

A Comprehensive Review of Deep Learning Techniques for Detecting and Classifying Cataracts and Glaucoma

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Abstract. Artificial intelligence (AI) and deep learning have recently attracted a lot of attention as potential tools for the early detection of ocular diseases. Reason being, these innovations have the potential to substantially enhance therapeutic options and healing rates. With the use of algorithms built using massive medical datasets, a number of common eye disorders may now be detected automatically. These include myopia, diabetic retinopathy, macular degeneration, cataracts, and glaucoma. On a worldwide basis, cataracts and glaucoma are two of the leading causes of permanent visual loss. However, testing the viability of AI for the diagnosis of these two illnesses has been sparse in comparison to other age-related eye problems. An extensive review of deep learning algorithms for glaucoma and cataract detection using slit-lamp and fundus images and other relevant data is presented in this paper. As an added bonus, it explores state-of-the-art algorithms and models, preprocessing methods, retinal image databases, and performance evaluation standards. The main foci of this research are cataract diagnosis and glaucoma detection and classification. via the dissemination of new scientific knowledge to researchers and ophthalmologists via this comprehensive review, this study aspires to contribute to the progress of ophthalmology and the field overall.

Keywords: Eye disease, Cataracts, Glaucoma, Deep Learning (DL), AI.

1. INTRODUCTION

The World Health Organization cataloged that 285 million individuals globally fight against some form of visual loss [1]. Amongst this chunk, 39 million suffer vision loss, while the rest bear an atypical visual phenotype. Notably, pathology in cataracts constitutes 33% of the count of those with vision loss and a much more alarming 51% in blindness [2]. The American Academy of Ophthalmology defines cataract as a lens opacity [3]. The study agrees with risk factors for cataracts, which are age, diabetes, high blood pressure, tobacco use, and previous radiation [4]. Here are the many forms of cataracts, where they come from, and the dangers associated with them [5]:

1. Developmental and congenital: heredity, abnormal lens development in fetuses and infants during pregnancy, maternal undernourishment, infection, malnutrition, medications, radiation exposure during pregnancy or the first few years of life, metabolic disorders beginning at birth or continuing into childhood or adolescence, traumatic birth, congenital abnormalities, and ipsilateral. Could be there since birth or throughout teenage years.
2. Age-related: Factors such as mineral deficiencies, smoking, oxidative stress, systemic diseases, and dehydration are associated with aging. People over the age of fifty often experience this.

3. Traumatic: The foreign body-rupturing new revolutionary capsule. Workers in similar occupations, such as glassblowers and janitors, are also at danger.
4. Difficulty: Many inflammatory and degenerative eye diseases have complications. Individuals suffering from disorders of the skin, allergies, eyes, diabetes, emphysema, asthma, and glaucoma.
5. metabolic: diabetes, galactosemia, and other metabolic diseases. Some enzymes and hormones are absent at birth in patients.
6. Dangerous: NSAIDs and steroids in particular. Administering harmful medications and steroid treatment.
7. Electrical waves at high frequencies, as well as infrared, X-ray, and ultraviolet radiation. A person may be subjected to high voltage, artificial radiation, or intense sunshine.

The refractive lens is mostly translucent and subject to degenerative changes that cause a loss of transparency, resulting in deteriorating optical properties. This ultimately leads to the development of cataracts. Cataracts can cause visual abnormalities, such as difficulty distinguishing colors or seeing everything as blurry. Most often, colors do not have a particularly white undertone. They can become washed out, desaturated, unsaturated, or pastel, making accurate distinctions hard. They also transmit increased lights, which cause glare and halos around lights. Above all, cataracts cause a significant increase in the botheration of dark or blurry vision. When the foreground and background colors and values are almost same, objects will be difficult to make out, particularly in low-contrast environments. The most common kind of cataract to appear first is a nuclear cataract. Lens nucleus involvement is a hallmark of this cataract subtype. It encases the lens's core right up to its inner surface, just next the eye. Along with the brownish or yellowish undertones, the haziness is amplified by the opacity in this instance. It acts as a barrier to light and a mirror for the lens's internal physiological changes [1]. Figure 1 illustrates the different stages of how severe cataracts can be.

