more articles were removed, leaving 21 relevant articles. Further details about PRISMA can be found in [19].

## III. GLAUCOMA DETECTION TECHNIQUES

### *A. The Selected Reviewed Papers*

Regarding the selected reviewed papers, researchers either used only ML techniques, or exclusively DL methods, or ensemble learning that employs different ML and/or DL models.

#### *1) ML Models*

Several publications have deployed ML models for glaucoma detection. Authors in [20] employed the Enhanced Grey Wolf Optimized Support Vector Machine (EGWO-SVM) for image processing. Initially, they eliminated noise using the Adaptive Median Filter (AMF). Subsequently, the Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), and global features were utilized for feature extraction. For the classification, the EGWO technique, along with the SVM, was employed. The ORIGA database was used for testing, which produced remarkable performance metrics, that is, an accuracy of 94%, specificity of 92%, and sensitivity of 92%. Authors in [21] attempted to create models, able to detect glaucoma using ML algorithms and image feature descriptors in a publicly accessible retinal fundus image database. The goal was to classify the images as either normal or abnormal. The classification process occurred in two stages: first, the image features were extracted using specific filters, followed by training a tree-based ensemble classifier. Then, this classifier was tested to achieve optimal accuracy. The experiment was carried out iteratively exploring three effective filters, the Edge Histogram (EH), Pyramid Histograms of Orientation Gradients (PHOG), and Fuzzy Color and Texture Histograms (FCTH). They evaluated a combination of filters to determine the most effective one. They concluded that the employment of the EH filter in conjunction with the FCTH using a Random Forest (RF) classifier achieved the highest accuracy, 80.43%, while its Area Under the Receiver Operating Characteristic (AUROC) curve score was 0.884. Authors in [22] utilized four different ML classification methods in the Electronic Health Records (EHR) from more than 650 medical facilities in the US to predict glaucoma before the manifestation of clinical symptoms, allowing for potential early intervention and preventive treatments. The XGBoost, Multilayer Perceptron (MLP), and RF exhibited similar favorable results with an AUROC score of 0.81, while Logistic Regression (LR) achieved a score of 0.73. These models effectively predicted glaucoma one year before its onset based on patient EHR data, indicating the ML potential to identify patients before they develop glaucoma. Authors in [23] explored the Drop-Coating Deposition Raman Spectroscopy (DCDRS) as a non-invasive method to distinguish glaucoma patients from healthy individuals using tear samples. Raman spectra from 63 individuals were analyzed. The Principal Component Analysis-Linear Discriminant Analysis (PCA-LDA) was used to identify key features in the high-dimensional data. An SVM classifier based on PCA-LDA results categorized the samples, achieving 93.2% accuracy. The differences in the protein and lipid content in the tears contributed to the classification. With a 30% validation score, the accuracy remained at 90.9%.

Authors in [24] proposed the SVM and K-means clustering to determine the Cup-to-Disk Ratio (CDR) from fundus images. The SVM outperformed the K-means in terms of accuracy and consistency. They used a convex hull approach for diagnosis and classification and developed a web application for inexpensive and user-friendly screening. The SVM achieved better accuracy and consistency in the CDR determination. The identification of early-stage glaucoma's severity was possible, with the web application offering a cost-effective screening tool. The limitations in this paper were that the convex hull algorithm for contour joining might be slow and that the study relied on Optical Coherence Tomography (OCT) images captured by trained professionals with specialized equipment. Authors in [25] presented a modified dichromatic reflection model to separate specular reflections from corrupted fundus images. For this separation task, a modified U-Net Convolutional Neural Network (CNN) model was used, which can be also utilized to accurately segment relevant Regions Of Interest (ROI) from the preprocessed images. The relevant features were extracted from the segmented images, likely representing the morphological and structural characteristics related to glaucoma. An SVM classifier, trained with different kernels, was applied to classify the images into glaucomatous or non-glaucomatous categories based on the extracted features. After having compared seven existing methods to obtain diffuse and specular components, they adopted the one that produced the highest quality images and used the output image in the subsequent steps of the screening process. The experimental results demonstrated that the introduced model achieved a maximum improvement of 37.97 dB in PSNR and 0.961 in SSIM during the preprocessing step. The model attained an accuracy of 91.83%, a sensitivity of 96.39%, a specificity of 95.37%, and an AUROC of 0.971. Authors in [26] proposed automating the glaucoma diagnosis utilizing fundus images. Their framework operates as follows: ROIs are decomposed into components using the Bi-Dimensional Empirical Mode Decomposition (BEMD) algorithm. The DL features are extracted from these decomposed components using the VGG19 CNN architecture. These features are then aggregated for each ROI adopting a bag of features approach. Due to their high dimension, the features are subsequently reduced using PCA. The resulting bags of features serve as input to an SVM classifier for the final diagnosis. The public databases ACRIMA and REFUGE were employed for model training, while the testing involved a combination of the ACRIMA, REFUGE, ORIGA-light, RIM-ONE sjchoi86-HRF, and Drishti-GS-GS1. The REFUGE-trained model achieved accuracies of 98.31%, 98.61%, 96.43%, 96.67%, 95.24%, and 98.60% in ACRIMA, REFUGE, RIM-ONE, ORIGA-light, Drishti-GS-GS1, and sjchoi86-HRF, respectively. Similarly, the ACRIMA-trained model achieved accuracies of 98.92%, 99.06%, 98.27%, 97.10%, 96.97%, and 96.36% in the same databases, respectively.

