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Revolutionizing Ophthalmic Care: The Impact of Artificial Intelligence

Oftalmolojik Bakımda Devrim: Yapay Zekanın Etkisi

L. Subha[1], Atul Sharma[2], Anita Misra[3]

[1]Department of Ophthalmology, Sree Balaji Medical College and Hospital, Chennai, India
[2]Department of Ophthalmology, Padma Eye Care Center, Jabalpur, India
[3]Department of Ophthalmology, S.C.B Medical College and Hospital, Cuttack, India

ABSTRACT

Progress in digital health and telemedicine has brought forth instruments can enhance the accessibility and efficacy of eye care services. Current research shows how technology-enabled approaches are changing the way care is provided. Traditional diagnostic methods rely on physician expertise, resulting in high misdiagnosis rates and data inefficiency. Integrating ophthalmology with artificial intelligence (AI) promises to overhaul current diagnostic approaches, potentially making a significant clinical impact. Deep learning, an emerging facet of machine learning (ML), can uncover complex data structures without explicit rule specifications. The review centers on the revolutionary potential of AI in the identification and treatment of ocular disorders, such as diabetic retinopathy, degenerative maculopathy, retinal diseases, corneal diseases, anterior ocular region issues, and glaucoma. It explores AI-driven advancements in image analysis, pattern recognition, and ML techniques for individualized treatment plans, early diagnosis, and categorization. The difficulties with data standards, interpretability, and integration are discussed in this paper into clinical practice. It also emphasizes the potential of AI to enhance screening efficiency, reduce physician workload, and improve patient outcomes in ocular pathologies.

Keywords: Deep learning, glaucoma, diabetic retinopathy, ophthalmology, artificial intelligence, degenerative maculopathy

ÖZ

Dijital sağlık ve tele-tıp alanındaki ilerlemeler, göz bakımı hizmetlerinin erişilebilirliğini ve etkinliğini artırabilecek araçların ortaya çıkmasını sağladı. Güncel araştırmalar, teknoloji destekli yaklaşımların bakımın sağlanma biçimini nasıl değiştirdiğini gösteriyor. Geleneksel tanı yöntemleri hekim uzmanlığına dayandığından yanlış tanı oranları yüksek ve veri yetersizliği fazladır. Oftalmolojinin yapay zeka (YZ) ile bütünleştirilmesi, mevcut tanı yaklaşımlarını baştan aşağı değiştirmeyi ve önemli bir klinik etki yaratmayı vadediyor. Makine öğreniminin (ML) yeni ortaya çıkan bir alanı olan derin öğrenme, açık kural tanımlamaları olmadan karmaşık veri yapılarını ortaya çıkarabilir. Derlemede, diyabetik retinopati, dejeneratif makülopati, retina hastalıkları, kornea hastalıkları, ön göz bölgesi sorunları ve glokom gibi göz bozukluklarının tanımlanması ve tedavisinde YZ'nin devrim niteliğindeki potansiyeli ele alındı. Kişiye özel tedavi planları, erken tanı ve kategorizasyon için görüntü analizi, desen tanıma ve ML tekniklerindeki YZ destekli gelişmeleri araştırıyor. Bu makalede veri standartları, yorumlanabilirlik ve klinik uygulamaya entegrasyondaki zorluklar tartışılmaktadır. Ayrıca YZ'nin tarama verimliliğini artırma, hekim iş yükünü azaltma ve göz patolojilerinde hasta sonuçlarını iyileştirme potansiyeline de vurgu yapılıyor.

Anahtar Sözcükler: Derin öğrenme, glokom, diyabetik retinopati, göz hastalıkları, yapay zeka, dejeneratif makulopati

INTRODUCTION

Artificial intelligence (AI) uses computer algorithms to imitate the human intellect, which is becoming increasingly common in medicine. AI in medicine enables rapid and accurate analysis of medical data, which is beyond the ability of human doctors. Machine learning (ML), a subset of AI, adapts its parameters based on data to generate computer algorithms for making predictions and responding to data. The integration of AI is particularly advantageous in ophthalmology, where the field's extensive use of digital imaging techniques made many modalities to be used