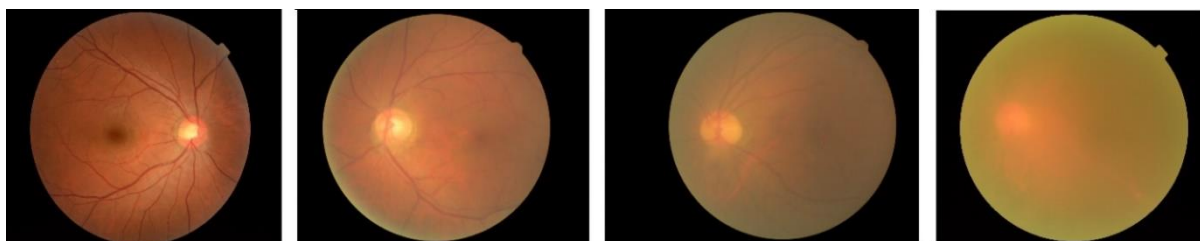
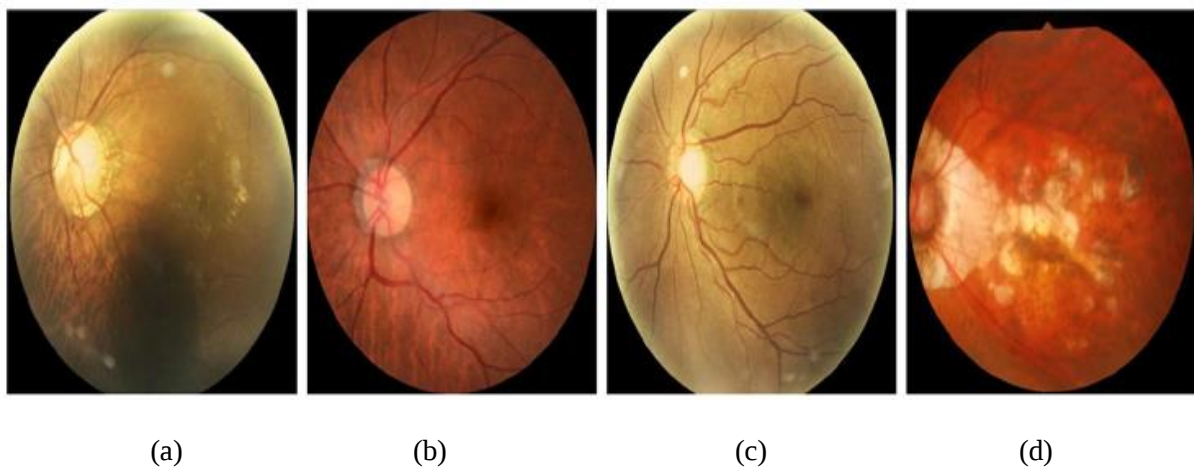


Fig.1. “Different types of cataract images, (a) normal (non-cataract), (b) mild cataract, (c) moderate-cataract, (d) severe cataract” [6].

It deserves emphasis that cataract pathology causes about 33% of the cases of vision disorder, where blinding is an even higher 51% shocking [2]. There are currently two main forms of cataract in the eye: nuclear cataract [7] and cortical cataract [8]. The severity of cataract conditions is progressively increasing. There has been a recent increase of 43.6% in the number of instances. Of the total number of cataracts, 23.1% are nuclear, 13.1% are posterior subcapsular (PSC), and the rest are cortical. Nonwhite groups have a greater frequency ($p = 0.001$) [9]. Cataracts may be classified as nuclear (NC), cortical (CC), or posterior subcapsular depending on where the cloudiness is located inside the lens. NC pertains to the central region, characterized by opacity and hardening, leading to a complete whitening of the center over time. CC is characterized by white, wedge-shaped, or radial opacities originating from the periphery and extending in a spoke-like fashion toward the center of the lens [10, 11]. Granular opacities behind the lens capsule are a feature of PSC, rather than the specks being likened to small crumbs or grains of sand [12]. One study applied active shape models using more than 5000 training examples to