#### *2) DL Models*

Numerous publications have utilized DL models for glaucoma detection. Authors in [27] used labeled fundus images from 13 diverse data sources. These included BMES, GHS, and 11 publicly available databases. To minimize data discrepancies, they developed a standardized image processing strategy to extract images centered on 30° discs from the original data. The testing model involved a total of 149,455 images. For the BMES and GHS cohorts, the AUROC curve achieved 0.976 and 0.984 scores at the participant level, respectively. At a specific specificity of 95%, sensitivity was 87.3% and 90.3%, respectively. The AUROC values in the eleven databases ranged from 0.854 to 0.988. Authors in [28] employed the AlterNet-K, a compact model that merges ResNets and multi-head self-attention, which was trained in the Rotterdam EyePACS AIROGS database and achieved 91.6% accuracy, 0.968 AUROC, and 91.5% F-score in glaucoma detection. The model's success is attributed to its alternating pattern of ResNet blocks and multi-head self-attention, which leverages their complementary strengths for better generalizability. The results suggest that smaller, parameter-efficient CNNs combined with multi-head self-attention can achieve high accuracy in medical image classification tasks, potentially outperforming larger models. Authors in [29] proposed a lightweight CNN to detect retinal disorders, focusing on binary judgments, meaning distinguishing healthy and non-healthy cases, specifically within non-healthy image screening. They evaluated its performance in two well-defined public databases. CNN reached an accuracy of 99.67% in the DR and 96.5% in the GL databases. Furthermore, in the context of non-healthy screening, aiming to differentiate between different retinal disorders, CNN achieved an accuracy of 99.03% when distinguishing between cases of GL and DR. Authors in [30] proposed a novel CNN architecture called ProspectNet, which outperformed two established pre-trained networks, VGG16 and DenseNet121, by exhibiting higher accuracy with reduced computational time and complexity. They used a combination of the DRISHTI-GS and the GL type Kaggle databases, containing ocular color fundus images of normal and glaucomatous eyes. The ProspectNet achieved an AUROC of 0.991, a specificity of 98%, and a precision of 98%. Authors in [31] employed DL techniques to identify open-angle glaucoma in fundus images based on three distinct architectures, VGG16, VGG19, and ResNet50. They classified the eyes as positive or negative for glaucoma using the Kaggle database. In particular, the data augmentation significantly improved all three models' performance, with accuracy ranging from 93% to 97.56%. Among them, VGG19 obtained the highest accuracy, 97.56%.

Authors in [32] proposed a technique for OD segmentation and classification using the DL and Pattern Classification Neural Networks (PCNs). First, they resized the input image and employed level-set segmentation for the OD segmentation. AlexNet was used for the classification. Additionally, the glaucoma images were fed to the PCN to be classified as initial, moderate, or severe stages. The Neural Network (NN) was trained utilizing statistical features and the CDR. This work, performed in the DRISHTI-GS, LAG, and RIM-ONE databases, achieved accuracy, sensitivity, and specificity of 98.42%, 97.6%, and 97.5%. Authors in [33] deployed the Restricted Boltzmann Machines (RBM) to extract features from retinal images for anomaly classification. They also utilized the U-network for image segmentation, and the Squirrel Search Algorithm (SSA) for hyperparameter tuning. Accuracy of 99.2% was achieved in the RIM-ONE database. Authors in [34] introduced a Deep Neural Perona-Malik Diffusive Mean Shift Mode Seeking Segmented Image Classification (DNP-MDMSMSIC) model for early glaucoma and Stargardt disease detection. The DNP-MDMSMSIC uses the space-variant Perona-Malik Diffusive preprocessing to reduce noise while preserving the edges, feature extraction to extract the intensity, color, and texture with high accuracy, and the mean shift-mode-seeking segmentation to segment the image based on its features. The Bregman divergence function, which classifies images based on the segmented region similarity, was also employed. The DNP-MDMSMSIC achieved an 8% higher accuracy and a 20% faster detection than previous methods in the ACRIMA database. Authors in [35] proposed the Max-Pooling Convolutional Neural Kuan-Filtered Tobit Regressive Segmentation-Based Radial Basis Image Classifier (MPCNKFTRS-RBIC) for early glaucoma and Stargardt disease detection with high accuracy and low processing time. This model utilizes a weighted adaptive Kuan filter to preprocess the images, feature extraction to extract intensity, color, and texture accurately, Tobit regressive segmentation to partition the images based on their features, and the radial basis function classifier. The model exhibited good performance on different metrics, in various image sizes and databases. Authors in [36] analyzed the retinal nerve fiber layer damage for glaucoma detection, involving two steps, preprocessing and classification. At the first step, unnecessary parts, like OD and blood vessels, should be removed to aid the analysis. For classification, nine DL architectures were employed. The method achieved the highest accuracy, 92.88%, and an AUROC of 0.8934 in the ORIGA database.