Address for Correspondence/Yazışma Adresi: Anita Misra, MD, Department of Ophthalmology, S.C.B Medical College and Hospital, Cuttack, India
E-mail / E-posta: misraanita13@gmail.com
ORCID ID: orcid.org/orcid.org/0009-0000-5694-2126

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together with quantifiable parameters such as visual acuity or foveal thickness. A significant dataset is made available by the growth of multi-modal digital images and electronic medical databases in ophthalmology for AI analysis. ML, which was originally introduced by Arthur Samuel in 1959, refers to an AI process in which a machine autonomously generates its programing and acquires the ability to execute tasks independently (1). In supervised ML models, the machine learns from pre-existing data containing accurate answers, making it particularly valuable for classification purposes, whether dealing with categorical values like "disease" or "no disease" or variables that may take on any value within a range, such as height or weight (2). The process involves utilizing a validation dataset to assess external validity. Conversely, unsupervised ML involves examining data without predefined answers, with the primary objective of modeling the data structure or distribution to gain insights. This method is especially useful for identifying associations among data. The integration of the capabilities of human doctors with those of deep learning (DL) algorithms is anticipated to reduce mistakes in diagnoses and therapies inherent in the existing systems (3,4). These models provide more accurate recommendations from basic eye care services provided in the community to professional ophthalmologists, ultimately optimizing diagnosis. Tele ophthalmology has significantly contributed to enhancing the availability of eye screening and facilitating distant expert evaluations in rural areas. This can be achieved via synchronous and mixed synchronous-asynchronous solutions (5) or "store, forward and video consultation" methods (6). However, despite the improved clinical outcomes shown by digital ophthalmology solutions, their growth potential is constrained by the need for more infrastructure and professionals to implement them. Unlike telemedicine and AI, which are not restricted to specific locations (such as to address the demand for eye hospitals that specialize in certain eye conditions or the availability of knowledgeable eye care professionals), these solutions may be combined with other technological advancements, such as imaging apparatus, to effectively deliver and improve primary care and eye screening services. Given the documented relationships between clinical features and disease severity in major eye issues, AI is particularly well-suited for use in eye screening. Early detection and treatment of ocular conditions are critical for preventing visual impairment and improving the general quality of life. Traditional diagnostic approaches rely heavily on doctors' expertise and limited expertise, leading to a significant occurrence of misdiagnosis and ineffective use of medical data. Integrating AI with ophthalmology can transform the disease diagnosis paradigm, yielding substantial clinical benefits. DL, an emerging facet of ML, can reveal intricate patterns within datasets without requiring explicit rule specifications. DL algorithms automatically learn the features of input data in an unsupervised manner, eliminating the need for manual segmentation and depiction of lesion areas (7). However, the training of DL algorithms requires a large dataset. Transfer learning involves retraining an algorithm that has undergone pretraining on many generic images, particularly on a focused dataset, and transferring the same for diagnosis usage. This methodology allows for a precise model with comparatively few training datasets. Heat maps can be used to identify pixels that impact image-level predictions. This method is particularly useful in the medical industry because heat maps help visualize and identify probable aberrant regions in input images. These regions can then be further reviewed and analyzed (8,9). This feature can provide immediate verification of computerized diagnoses during patient treatment. Several established DL techniques include convolutional neural networks (CNN), deep boltzmann machines, deep kernel machines, deep recurrent neural networks (NN), and models of both short-term and long-term memory.