achieve 95.00% accuracy [13]. Li et al. developed the Discrete State Transition (DST) ResNet model. They solved the vanishing gradient problem and achieved a 94.00% accuracy for cataract recognition. By using residual connections, the suggested DC-NN design solves the bursting and disappearing gradient issue. It can do away with picture preprocessing and induce high-dimensional features [14].

Glaucoma is defined as a global cause of irreversible blindness. Glaucoma is characterized as optic neuropathy, which induces the destruction of retinal ganglion cells in concomitance with irreversible loss of vision. Such eye diseases are prompted by certain structural changes within the retina, primarily within the optic nerve head region. Probably, the most widespread form of glaucoma is a disease of an open-angle. It progressively obstructs the drainage system at the angle between the iris and cornea, resulting in eyelid area expansion and elevated intraocular pressure, as reported by a growing number of sources. Despite these factors, it remains a serious ocular disorder since it is incurable; however, early identification may avoid significant vision loss. Current prevalent deep learning approaches include the lightweight design of MobileNet. In this study, data have been categorized into cataract, glaucoma, and normal utilizing transfer learning models to get optimal results from the benchmark [15]. According to the World Health Organization (WHO), 3.54% of people between the ages of 40 and 80 have glaucoma. Those who are afflicted run the risk of irreversible visual impairment. One in eight people have glaucoma, and the risk is highest in those under 40 years old compared to those over 80. Glaucoma is believed to be caused by increased intraocular pressure, which damages the optic nerve and blood vessels in the eye. Glaucoma may damage the optic nerve, which can lead to double vision loss and, in the worst case scenario, total blindness. Many different types of glaucoma may develop, including those caused by trauma, angle-closure, primary open-angle, congenital, pseudoexfoliation, and uveitis. The complexity of these types is evident from the fact that their occurrence varies among racial and ethnic groupings. Glaucoma develops when damage occurs to the optic nerve. The structure of the optic nerve head is seen in Figure 2. This group includes the vast majority of glaucoma patients. A small, partially obstructed segment of the drainage tube is responsible for the developed intraocular pressure. Consequently, the patient experiences early warning signs long before specific symptoms, such a decrease in peripheral vision in the afflicted eye, manifest. This occurs often. In acute glaucoma, often called "narrow-angle" glaucoma, the drainage system of the eye completely fails, leading to an abrupt rise in intraocular pressure (IOP) [16].