### 3) *Ensemble Learning*

Various publications have utilized ensemble learning methods, employing different ML and/or DL models. Authors in [6] proposed a multi-step system for automatic glaucoma detection. The process involved preprocessing images and determining the ROI through the analysis of statistical features. Then, clinical and texture-based features were extracted from ROI. Finally, an ensemble of classifier models was constructed using dynamic selection techniques. Evaluations were carried out in both public databases and 300 hospital images. The most promising results came from a combination of RF models with the META-DES dynamic ensemble selection technique. In the hospital database, this method achieved an impressive 100% accuracy, specificity, and sensitivity. The average accuracy, specificity, and sensitivity in the RIM-ONE and DRISHTI-GS databases reached 97.86%, 100%, 93.85%, 97%, 90%, and 100%, respectively. Authors in [37] deployed an average voting ensemble of multiple CNN models trained using the REFUGE database, which achieved the highest accuracy, 98%, and AUROC score, surpassing the individual VGG-16, ResNet-50, and MobileNet models. Among the single CNN models, ResNet-50 demonstrated the best performance. Ensemble methods can significantly improve predictive performance, but by including weaker-performing models can negatively impact the overall results. Authors in [38] developed a system, powered by CNN, for detecting glaucoma using fundus color images. The system isolates OD with a YOLO network and then classifies images using the

MobileNet. An extensive testing carried out with seven CNNs showed 97.4% accuracy, 97.3% F-score, 97.5% sensitivity, 97.2% specificity, and 0.993 AUROC. Authors in [39] presented a new Computer-Aided Diagnosis (CAD) system for diagnosing DR and glaucoma in multiple eyes simultaneously, which is a game changer for large-scale screening, since it reduces the demand for manpower and time. A segmentation-independent approach was adopted to avoid image quality issues, as well as an ensemble of an RF classifier with CNN, which captures essential image details. Finally, the employed sum rule combined the strengths of the RF and DL models for improved accuracy.

### B. *Databases*

The databases considered in the selected papers are illustrated in Figure 2.

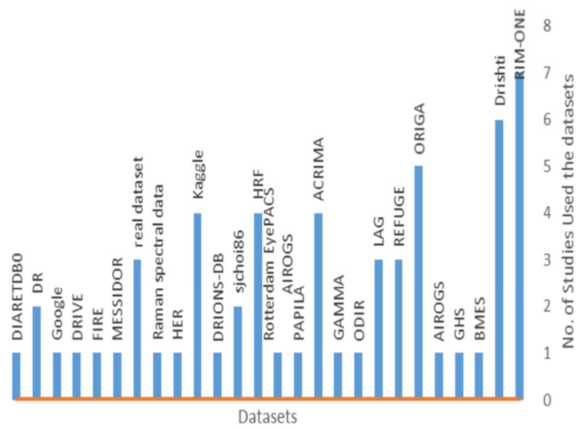


Fig. 2. Databases considered in the selected studies.

### C. *Evaluation Criteria*

Different evaluation criteria have been utilized to analyze the effectiveness of the proposed models [40, 41]. Table I provides a clear and concise overview of these criteria.

