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Applications of Artificial Intelligence in Ophthalmic Diseases

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Abstract

The rapid development of artificial intelligence (AI) technology is profoundly reshaping all walks of life, especially in the medical field. AI provides innovative tools for medical diagnosis, treatment, and management and lays a solid foundation for personalized medicine and precision medicine. This paper reviews the latest progress in the application of AI technologies such as machine learning (ML) and deep learning (DL) in ophthalmic diseases.

Keywords

Artificial Intelligence, Ophthalmology, Screening, Diagnosis, Prevention, Treatment

1. Introduction

In the 21st century, the rapid development of artificial intelligence (AI) technology has quietly infiltrated all walks of life, especially in the medical field. From basic medical research to the application of clinical diagnosis and treatment, from disease diagnosis to prognosis evaluation, from disease prevention to health management, AI technology is empowering the medical field at a great speed so that the model of medical services [1].

The examination results of ophthalmology are mostly in image or digital form, which is an important prerequisite for the application of AI. At present, AI algorithms in the field of ophthalmology are mainly supervised learning. Traditional machine learning techniques such as support vector machines (SVM) and random forest (RF) show robust computing power and excellent performance in processing clinical data in digital or text forms. They have also been applied to small samples of ophthalmic image processing in the early stage. With the exponential growth of clinical data, the big data information in ophthalmic images has too high computational complexity and low efficiency for traditional machine learning algorithms. The ability of neural networks in feature learning and image processing of complex structures of large samples and high-dimensional data makes it one of the popular AI technologies in the field of ophthalmology. Transfer learning technology can transfer the trained model parameters to the new model, thus significantly reducing the sample size required for new model training and improving the efficiency of model optimization [2].

In China, the development of ophthalmologists is not balanced, the overall technical level is low, and the proportion of ophthalmologists is unreasonable [3]. AI can significantly improve diagnostic efficiency. It provides innovative tools for screening, diagnosis, treatment, and prognosis management of various eye diseases and shows excellent potential in personalized medicine and precision medicine [4].

This review summarized the main progress of AI in the field of ophthalmology in recent years.

2. Myopia

With the popularization of digital technology and the increase of people's exposure to electronic equipment, the incidence of myopia has increased rapidly [5]. According to statistics, there are more than 1.4 billion myopia patients in the world [6], and the overall myopia rate of adolescents in China is much higher than the world average. The development of ophthalmologists in China is not balanced, and traditional medical methods have been difficult to meet the needs of myopia prevention and control. AI technology has gradually become an important tool in myopia prevention and control. AI can process a large amount of visual data through deep learning, pattern recognition, and computer vision and extract valuable information. It has been applied in the prevention, screening, treatment of myopia and diagnosis of pathological myopia [7].

2.1. Personalized Treatment

Using AI technology to provide precise and personalized treatment for school-age children will likely prevent myopia development. Recently, some new smart wearable devices have appeared on the market, which can detect children's and adolescents' eye postures and habits in real time. The representative device is the "cloud clip" developed by the Aier Eye Institute of Central South University [8]. Research shows that wearing a cloud clip can effectively prevent lousy posture and close reading and writing behavior and can still be maintained for some time after stopping wearing, slowing down myopia's formation and progress [9].

2.2. Myopia Screening

At present, the most important means of myopia screening in China is in the annual physical examination of primary and secondary schools, professionally trained nurses or technicians enter the school for naked eye vision examination, and then refer children with abnormal vision to the hospital for further optometry to confirm the diagnosis [10]. Some new technologies assisted by AI can remotely monitor the refractive status of adolescents in real time through mobile intelligent devices, which is conducive to the large-scale promotion and popularization of myopia screening, effectively reducing the time cost and labor cost, and is of great significance to the public health prevention and control of myopia [11].

Jaeb Visual Acuity Screener is an open and free myopia screening software [12]. Parents can use a home computer to screen children for myopia at home. SVone is an external device that can be connected to a common smartphone on the market and can be used for refractive screening at any time [13].

2.3. Myopia Prediction

The smartphone application developed by Ma *et al.* predicted that the sensitivity and specificity of myopia in the future were 0.83 and 1.00, respectively [14]. Also, the prediction model of juvenile myopia progression established by Yang *et al.* has good performance and accuracy [15].