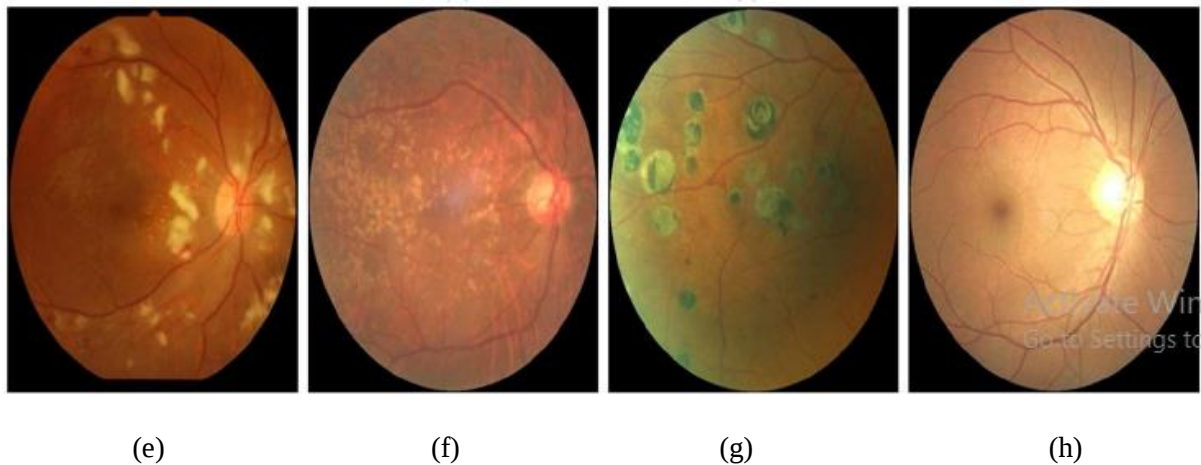


Fig. 2. “Images of glaucoma in different cases: a) normal macular epiretinal membrane; (b) mild nonproliferative retinopathy; (c) pathological myopia; (d) hypertensive retinopathy; (f) laser spot; (g) moderate nonproliferative retinopathy; and (h) mild nonproliferative retinopathy” [16].

As a result of the tremendous progress made in machine learning and deep learning, these industries are well-positioned to embrace deep learning approaches by incorporating a wide variety of domains into AI frameworks. A new branch of AI based on the ideas of machine learning has recently arisen: deep learning. It uses artificial neural networks with multi-layered artificial neurons to mimic the way the human brain operates physiologically. Systems that can absorb and understand data from visual and textual information, like voice recognition, are created using deep learning technology. Lung cancer diagnosis, breast cancer secondary lymph node metastasis identification, and real-time colon adenomas and polyp detection are just a few of the medical applications where the findings have shown promise. Artificial intelligence systems are mostly used in ophthalmology because they may improve the accuracy of identifying age-related eye diseases by analyzing large datasets of patient information and photographs. Diabetes retinopathy, glaucoma, and age-related macular degeneration are all diseases that fall within this category [17]. Algorithms in machine learning and artificial intelligence have been crucial in defining the 21st century's environment. A plethora of academic studies has arisen using deep learning techniques for the diagnosis and categorization of many illnesses, notably COVID-19.[18], gender [19], cataract [6, 15, 17, 20-34], and glaucoma [15, 16, 35-40], detection and classification of cataract or glaucoma are given in Figure 3. A typical structure regarding cataract or glaucoma detection and classification is presented in Figure 3.

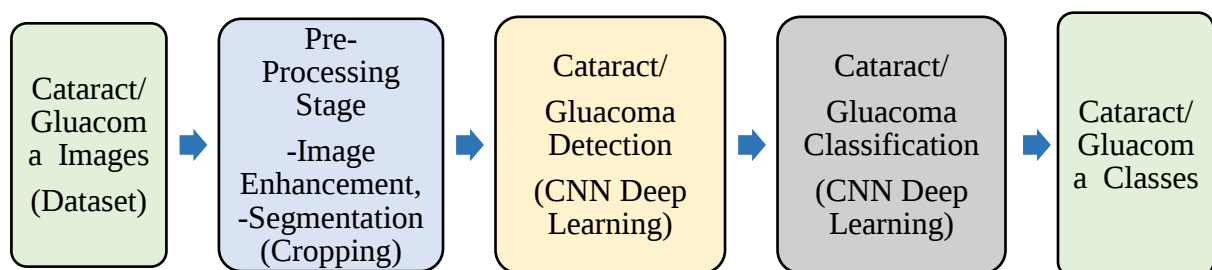


Fig.3. The structure of the automatic detection/classification cataract/glaucoma system [34].

2. LITERATURE WORK

A recent investigation employs pre-trained deep learning architectures to identify and categorize models of computer-aided diagnostic (CAD) systems. The automated identification and categorization of cataracts and glaucoma through retinal imagery have garnered significant attention within the domain of medical imaging. Numerous scholarly articles pertaining to this subject assert that the methodology typically encompasses three fundamental phases: preprocessing, feature extraction, and classification. The existing literature delineates two primary objectives: the identification or classification of cataracts, as well as the detection or classification of glaucoma.