AI's Importance in Ophthalmology

Over the last 5 to 10 years, advancements in computing ability and the accessibility of extensive datasets and the development of DL have been driven by AI. Recent research utilizing advanced AI methodologies, including DL, has demonstrated robust outcomes, surpassing human performance in various domains in medicine and healthcare. Unlike traditional ML methods, which require expert eye doctors to annotate specific clinical characteristics in images for AI model development (referred to as "supervised learning"), DL employs a different approach known as "unsupervised learning." DL eliminates the need for individual feature labeling by training the model on complete images annotated by professionals with clinical diagnosis or disease severity. This enables AI to generate norms by autonomously learning discriminative features to classify diagnoses or severity. When it comes to classifying ophthalmic imaging data-such as color fundus photography (CFP), which is used to identify various eye disorders like diabetic retinopathy (DR)-DL algorithms have demonstrated clinically acceptable performance. Compared to 2-dimensional CFPs, optical coherence tomography (OCT) imaging provides comprehensive 3-dimensional data, which can enhance the efficacy of existing CFP-based screening techniques. Finding retinal characteristics that match common eye disorders like glaucoma, age-related macular degeneration (AMD), and DR (10,11), and predict AMD progression using OCTs (12), as well as classifying glaucoma using ophthalmic imaging (13,14). These advancements mistake rates that are lower than generally acknowledged signify the promising role of DL in revolutionizing the field of ophthalmology. Despite the positive findings in research studies regarding the impressive performance of DL in clinical validation, there is a need for more investigations assessing its practical applications in real-world utilization. The concept of a "fully automated model" implies a system that operates independently without human provider or participation because the AI system itself takes the initiative to refer patients to ophthalmologists when necessary or to identify individuals suitable for ongoing community-based monitoring. On the other hand, a "semi-automated model" encompasses various scenarios involving human graders or ophthalmologists, collaborating with the DL to enhance patient classification and serving as a tool for triaging individuals. DL algorithms relying on AI can be incorporated into a "semi-automated model", wherein a human evaluator (such as a doctor or optometrist) intervenes in categorizing imaging data identified as abnormal by the AI. The computer-based machine learning (CML) methods used in AI diagnosis include decision trees, random forests (RF) (15), support vector machines (SVM) (16), Bayesian classifiers (17), k-nearest neighbors (18), k-means (19), linear discriminant analysis (20), and NN (21). Within this array, RF and SVM stand out as the most frequently employed CML technologies in the field of ophthalmology. DL, an emerging ML technology, possesses the capability to uncover intricate structures within datasets without the necessity of explicitly specifying rules. DL algorithms autonomously learn features from unsupervised input data, eliminating the need for manual segmentation and depiction of lesion areas. Training the DL algorithm demands a substantial dataset. Transfer learning involves retraining an algorithm previously trained on a vast array for a dataset of diverse photos/images (22). This approach enables the creation of a very precise model even when using a relatively small training sample. Heat maps provide the potential to unveil the individual pixels that contribute to predictions made at the picture level. Within medicine, this visualization technique can accurately identify and highlight areas in the input picture that may be considered aberrant. This, in turn, makes it easier for medical professionals to evaluate and analyze these regions further. At the point of service, it might help with the instantaneous clinical validation of computerized diagnoses. Numerous techniques are used in DL, including CNN, deep Boltzmann machines, deep kernel machines, deep recurrent NN, and long- and short-term memory. A variety of CML techniques, such as decision trees, RF, support SVM, Bayesian classifiers, k-nearest neighbors, k-means, linear discriminant analysis, and NN, are used in the field of ophthalmology for AI diagnosis. The two CML technologies most frequently applied in the field of ophthalmology are RF and SVM Figure 1.

Diabetic Retinopathy

DR screening is essential for allowing early detection and treatment, which averts vision loss. AI has been investigated in the identification of DR using a variety of imaging modalities, such as OCT pictures, ultra-widefield (UWF) imaging, and even smartphone retinal photographs. The intraretinal fluid shown in OCT scans can be precisely identified by CNNs. With its ability to view up to 200° of the fundus, UWF imaging may be able to detect more peripheral diabetes conditions. The scarcity of imaging equipment and restricted accessibility are obstacles to efficient DR screening. An impressive solution is an offline AI system that runs on a smartphone and has a high accuracy in recognizing severe DR (23). In an effort to address this worldwide health issue, AI has been used to predict the risk of DR and its progression in people with diabetes. Recognizing particular irregularities, such as macular edema (24-27), With CML, exudates, microaneurysms, and neovascularization on the optic disk are made possible. To guarantee prompt attention and intervention, a system that focuses on rapid and effective proliferative DR detection has been created (28). DR identification was made possible by Gulshan et al.'s (24) groundbreaking work, which used DL and massive fundus imaging datasets to train a deep CNN. Using supervised learning, a deep CNN is trained. According to their research, DL methods have a high sensitivity and specificity and can identify referable DR with a great degree of accuracy (29). Furthermore, a CML-based computer-aided diagnostic (CAD) system that makes use of OCT angiography images was employed. It successfully identified non-proliferative DR with high accuracy automatically Figure 2.