2.4. Diagnosis of Pathological Myopia

Hemelings *et al.* developed a model based on a deep learning algorithm using color fundus photography, which can successfully diagnose pathological myopia and classify fundus lesions caused by it [16]. Moreover, Li *et al.* trained four independent deep learning models using OCT image reports [17]. Sogawa *et al.* also used OCT images to construct convolutional neural network models to assist in the diagnosis and identification of pathological myopia fundus complications [18].

3. Corneal-Related Diseases

AI also shows great potential in the field of corneal-related diseases. A number of studies have applied AI to keratoconus and infectious keratitis.

3.1. Keratoconus

Keratoconus (KC) is a non-inflammatory corneal dilatation eye disease that often leads to corneal asymmetry, progressive thinning, and irregular astigmatism ultimately leading to visual loss. The lack of early diagnostic tools has led to a low diagnostic rate of KC [19]. As a new generation of diagnostic tools, AI can use multimodal ophthalmic imaging to analyze multiple parameters to improve the diagnosis and treatment of early KC in the case of poor sensitivity of a single instrument or single parameter diagnosis of early KC. The early diagnosis of keratoconus is complex, and it is necessary to comprehensively analyze the corneal topography and biomechanical characteristics in the evaluation process. The AI model based on corneal topography (EyeSys System 2000, Tomey, Orbscan, Pentacam) and anterior segment optical coherence tomography can help the early diagnosis of keratoconus [20] [21].

3.2. Keratitis

Microbial keratitis (MK) is one of the leading causes of corneal blindness worldwide [22]. However, the analysis of the severity of keratitis in clinical practice is highly subjective and relies heavily on the diagnosis of the observer, which is time-consuming and labor-intensive [23]. Therefore, there is an urgent need for an AI-based algorithm to quickly and accurately diagnose microbial keratitis. In 2018, Wu *et al.* used an adaptive robust binary pattern (ARBP) combined with a support vector machine algorithm to construct an automatic diagnosis algorithm to diagnose and identify microbial keratitis accurately [24]. This method has good advantages compared with the results of corneal scraping. Unlike the algorithms that identify keratitis diseases alone, the deep learning system developed by Wu *et al.* can identify keratitis and other ocular surface diseases, identify information related to diagnosis, and provide treatment recommendations. Although there are not many studies on AI based on keratitis, AI has shown good feasibility in the diagnosis of keratitis [25].

4. Cataract

Cataract is the leading cause of visual impairment worldwide and one of the most serious causes of blindness [26]. With the progress of China's aging population and the increase of the elderly population, by 2050, China's cataract blindness cases are expected to reach 20 million. Early diagnosis and surgical treatment of cataracts are essential to improving patients' quality of life with low vision [27]. With the continuous improvement of AI's ability to classify images and videos, people can screen and diagnose cataracts without the intervention of clinicians, further reducing the cost of cataract diagnosis and treatment and improving the efficiency of cataract diagnosis and treatment [28].

4.1. AI Diagnosis of Cataract

The clinical diagnosis of cataract depends on the degree and location of lens opacity observed under the slit lamp biological microscope, combined with the patient's visual acuity, medical history, and other information to make a diagnosis. At the same time, AI uses slit lamp microscope images and fundus images to make a diagnosis of cataracts [28]. In 2010, Xiang D *et al.* proposed the use of AI to identify slit lamp microscope images for the diagnosis of nuclear cataracts. A 38-point shape model was used to detect the nuclear area in the lens, and meaningful and accurate features were extracted to compare with four standard photos for grading. The first system that can automatically detect the nuclear area in the slit lamp image was proposed and tested in a database of more than 5000 images. The results showed that up to 95% of the photos can be automatically diagnosed without user intervention [29]. Then, in 2019, Zhang H *et al.* proposed a multi-feature superposition mode. Using the DL algorithm, the cataract was automatically divided into six levels according to the fundus image, which required three processes: First, the deep neural network performs feature extraction on the fundus image; then, the texture features of the original image and blood vessel image are obtained. Finally, the superposition is used for multi-model training. The superposition can use multiple classifiers for ensemble learning to reduce the comprehensive error, thereby improving the effect of cataract grading diagnosis. The accuracy of the six-level classification of cataract by this method can reach 92.66% on average and up to 93.33%. Using this method to classify cataracts into four grades, the accuracy can reach 94.75%, which is at least 1.75% higher than the existing methods [30].