2.1. THE APPLICATION OF DEEP LEARNING TECHNIQUES FOR CATARACT DETECTION AND CLASSIFICATION

In [20], Automated nuclear cataract diagnosis. Nuclear cataracts were assessed by slit lamp lens imaging for opacity. The lens images were physically described using a modified active shape model. Local features were determined using anatomical landmark-based clinical grading. SVM regression was used to create the degree prediction classification model. The approach was tested using clinical photos and ground truth data. Nearly five thousand slit-lamp pictures were evaluated. The feature extraction success rate was 95% with an average classification error of 0.36.

In [21], Research examined automated nuclear cataract diagnosis. Lens pictures were analyzed for anatomical characteristics after changing the active form model. We used clinical grading, which uses anatomical landmarks, to acquire area information. An SVM application Regression predicted degrees. First-ever automated nuclear zone identification in slit lamp pictures. This method has a 95% success rate with over 5,000 clinical pictures and clinical ground truth.

In [22], This research presents a method for automatically learning nuclear cataract severity criteria from slit lamp images. Local filters were first constructed by collecting picture components from lenses with the same graduation grade. Using previously trained filters, recurrent neural networks extracted more higher-order data from convolutional neural networks. Features were utilized to determine cataract grade using support vector regression. The results are: This approach was validated using 5,378 population-based pictures. Clinical categorization caused a mean absolute error of 0.304, with R0 having 70.7% precise integral agreement, Re0.5 88.4%, and Re1.0 99.0%.

In [23], The automatic algorithm sorts fundus photos according to cataract kind and evaluates them. Fundus pictures, feature extraction, and image preprocessing techniques were used for automatic grading and categorization. In order to classify and grade cataracts in fundus pictures, the study used feature extraction approaches based on sketches and wavelet transforms. Cataracts were categorized as either mild, moderate, or severe using Multi-Class Discriminant Analysis. In order to assess the system, a database was built with fundus photographs illustrating various degrees of cataract severity. In binary classification, the wavelet transform achieved an accuracy of 90.9% while in cataract classification, it achieved 77.1%. Results obtained from wavelet transform analysis are closely matched by the sketch-based technique, which attained accuracy rates of 74.0% for binary classification and 86.1% for grading.

In [24], This study employed fundus retinal images to detect cataracts. Computer-assisted cataract classification includes normal, moderate, severe, and extremely severe. Category classification using a transfer-learned CNN. A support vector machine (SVM) classifier analyzed CNN characteristics for this study. Ophthalmologists graded fundus cataract pictures from numerous public sources as stage four. The four-stage classification has 92.91% accuracy.

In [31], For nuclear cataract detection and severity classification, the team employed a smartphone camera placed on a slit lamp to capture photos of the eyes and test the algorithm. The algorithm's purpose was to measure cataracts using central lens photometric features. By using YOLOv3, the lens

focal plane was found. We then determined cataract level using an SVM classifier on the feature's conjugate greys and the ShuffleNet deep learning network. Smartphone images taken in front of the slit light were used to build 819 algorithms, including one for testing. The model achieved 93.5% accuracy, 95.4% Kappa, 92.3% F1, and 0.9198 AUC.

In [30], When AWGN is present, this research uses strong CACD to select networks. The system uses autonomous support vector networks trained locally or globally on data from three noise levels. Use a pre-trained convolutional neural network to automatically extract information from fundus retinal images. AWGN was used to create noisy fundus retinal images for testing and analysis. NIQE scores indicate that the Eye PACS dataset yielded high-quality fundus retinal images with a test accuracy of $92.97 \pm 1.75\%$.

In [6], Two experienced graders utilized slit-lamp and retro-lens imaging to evaluate LOCS III. The labeled dataset was divided for training, validation, and testing. AI approaches utilized an area detection network to reduce data duplication, entropy loss to reduce dataset constraints, and Class Balance Loss to correct class imbalances. Best-performing AI algorithms were ResNet18, WideResNet50-2, and ResNext50. Diagnostic and LOCS III result projections from the AI platform are below. AI platform diagnoses with 98.82% accuracy. A deep learning system using 2D discrete Fourier transform spectra of fundus pictures can detect and describe early cataracts. Fundus picture spectrograms are created using 2D DFT to extract features for deep learning models. A Softmax classifier classifies the features. Ophthalmologists divided open-source fundus pictures into four categories. Public fundus photos cannot diagnose cataracts. Our technique includes fundus image quality evaluation. Experimental results show that the suggested approach beats state-of-the-art four-level categorization with 93.10 percent accuracy.