Degenerative Maculopathy

Degenerative maculopathy is a prevalent contributor to vision impairment, affecting million individuals globally. Timely identification and intervention can significantly mitigate the risk of vision loss. Given the substantial impact of the disease, AI holds the potential to facilitate widespread screening through the analysis of retinal images and OCT, doing away with the requirement for in-person evaluations. The advancement of this domain has traces its origins from ML, utilizing datasets comprising fewer than 1000 images to the current state of a collection of more than 490,000 photos; the dataset demonstrates impressive sensitivity and specificity (30). Feeny et al. (31) developed a DL technique to identify abnormalities using over 130,000 pictures from 4,613 patients automatically. Their DL system had a remarkable accuracy rate of 92% in identifying persons with intermediate and advanced stages of diabetes mellitus. This was achieved using DL techniques, including examination of optical OCT, fundus pictures, and OCT angiography images, which improved the accuracy (32). A fluid volume measurement technique for neovascular diabetic macular edema patients has been created using AI. This efficiently tracks the favorable response to medical intervention. Furthermore, a number of significant characteristics linked to AMD, such as pigment epithelial detachment and intraretinal fluid and subretinal fluid, have been measured using

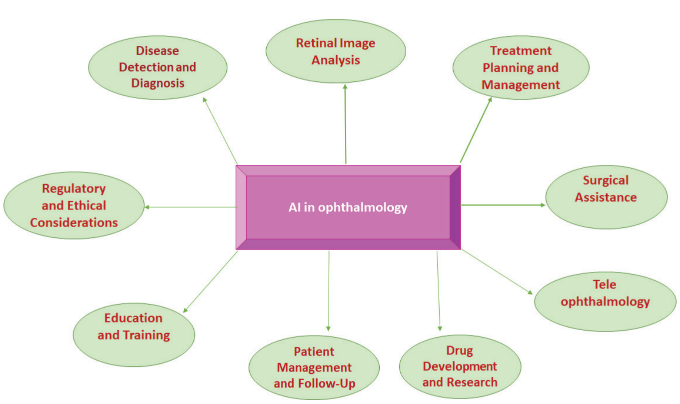

Figure 1. Various facets of AI in ophthalmology.

AI: Artificial intelligence.

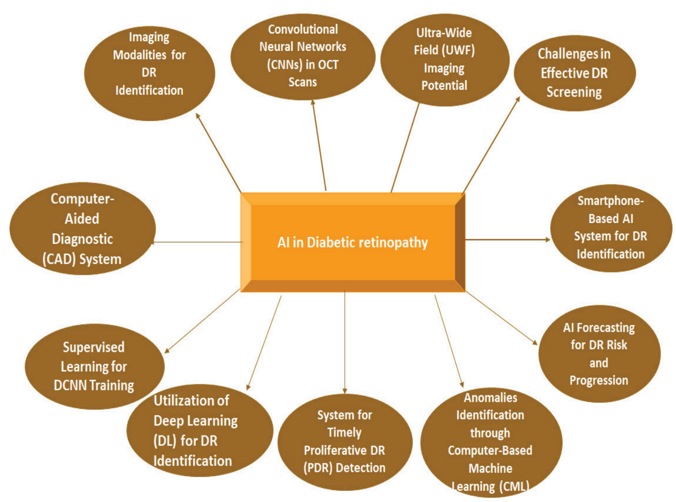

Figure 2. AI in diabetic retinopathy.

AI: Artificial intelligence, DR: Diabetic retinopathy, OCT: Optical coherence tomography, DCNN: Deep convolutional neural networks.

DL techniques. Research has focused on examining fundus images to identify drusen (33), fluid (34), reticular pseudodrusen (35), and geographic atrophy (36). With a usual accuracy rate of over 80%, the detection also includes the ability to forecast drusen regression, an important anatomical indicator distinguishing intermediate AMD and the beginning of severe AMD (37). This prediction is assisted by a specialized, fully automated ML algorithm. The process involves the application of automated image analysis techniques to recognize and characterize individual drusen at the initial assessment, with ongoing monitoring of their progression at subsequent visits. By leveraging this characterization and analysis, a survival analysis-based possibility of hazards and the anticipated deterioration of each individual drusen were determined using the ML method. Most importantly, automated retinal lesion detection and disease activity analysis demonstrate that it is feasible and holds considerable potential as a dependable tool in clinical practice Figure 3.