4.2. AI Optimization of Intraocular Lens Diopter Calculation

With the improvement of people's living standards, the high demand of human beings has promoted the rapid development of cataract surgery from vision restoration surgery to precise refractive surgery. After cataract surgery, patients generally accepted that the postoperative refractive goal is within 0.50 D of emmetropia or mild myopia. Any single unoptimized formula can only reach 70% - 80%, and about 25% of patients deviate from the target diopter more than 0.50 D [31]. To this end, Siddiqui *et al.* proposed an AI-integrated intraocular lens calculation formula system, which integrates other formulas and is suitable for calculating typical and atypical axial length, corneal curvature and anterior chamber depth. Clinicians do not need to find the most matching calculation method from multiple formulas. It first uses axial length, corneal curvature, anterior chamber depth, lens constant, and target refractive value as input parameters and then adjusts the calculation with axial length, corneal curvature, and anterior chamber depth to achieve the purpose of optimizing the formula [32].

5. Glaucoma

Glaucoma is an optic neuropathy characterized by progressive death of retinal ganglion cells (RGC) and their axons [33] [34]. In China, the prevalence of glaucoma in people over 40 years old is about 2.6%, and the blindness rate is about 30.0% [35]. The onset of glaucoma is insidious. Most patients are in the middle and late stages of the disease when they are diagnosed [33], and the optic nerve function has suffered severe irreversible damage. Therefore, early diagnosis and timely intervention significantly reduce visual function damage and improve prognosis in glaucoma patients. Existing evidence shows that various AI methods can improve the diagnostic accuracy of early glaucoma and reduce missed diagnoses and misdiagnoses [34] [36]. AI has high sensitivity and specificity in detecting glaucomatous optic neuropathy from fundus color photography, which is expected to improve the screening efficiency of glaucoma, expand the screening population, and simplify the work of ophthalmologists [37].

5.1. Glaucoma Screening

Currently, glaucoma screening techniques mainly include intraocular pressure examination and fundus photography. AI is primarily combined with fundus photography in the early screening of glaucoma. Fundus photography is the most rapid and simple method to judge glaucoma optic nerve damage. At the same time, intraocular pressure examination is the gold standard for glaucoma screening, and it can also be used as an essential auxiliary diagnostic basis for fundus photography [38]. In recent years, there have been many DL studies on glaucoma recognition by fundus photography, which are mainly applied to fundus image recognition from two aspects: one is to obtain an apparent cup-disc ratio (C/D) from the fundus image or directly classify the recognized image as a whole to detect the presence of glaucoma lesions; based on the first aspect of the study, Li Developed a DL network (ResNet101) that uses color fundus images to recognize glaucomatous optic neuropathy (GON). In this study, 34279 fundus images were used to train and test the DL model. The results showed that the sensitivity was 0.957, the specificity was 0.929, and the area under the receiver operating characteristic curve (AUC) was 0.992. This is a study based on a large database with high credibility. This DL algorithm can efficiently and low-costly provide experts with auxiliary diagnostic advice and help primary medical institutions conduct large-scale glaucoma screening. The other is to predict the OCT (Optical Coherence Tomography) detection value by identifying the fundus image through the "machine-to-machine" mode, such as by predicting the thickness of the retinal nerve fiber layer (RNFL). Based on the second aspect of the study, the principle of this kind of model is to accurately predict the measurement parameters of OCT examination by identifying fundus images which can more accurately identify glaucoma lesions [39]. In a study by Medeiros *et al.*, a CNN was trained using OCT data from 32,820 fundus photographs to evaluate the fundus photographs and predict the average RNFL thickness detected by OCT. The predicted RNFL thickness has a high similarity to the actual measured RNFL thickness. The AUC of using these expected values to distinguish glaucoma from normal eyes is 0.944, while the AUC measured using the actual RNFL value is 0.940, and the results are almost the same. Therefore, the "machine-to-machine" model can promote the combination of multimodal data and strengthen the connection between multiple glaucoma examinations [40]. China has put forward uniform standards for data acquisition, algorithm model construction, and hardware requirements of AI glaucoma fundus photography-assisted screening systems [41]. With the rapid development of AI in fundus image recognition ability, combined with more standard clinical guidelines, early screening of glaucoma will be more efficient, high-accuracy, and low-cost.

5.2. Accurate Diagnosis of Glaucoma

Fundus photography is very convenient and economical and is suitable for assisting large-scale glaucoma screening in grassroots areas. However, further accurate diagnosis requires the combination of OCT and visual field examination results. Both methods are objective criteria for judging glaucoma damage. At the same time, some studies combine OCT with the diagnosis of visual field examination, analyze the function and structure, and propose the objective criteria for glaucoma diagnosis from the structure and function [42], and obtain more reasonable and accurate diagnostic results.