In [34], This article uses a convolutional neural network as a deep-learning model to detect, identify, and classify cataracts using colored fundus pictures. 300 of the 400 color photos show normal eyes and 100 reveal cataracts. Finally, we automated histogram equalization and contrast-limited adaptive equalization before analyzing these datasets. The study compares DenseNet201, ResNet-101, and GoogLeNet. The first set shows original source photos, the second histogram equalization (HE), and the third a mix of both. Densenet201 outperformed GoogLeNet-based models with over 98% classification accuracy.

2.1. USING DEEP LEARNING TECHNIQUES FOR GLAUCOMA DETECTION AND CLASSIFICATION

In [16], Researchers have used deep learning algorithms to predict glaucoma before it appears. The deep learning system analyzes glaucomatous photos to diagnose the ailment. The U-Net architecture for optic cup segmentation uses a pre-trained optic disc feature extraction model for glaucoma detection. DenseNet-201 DCNN will extract features. Decision-critical neural network (DCNN) diagnosis of glaucoma. For patient diagnosis, this study aims to distinguish glaucoma from retinal fundus photos. Results from the system's model include glaucoma positives and disadvantages. Accuracy, precision, recall, specificity, F-measure, and F-score are used to evaluate models. The model was 96.9% accurate.

In [41], EfficientDet-D0 is a deep learning model based on EfficientNet-B0. A three-stage glaucoma localization and classification approach is provided. EfficientNet-B0 feature extractors identify suspicious data's underlying characteristics. The BiFPN module uses EfficientNet-B0 to fuse critical points top-down and bottom-up. The last step is to predict the glaucomatous lesion's location and kind. The Online Database of Retinal Fundus Images for Glaucoma Analysis (ORIGA) was utilized to assess resilience rigorously. The study confirmed its applicability to different datasets using the High-Resolution Fundus and Retinal Image Database for Optic Nerve Assessment. Model recall was 0.97 and AUC 0.979.

In [37], A public fundus image collection has been made accessible for deep learning glaucoma investigations. The 2,000 pictures from 1,000 persons in the "Brazilian Glaucoma" dataset are distributed evenly between glaucoma and healthy subjects. Smartphones were attached to Welch Allyn panoramic direct ophthalmoscopes to take pictures. This research developed an autonomous glaucoma detection system using deep learning and a convolutional neural network ensemble model. By using five-fold cross-validation, we trained and optimized the glaucoma classification model and measured accuracy, sensitivity, and specificity. This method recognized glaucoma 90.0% of the time on fundus pictures. A smartphone-acquired fundus picture and AI diagnostic system glaucoma diagnosis was accurate.

In [35], Convolutional neural networks (CNNs) have enabled a memory- and computationally efficient autonomous glaucoma detection method, a significant cause of blindness worldwide. Bifurcated glaucoma detection in color fundus photographs is possible with this instrument. Authors locate optic nerve head using YOLO-CNN architecture. MobileNet classifies the area as "non-glaucoma" or "glaucoma" using this information. We improved the original YOLO network and made it smaller. The authors investigated seven cutting-edge CNNs, including MobileNetV2 and MobileNetV3, InceptionV3 and ResNet50, 18-Layer CNN, and InceptionResNetV2, across computational complexity. The findings were collected from 6,671 fundus images from seven public glaucoma databases. The system has 97.2% specificity, 99.3% AUC, 97.4% accuracy, and 97.3% F1 score.