TABLE I. SUMMARY OF THE CONSIDERED EVALUATION CRITERIA

| Metric | Definition | Interpretation | Limitations |
|---|---|---|---|
| Accuracy | % of correct predictions | Overall performance | Misleading in imbalanced databases |
| Specificity | % TN correctly identified | Effectiveness in avoiding FP | Not relevant if TN are unimportant |
| Sensitivity (Recall) | % TP correctly identified | Ability to find all relevant cases | Not relevant if FN are unimportant |
| Precision | % of positive predictions that are actually correct | Proportion of positives that are TP | Not relevant if FP are unimportant |
| F1 score | Harmonic mean of precision and recall | Balanced view of precision and recall | Requires equal importance of FP and FN |
| AUROC | Area under ROC curve | Performance across different classification thresholds | Complex interpretation, not directly indicating class probabilities |

## IV. DISCUSSION

The current paper reviewed several studies that use ML and DL techniques related to the automatic detection of glaucoma, which is substantial, since early disease detection can limit its progression and prevent it from leading to very severe conditions, such as complete loss of vision. The aforementioned techniques include several algorithms, some of which have been used without any improvement or addition in the way they are implemented, while others have been enhanced. They also entail algorithms which have been combined, demonstrating promising results. As observed, the total number of scientific papers for a specific year, 2023, just in the Scopus database was 324. This means that the automatic diagnosis of the glaucoma disease using ML or DL techniques has recently gained importance due to the latter's success in the detection of diseases in general and glaucoma in particular.

The PRISMA guidelines were applied to filter the related work and effectively select the important papers employing the systematic method and meta-analysis. Therefore, the utilized techniques, databases, evaluation criteria, and the results of each technique were extracted from each related work.

The reviewed studies were carried out in different databases from several sources, which were either freely available on scientific websites or were obtained from patient hospital records. The databases included medical images of glaucoma, such as fundus images. The utilization of preprocessing methods contributed to the improvement of the performance metrics.

The researchers in the selected papers used different methods of ML, DL, and ensemble learning. The best performance metrics obtained using ensemble learning, were for the homogeneous RF classifiers, tested in the hospital database, which achieved 100% accuracy, 100% specificity, and 100% sensitivity [6]. The reason the RF method obtained greater accuracy than the other ones is that it combines the predictions of multiple Decision Trees (DTs) to make the final prediction. However, the best performance metrics obtained using ML were for the SVM, which achieved accuracies of 98.31%, 98.61%, 96.43%, 96.67%, 95.24%, and 98.60% in the ACRIMA, REFUGE, RIM-ONE, ORIGA-light, DRISHTI-GS, and sjchoi86-HRF databases, respectively, by using the REFUGE-trained model. On the contrary, the accuracy SVM obtained utilizing the ACRIMA-trained model in the same databases was 98.92%, 99.06%, 98.27%, 97.10%, 96.97%, and 96.36%, respectively [26]. Finally, the best performance metrics attained utilizing DL were for a lightweight CNN, which was deployed to distinguish between non-healthy and healthy images. In specific, it achieved an accuracy of 99.67% in the DR database and 96.5% in the GL database. In the context of non-healthy screening, CNN accuracy was 99.03% when distinguishing between the GL and DR cases [29].

In summary, the considered studies demonstrated promising results. Each of them involved a different accuracy value for glaucoma detection depending on the type of database and the techniques used. The potential of these methods to enhance early glaucoma identification and patient care is demonstrated, but many of these promising computer vision approaches have not been adequately tested in practical, real-world scenarios. This raises concerns about their effectiveness when applied to actual clinical or diagnostic problems. To bridge this gap, a crucial step is fostering close collaboration between computer vision engineers and clinicians. Such interdisciplinary teams can ensure a more gradual and informed deployment of the ML and DL algorithms in real-world settings.

## V. V. CONCLUSIONS

This paper presents the results of a systematic review and its meta-analysis. It explored various ML and DL models used to detect glaucoma. The main goal of these models is to provide a direct clinical diagnosis and the timely identification of patients with glaucoma, who need referrals or surgical intervention that could minimize vision loss and visual field defects. Given the challenges the healthcare system faces, the combination of ML and DL methods with medicine is becoming increasingly important to meet the growing medical demands. An ML and DL analysis reveals that their segmentation and judgments are in line with those made by ophthalmologists in their diagnoses. In addition, these methods can also help detect certain features that may go unnoticed by humans. This capability is expected to play a crucial role in future advancements, as it will improve people's understanding of the disease mechanisms and will collect more information from raw images.

The results presented in these studies offer compelling evidence of the promising performance of ML and DL methods. Detecting glaucoma in a timely and accurate manner can be a benefit for millions of people. These technological advances not only have the capacity to improve diagnostic precision, but also hold the promise of enabling earlier interventions and improved patient outcomes. The fusion of cutting-edge technology with the expertise of ophthalmologists offers a potent synergy that can lead to an improved quality of life for patients and a brighter future for vision health.

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