5.2.1. Optical Coherence Tomography (OCT)

In recent years, numerous studies have utilized deep learning techniques applied to OCT images and data to detect glaucoma. The input data modes for these deep learning models can be categorized into three main types: first, inputting quantitative parameters, thickness maps, deviation maps, and similar data obtained by traditional OCT detection and automatically segmented by computer. For example, Lee *et al.* integrated DL by inputting the thickness and deviation maps of RNFL and GCIPL and extracting features from them. The AUC of the algorithm is 0.990, which achieves excellent performance and can accurately distinguish glaucoma and normal eyes [43]. Second, inputting is performed using undivided two-dimensional scans. Thompson *et al.* used the undivided two-dimensional scanning image for DL algorithm training to identify glaucoma and healthy eyes efficiently. Compared with traditional OCT, their algorithm has better diagnostic performance for glaucoma structural changes [44]. Third inputting is done using undivided three-dimensional scans. In the study based on unsegmented 3D scan images, the DL algorithm can make full use of the relevant information of glaucoma lesions [45]. In addition, Maetschke *et al.* developed an undivided OCT three-dimensional scanning image specifically designed to identify qingguang [46].

5.2.2. Vision

Visual field examination is an essential basis for the diagnosis of glaucoma. In the early study of Li *et al.* 4012, pattern deviation probability maps were input to classify glaucoma, and CNN was used for testing, training and verification. The results showed that the AUC was 0.876, better than the other two glaucoma classification criteria. At the same time, the accuracy rate was also higher than that of glaucoma doctors and experts. The specificity and sensitivity were 0.826 and 0.932, respectively. An unsupervised algorithm called prototype analysis appears to quantitatively classify and independently analyze the defect patterns of the field of view. This method is similar to traditional statistical analysis [47]. In the study conducted by Elze *et al.*, unsupervised learning was applied to analyze 13,321 Humphrey visual fields. The aim was to identify various patterns of visual field defects and to detect those associated with retinal nerve fiber layer (RNFL) damage. The results obtained can help quantify different subtypes of visual field defects related to glaucoma [48]. Moreover, in subsequent studies, factors such as non-glaucomatous visual field defects and lens edge artifacts were excluded to enhance the accuracy of the results [49].

5.2.3. OCT Combined with Visual Field

The application of single-modality AI based on OCT or visual field has made some progress, and the application of multi-modality AI combined with OCT and visual field has also achieved initial results. Various studies have shown that the diagnostic performance of AI test learning on structure and function is better than that of AI test learning on structure or function alone [50] [51]. Therefore, a series of multimodal AI studies based on the combination of OCT and visual field have emerged. In the study of Xiong *et al.*, a new DL algorithm based on OCT and visual field-paired data input was developed. For the first time, the superiority of the dual-modality diagnostic algorithm over the single-modality was verified on the large sample of OCT-visual field-paired data. Due to the complementarity of OCT and visual field, the dual-modality algorithm can accurately identify glaucoma patients. It is the world's first big data examination of joint function (visual field) and structure (OCT). The AUC reaches 0.943, which is better than any single modality detected in the same period [52].

6. Fundus Diseases

With the increasing aging of the population in China, the prevalence of fundus diseases is increasing year by year. Fundus is the only part of the whole body that can be observed directly and intensively with the naked eye to arteries, veins and capillaries. Many systemic diseases can be reflected from the fundus, such as diabetes, hypertension, kidney disease and so on. Early diagnosis of fundus diseases is very important [53].

6.1. Diabetic Retinopathy

Diabetic retinopathy (DR) is the leading cause of visual loss and preventable blindness in adults aged 20 - 74 [54]. Therefore, through early screening of DR, it is found that patients who need systematic ophthalmic examination and treatment are expected to avoid permanent visual loss. AI-related research on DR is the earliest, largest and most mature in the field of ophthalmology, especially in DR screening, progress risk assessment, and remote diagnosis and treatment [55].