Other Retinal Disease

A DL model effectively identifies referable retinal illness using OCT images, exhibiting performance levels with retina subspecialists. This approach demonstrated competence in identifying diseases, including geographic atrophy, drusen, macular edema, macular holes, vitreomacular traction, central serous retinopathy, and epiretinal membrane membrane (38). The algorithm could accurately forecast retinal function in microperimetry for patients with stargardt disease by analyzing the structural characteristics of OCT using DL techniques. AI systems have shown the capacity to detect disorders, such as Macular telangiectasia, sickle cell disease, pachychoroid vasculopathy, and central serous retinopathy (39-42). Abnormal development of blood vessels in the retina is known as retinopathy of prematurity (ROP), which is a significant cause of juvenile blindness. The ETROP trial results highlight the critical need of early screening and intervention to improve visual outcomes for ROP (43). Recent developments suggest that AI may play a major role in ROP diagnosis, which would improve treatment outcomes. When evaluated on an independent dataset of 100 photos, a DL algorithm trained using wide-field retinal photographs outperformed six out of eight ROP experts in terms of diagnostic skill (44).

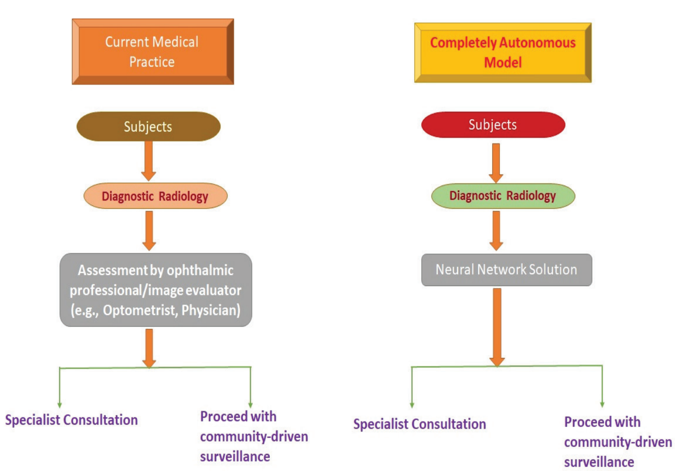

Figure 3. Degenerative maculopathy.

Corneal Disease

AI has lately been studied in anterior eye segment illnesses (45). It has shown promising results in accurately predicting the diagnosis of many corneal conditions, such as infectious keratitis (IK), keratoconus, pterygium, endothelial diseases, and difficulties associated with corneal transplantation. Dealing with clinical difficulties related to IK, such as accurately diagnosing the condition owing to variables including limited culture yield, absence of pathogen-specific characteristics, and infections caused by several microorganisms, continues to be an important element (46) for the treatment. Slit-lamp photos, often used in clinical settings to record and track IK and other disorders affecting the surface of the eye, have shown their ability to precisely diagnose different problems of the front part of the eye, such as IK, pterygium, conjunctivitis, and cataract (47). A unique DL system was created to automatically distinguish between fungal keratitis and non-fungal keratitis in corneal pictures (48). Furthermore, AI has shown its effectiveness in identifying corneal ectasia, namely keratoconus, by aiding in the early identification of suspected keratoconus, also known as forme fruste keratoconus, which can be difficult to diagnose. Numerous AI techniques, like automatic decision-tree classification (49), feedforward NN, CNN, and SVM learning, have been studied and proven to be successful (50). AI technologies, such as Keratodetect and ectasia status Index have been developed to diagnose keratoconus early and evaluate patients prior to refractive surgery. The anterior segment OCT, corneal topographies, and tomographies are used by these algorithms to analyze (51). Current endeavors have concentrated on formulating CNN algorithms that use numeric data matrices to enhance efficiency and flexibility for various topographical scenarios. AI has lately been used to investigate susceptibility genes linked to keratoconus. Hosoda et al. (52) identified particular gene regions linked to keratoconus susceptibility using IBM's Watson drug delivery. A genome-wide association study focusing on central corneal thickness was used to achieve this. DL algorithms have been applied to OCT images to distinguish between normal and edematous corneas (53). Fuchs endothelial corneal dystrophy was diagnosed using AI at an early stage (54). The clinical feature of using *in vivo* confocal microscopy images to evaluate the characteristics of the subbasal nerve plexus and establish connections with ocular and systemic illnesses has recently increased. The process of manually and partially automating the analysis of nerve fiber characteristics is well-recognized as arduous and time-intensive. However, the use of computer vision algorithms has greatly eased the automation of nerve analysis (55). Correlations between ocular nerves and diabetic neuropathy have been established using CNN-based approaches (56). The suggested technique entails the examination of three images from each eye, which allows for a thorough study similar to the clinical procedure performed by humans, eliminating the need for creating montages and acquiring additional images. Examining cataract pictures with computer-aided analysis is desirable. This entails automatically detecting and evaluating cataracts by fundus photography and/or slit-lamp photography. Although this method is perfect for identifying abnormalities of both the anterior and posterior segments concurrently, it must take into account any factors that could cause confusion, such as constricted pupils or vitreous opacities. Two SVM classifiers and a fully connected NN were used to identify and classify cataracts using resnet18 (Residual