In [39], Deep learning was used to automate retinal imaging and glaucoma detection in the research. Retinal images and masks of the optic disc and cup helped identify glaucoma. Segmentation was done using U-Net and a pre-trained residual neural network (ResNet34), and classification with EfficientNetB0. This work used public datasets ORIGA, REFUGE, RIM-ONE DL, and HRF to verify the suggested technique. Pre-processing techniques were tested and the U-Net model compared to five pre-trained backbones: ResNet34, ResNet50, VGG19, DenseNet121, and EfficientNetB0. Data augmentation and transfer learning improved model training. The segmentation model has an AUC of 0.98. The HRF dataset classification model has 98% training accuracy and 100% test accuracy. It has 100% test accuracy and 99.9% performance on the ORIGA dataset. It scored 99% accuracy and 99.9% performance on RIM-ONE DL.

In [40], ResNet50 and VGG-16, two convolutional neural networks, enabled a new glaucoma detection method. Independent studies of pre-processed retinal pictures and post-processing forecasts provided a complete assessment of glaucoma's effects. Our hybrid design had 95.41% accuracy, 88.37% recall, and 99.37% precision. This setup's careful accuracy-recall balance yields a 93.52% F1 score. The hybrid framework correctly diagnoses glaucoma, according to the results.

Table 1. The comparisons between existing works

Refs.	Dataset size (no. of images)	Deep learning Model	Accuracy (%)	Training/ Validation/ classification of a single image (Sec)	Applications
[6]	1,835	CNN with 2D-DFT	93.1	160/30/0.75	Cataract
[14]	1,355	DST-ResNet, EDST-ResNet	94 91.43	-----	Cataract
[16]	650	DenseNet-201	96.90	-----	Glaucoma
[20]	5,820	ASM with SVM Regression	95	-----	Cataract
[21]	5,850	SVM Regression	95	-----	Cataract
[22]	5,378	Convolutional-Recursive Neural Networks	99	-----	Cataract
[23]	445	Wavelet transforms sketch method hybrid of wavelet transforms	90.9 86.1 89.3	-----	Cataract

		and the sketch method			
[24]	800	Pretrained CNN SVM classifier	92.91	540/15/0.0085	Cataract
[30]	1,280	Pre-trained CNN-based CACD	92.97	-----	Cataract
[33]	3,500	LeNet-CNN	96	-----	Cataract
[34]	400	Densenet201, GoogLeNet, ResNet-101	98.33, 96.56, 88.69	40	Cataract
[36]	705	ResNet50, VGG19, AlexNet, DenseNet-201, and Inception-ResNet-v2	99.86, 98.58, 94.61, 99.01, 92.91	46	Glaucoma
[39]	650	U-Net ResNet34, ResNet50, VGG19, DenseNet121, and EfficientNetB0	99.9	150	Glaucoma
[40]	5,550	ResNet50, VGG-16	95.41	-----	Glaucoma
[41]	650	EfficientDet-D0 with EfficientNet-B0	97.1	0.2	Glaucoma

3. CONCLUSIONS

This development has facilitated the creation of innovative systems and strategies for the detection, classification, and evaluation of intraocular lens performance in cataracts and glaucoma. The rapid advancement of computational power, coupled with the exponential growth of big data, is poised to significantly transform clinical practice and care for cataracts and glaucoma in the near future. In the context of assessing and processing fundus, OCT, and visual field data, this research evaluates current literature organized by architectural types, including convolutional neural networks (CNNs), autoencoders, attention networks (ANNs), graphical neural networks (GANs), and geometric deep learning models. Experiments have demonstrated favorable outcomes in areas such as classification, segmentation, and glaucoma prediction. This will provide an additional advantage. The automatic analysis of routine tasks reduces diagnostic time and facilitates rapid, investor-attractive expansion into underserved regions. Long-term development and validation of solutions for clinical application require multidisciplinary techniques that integrate computer science, engineering, and medicine. This research highlights the significant potential at the intersection of artificial intelligence and ophthalmology. The primary aim is to conduct a comprehensive review and analysis of the current advancements in this highly promising and important topic.

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