6.1.1. Application of AI Model in DR Screening

Previously, AI systems relied on "hard coding" for image processing and detecting specific lesions. In the past decade, the assistance of deep learning algorithms has enabled AI systems to learn and improve independently according to the ever-expanding image database, which has improved the sensitivity and specificity of diagnosis [56]. Compared with traditional machine learning, the advantages of deep learning are reflected in high automation. First, it does not need to manually extract data and convert it into machine algorithms, relying on large data sets to generate representative data directly. Secondly, there is no need to set precise rules, and automatic operation without monitoring can be achieved by learning many examples of expected behaviors. A convolutional neural network is a widely used deep learning model. It can receive input images and assign various features to analyze retinal color images automatically [57]. The model has also been applied to frequency domain optical coherence tomography (SD-OCT), and its accuracy in identifying high-reflective lesions exceeds traditional methods [58].

However, although the automatic analysis model of retinal images can help improve the cost-effectiveness of DR screening, the acceptance of AI systems by patients and medical workers, medical ethical issues and false negatives are caused by insufficient algorithm learning capabilities [59].

6.1.2. Risk Prediction Model of DR Progress

The model for predicting the risk of DR occurrence and progression is based on the creation of a specific learning system, which can summarize and analyze the condition of a large number of different patients and the targeted treatment methods adopted by ophthalmologists [60] [61]. The popularization and application of electronic medical records have enabled the establishment of a health information database equipped with massive high-resolution images and promoted the further development of deep learning or AI models. This work is expected to optimize the care of complex chronic diseases such as diabetes and to predict the risk factors of DR in a personalized manner [62].

6.1.3. Remote Diagnosis and Treatment

The rapid development of science and technology provides technical support for remote diagnosis and treatment. Yeh *et al*. evaluated the effect of fundus images taken by handheld mobile devices on isolated islands where medical resources are scarce. The results showed that the device is easy to operate, which helps to expand the scope of DR screening, improve the patient's medical compliance, and meet the needs of DR telemedicine screening and referral in remote areas [63]. However, image resolution and rating need to be improved. At the same time, the AI rating system will be applied to the rapid primary screening of retinal images. Only the images with positive primary screening need to be further evaluated, graded, and processed by ophthalmologists to establish a telemedicine model with low workload and high income [64] [65].

6.2. Choroidal Neovascularization in Pathological Myopia

The incidence of pathological myopia (PM) has increased in recent years, the leading cause of visual impairment worldwide. Choroidal neovascularization (CNV) is one of the most serious complications of PM. It can cause macular lesions in the fundus, resulting in decreased vision, dark spots, visual deformation, visual field defects, etc. Optical coherence tomography angiography (OCTA) plays a vital role in diagnosing of CNV secondary to PM, clearly show the location and size of neovascularization. The existing research has effectively analyzed the standard choroidal structure and the automatic segmentation and quantitative analysis of blood vessels. Due to the presence of projection artifacts and signal attenuation, the accurate quantification and identification of PM-CNV is relatively difficult. However, deep learning networks are still performing strongly [66] [67]. However, due to the lack of a large amount of data to train a deep learning network, intelligent architecture and input selection are required. The network design uses a lot of input.

6.3. Retinopathy of Prematurity

Retinopathy of prematurity (ROP) is a vascular proliferative blinding eye disease that occurs in premature infants and low birth weight infants [68]. Early ROP screening and diagnosis are highly dependent on ophthalmologists. With the rapid development of modern medical imaging technology and the rise of telemedicine, artificial intelligence (AI) has been further applied in the field of ROP. The research and application of AI in ROP are mainly manifested in ROP staging, zoning, and severity of lesions [69].

6.3.1. AI in the Application of ROP Staging

Peng *et al.* proposed a new ROP staging method based on deep learning neural network model. The model classifies the 1 - 5 stages of ROP, and uses 1173 RetCam images for verification. The accuracy is 97%, which proves that the accuracy of this model is highly accurate [70].

6.3.2. AI Application in ROP Partition

Zhao *et al.* used CNN to perform deep learning on 9800 RetCam images. An algorithm model that can automatically identify the ROP I area was constructed with an accuracy rate of 91% by identifying and locating the location of the optic disc and the macular. This model is expected to reduce the workload of ophthalmologists and timely identify aggressive ROP (A-ROP) at the rear of area I or area II [71]. Peng *et al.* achieved automatic partitioning of ROP through a semi-supervised feature calibration adversarial learning model. This model is divided into a generation network and a composite network, and the feature calibration module is embedded in it to improve classification performance. This algorithm model was evaluated on 1013 fundus images of 108 patients, and good classification results were obtained [72].