Network) and Gray Level Co-occurrence Matrix. For discontinuous state transition, a deep NN with six grading levels was created as a result. The DST-ResNet and EDST-MLP models accurately detected and graded cataracts, respectively. Unlike cataracts in adults, cataracts in children show more variation. The choice of surgery is based on the likelihood of amblyopia, which is caused by a lack of visual stimulation (57). Performing pediatric tests presents difficulties, particularly in producing consistently high-quality slit-lamp pictures. The Apriori approach employs naive bayesian and RF prediction (58). After applying the synthetic minority oversampling approach to the datasets, three binary categories were resolved with average accuracy levels over 91%.

Anterior Ocular Region

Trachoma, a vision-threatening condition resulting from ocular infections with chlamydia trachomatis, was routinely investigated by analyzing eyelid images. There are two clinical trials: the PRET study, which focuses on eliminating trachoma in Niger, and the TANA trial, which aims to improve trachoma conditions in Northern Amhara (59). ML algorithms were used to identify trachomatous alterations (60) accurately. Furthermore, lacrimal scintigraphy (LS) has been established as a dependable and unbiased technique for evaluating tears and the lacrimal drainage system (61). ML and DL algorithms applied to LS images have demonstrated the ability to accurately diagnose lacrimal duct abnormalities in patients with a level of precision comparable to that of a skilled oculoplastic specialist. Ocular infections can cause trachoma, a disorder that can seriously impair vision. Thoracomatous alterations were successfully categorized using AI techniques, which let computers learn from experience and get better at it without having to be explicitly programed. LS has become a reliable and impartial technique for assessing tear flow and the lacrimal drainage system (62). Making use of DL and machine algorithms on LS images proved successful in classifying lacrimal duct pathology in patients, demonstrating accuracy on par with that of a proficient oculoplastic expert. The significance of meibomian glands (MGs) in maintaining ocular surface health is widely acknowledged, and the diagnostic technique involving the photographic documentation of eyelid MGs using Transillumination, often known as infrared light, is frequently employed for assessing and managing MG dysfunction. A DL approach was implemented to digitally partition and quantify the degree of MG atrophy in mimography images, thereby offering quantitative insights into gland atrophy. The algorithm demonstrated an impressive 95.6% accuracy in terms of grading meiboscores (63). An ML segmentation algorithm was employed to assess tear OCT and to measure meniscus thickness to quantify the amount of tear film (64). Although the sample size was small, the method consistently produced predictable findings. The researchers collected corneal topography data over time to develop a DL system for diagnosing keratoconus, a non-inflammatory condition of the cornea characterized by astigmatism and stromal thinning. The resulting model was able to predict cases of subclinical keratoconus with notable accuracy, and it also showed decent accuracy in keratoconus screening. A “NN”, designed and put into use by Dos Santos et al. (65), dubbed CorneaNet, especially for corneal OCT image segmentation. This algorithm was created to measure corneal thickness in patients with keratoconus and those with normal ocular conditions. The corneal thickness, primary layers (epithelium, bowman’s layer, and the middle stroma). The models exhibited comparable performance in detecting keratoconus, achieving an accuracy of validation levels between 99.45% and 99.57%. The application of DL was effective in identifying and classifying eyes with keratoconus, including the staging of the disease. Keratoconus is an irreversible condition that affects both eyes and is characterized by corneal weakening, protrusion, and scarring (66). Initially, it shows one-sided characteristics that may later develop, affecting both sides, except in uncommon situations (67). Identification of subclinical corneal ectasia poses a significant