6.3.3. Application of AI in Assessing the Severity of ROP

To quantify the severity of ROP, Campbell *et al.* used a "ROP Plus Severity Quantitative Rating Scale" derived from AI deep learning to score the degree of vascular changes in each posterior fundus image, where 1 - 3 points represent no plus, 4 - 6 points represent pre-Plus, and 7 - 9 points represent plus [73]. Campbell *et al.* compared the scores calculated by the "ROP plus severity quantitative score table" with the diagnosis results of 34 members of the ROP International Classification Alliance, and analyzed the ROP staging plus lesions. The kappa weighted value and Pearson correlation coefficient were 0.67 and 0.88, respectively, indicating that in the diagnosis of ROP staging plus lesions, the results of the ROP Plus Severity Rating Scale were highly consistent with the results of international ROP experts [74].

7. Squint

Strabismus is a disease in which both eyes cannot gaze at the same object at the same time when focusing due to abnormal coordinated movement of the extraocular muscles or central dysfunction [75].Strabismus affects the appearance and may cause amblyopia or binocular stereopsis dysfunction. Timely screening, diagnosis, and treatment of strabismus is necessary. Currently, the clinical examination methods of strabismus are mainly manual measurement and judgment. With the development and popularization of artificial intelligence, many advances have been made in the application of artificial intelligence and related technologies in diagnosing and treating strabismus [76]. De Figueiredo *et al.* developed another application based on residual neural network (ResNet) 50, which can diagnose strabismus by identifying different fixation positions of patients. The system was developed using different eye-gaze photos of 110 patients. The overall accuracy of the diagnosis of strabismus was between 0.42 and 0.92 and the accuracy was between 0.28 and 0.84 [77]. Fan *et al.* established a remote squint dataset and proposed a regression forecasting convolutional neural network (RF-CNN) framework. By segmenting the eye region of each image, the deep learning neural network is used to classify and identify the segmented region. The experimental results on the established remote squint dataset show that the proposed RF-CNN performs well in automatic squint detection in telemedicine applications. Strabismus correction surgery is the most important treatment for strabismus. Artificial intelligence technology can predict the efficacy of surgery and help strabismus patients choose the best surgical treatment strategy [78]. Leite *et al.* proposed a new method to assist in designing strabismus surgery based on a decision tree repressor algorithm. This method adopts two different application methods: multiple single-target models and multi-target models. Finally, the efficiency of the method is represented by the average difference between the value indicated by the method and the standard value given by the physician. In the most accurate model of this study, the average error of extraocular muscle surgery was 0.66 mm [79].

8. Orbital Diseases and Ocular Tumor Diseases

Orbital disease is a systemic disease that covers inflammation, tumors, vascular disease, metabolic disease, trauma, etc. Its differential diagnosis, staging and classification depend on imaging methods such as computed tomography (CT) and magnetic resonance imaging (MRI). Combining artificial intelligence with these imaging methods is expected to improve the accuracy and safety of diagnosing and staging of orbital diseases and ocular tumor diseases. Artificial intelligence has been widely used in diagnosing and predicting of thyroid-associated ophthalmopathy, orbital blowout fracture, melanoma, basal cell carcinoma, orbital abscess, lymphoma, retinoblastoma, and other diseases [80].

8.1. Graves Eye Disease

Graves ophthalmopathy (GO), also known as thyroid ophthalmopathy or thyroid-associated ophthalmopathy, is an autoimmune disease. It is the most common orbital disease in adults [81], which can cause incomplete palpebral fissure closure, diplopia, decreased vision, and limited eye movement and may even lead to blindness [82]. At present, deep learning technology has been widely used in the diagnosis, classification, staging, and prognosis evaluation of GO. Evaluating the activity of GO is very important for formulating of a disease treatment plan, and MRI has a significant reference value for the evaluation of activity [83]. Lin *et al.* adopted an algorithm that inherits and simplifies the traditional VGG16 network structure. This method has good generalization ability, increases the depth of the network, and reduces the problems of gradient disappearance and gradient explosion. A deep learning model was established using the labeled MRI data to distinguish the patient's active and inactive phases [84]. Differently, Yao *et al.* developed a two-stage deep learning method based on orbital 99Tcm-DT PA SPECT/CT images, which has high accuracy in distinguishing the activity of GO patients, low diagnostic cost, and a simplified examination process [85]. Thyroid dysfunction optic neuropathy (DON) is a serious complication of GO, which can lead to permanent visual loss [86]. Early diagnosis of DON is essential for the development of treatment options and improvement of prognosis. Wu *et al.* proposed a hybrid deep learning model to accurately identify suspected DON patients using CT. The hybrid model consists of a multi-scale multi-attention fusion module and a deep convolutional neural network. The model can accurately identify suspected DON patients and has positive significance for the diagnosis and prediction of suspected DON cases [87].

8.2. Uveal Melanoma

Uveal melanoma is adults' most common primary intraocular malignancy [88]. Timely and effective early screening and diagnosis are significant for prognosis [89]. Zhang *et al.* first used a deep learning method to automatically extract the iris color spectrum of the iris region based on the patient's anterior photo using the U-net model to screen patients who may have uveal melanoma. This method has shown excellent screening results in the Chinese population. However, due to the obvious racial differences in iris coloration and the existence of environmental challenges such as standardized iris color illumination brightness, the widespread promotion and application of this method may be affected [90].

8.3. Retinoblastoma

Retinoblastoma (RB) is the most common intraocular malignant tumor in children [91]. In treating RB, it is essential to segment the eye's standard structure and tumor tissue accurately. MRI and CT scans are often used for labeling in clinical practice. Kumar *et al.* developed a classifier based on fundus photography using convolutional neural network CNN models (AlexNet and ResNet50) to detect RB and distinguish tumor and non-tumor regions to provide a simple and accurate segmentation method. The final comparison results show that the model's classification performance is more accurate than other existing models [92]. In addition, some teams can use artificial intelligence deep learning algorithms to assess the severity of orbital abscess [93], evaluate whether the tumor invades the orbit to help doctors choose appropriate treatment options, and make high-precision pathological diagnosis of uveal melanoma [94] and eyelid malignant melanoma [95].

9. Application of Artificial Intelligence in Ophthalmic Treatment

9.1. Artificial Intelligence-Guided Retinal Laser Therapy

Panretinal photocoagulation (PRP) is recognized as an effective treatment for DR, but reports have found that about 33% of DR patients still have uncontrolled neovascularization after PRP, which may lead to complications such as retinal detachment and vitreous hemorrhage, which may affect the final prognosis [96]. Fu *et al.* introduced a new technology called targeted retinal photocoagulation (TRP), which is mainly based on the selective photocoagulation of the far peripheral retinal non-perfusion area (NPA) shown by fluorescein fundus angiography. This model is conducive to the precise positioning and implementation of TRP, which can effectively delay the progression of the disease [97].

9.2. Artificial Intelligence-Assisted Ophthalmic Drug Development

The emergence of AI technology provides new and strong support for drug research and development when new drug research and development is facing the triple dilemma of long cycle, high cost, and low success rate. In recent years, artificial intelligence has also been involved in the field of ophthalmic drug research and development, such as eye disease target discovery [98] [99], ophthalmic small molecule compound screening [100] [101], ocular pharmacokinetic model development [102] [103], ophthalmic clinical trials [104], etc. Help ophthalmic drug research and development to achieve a leap from precision to intelligence.

10. Conclusion

The application of AI in medicine is in full swing and changing with each passing day. In the future development of intelligent ophthalmology, promoting clinical application and maintaining medical equity will become key issues. Promoting the clinical implementation of intelligent ophthalmic technology requires the cooperation of governments, medical institutions, scientific research institutions, and enterprises to "jointly formulate policies, strengthen infrastructure construction, promote technology popularization and education, and promote medical and industrial cooperation" to achieve the comprehensive application and fair distribution of technology to provide patients with better and more convenient eye health services. At the same time, this review emphasizes the importance of medical equity in applying of intelligent eye technology, especially for the problems of resource allocation, technical accessibility, and education and training. We must recognize that only through continuous monitoring and evaluation, close cooperation of stakeholders, and learning from the experience of successful cases can we promote the implementation of intelligent eye technology and maintain medical equity to ensure that intelligent eye technology benefits a broader range of people to fairness and accessibility of intelligent technology-assisted eye health services. Looking forward to the future, with the continuous development of intelligent ophthalmology technology, we can expect the popularization and application of intelligent ophthalmology technology. Governments, medical institutions, technology developers, and all sectors of society should strengthen cooperation to work together to promote the development of intelligent eye technology to ensure that technology can benefit more people and provide more equitable and high-quality eye health services for patients around the world.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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