challenge. Both topography and tomography offer intricate data for each cornea to ophthalmologists. Despite the wealth of information distinguishing the several examined parameters, the distinctions between normal and subclinical keratoconus remain highly challenging for ophthalmologists. The Orbscan data employed SVM, multiple-layer perceptron classifiers, and radial basis function NN are examples of machine learning classifiers (MLC) (68). Each of these classifiers demonstrated proficiency in recognizing the previously mentioned corneal anomalies. Data from Scheimpflug tomography were selected over Orbscan information (69). Data from devices using Scheimpflug tomography-which generated three-dimensional, touch-free reconstructions of the anterior segment of the eye-were collected for the comparisons. After ML successfully differentiates between obvious corneal disorders, research efforts are directed toward creating AI that can recognize the subclinical features of corneal ectasia (70). Cataract, a condition characterized by a cloudy lens, affects many elderly individuals. Timely identification and intervention can significantly enhance the well-being of those with cataracts. ML techniques, including SVM and RF, have been used to detect and evaluate cataracts based on fundus photographs, ultrasound photographs, and visible wavelength photographs of the eye (71). Liu et al. (72) developed the first CAD system to classify and evaluate juvenile cataracts using CNNs. Additionally, a cloud-based platform with AI connectivity designed to promote cooperation between numerous hospitals has been developed. It is possible to design software for ophthalmologists and patients to use clinically, and the Zhong Shan Ophthalmic Center has documented the use of the program (72). These techniques are essential for creating surgical plans for horizontal strabismus and evaluating corneal power following myopia and corneal refractive surgery (73).

Glaucoma

Glaucoma is the second primary cause of permanent blindness globally. Detecting early-stage glaucoma has been proven effective in minimizing vision loss (74). The utilization of digital photography to capture images has been a prevalent technique for screening glaucoma, and its efficacy has been demonstrated in many telemedicine glaucoma programs. An extensive evaluation of persons suspected of having glaucoma may include gonioscopy, perimetry, tonometry, pachymetry, and spectral domain (SD) OCT (75). CFP of the optic nerve is an accessible and affordable way to check for glaucoma. Images of the optic nerve have been altered to help detect early signs of glaucoma more accurately thanks to ML. It is feasible to automate the early detection of glaucoma by integrating these algorithms into teleglaucoma screening protocols. Accompanying color fundus imaging with optic nerve OCT imaging has accelerated the creation of accurate DL algorithms for glaucomatous nerve damage detection. When DL algorithms are trained to assess monoscopic optic nerve pictures using SD-OCT, they outperform glaucoma specialists in identifying glaucomatous optic nerve damage. Standard automated perimetry evaluation is one application of ML that seems promisinged (76). Many datasets are available, including findings from an extensive visual field (VF) test that was carried out over a long period of time. With a high degree of reliability, AI can anticipate glaucoma up to four years ahead of official raw VF data needed for diagnosis. The progression of patterns, a vibrational ML classifier, outperformed guided progression analysis in identifying the progression of glaucomatous optic neuropathy in patients with glaucoma and those suspected of having the disease (77). With the use of screening and monitoring datasets, AI seeks to produce affordable decision support systems that are as sensitive and specific as or more so than current techniques. The optic cup-to-disc ratio (CDR) is a useful marker for glaucoma identification (78). AI algorithms can compute the CDR to assist in the diagnosis of early-stage glaucoma by using automated optic nerve head location and optic disc/cup extraction from retinal images (79). The most likely patch on OCT images was precisely identified by the SVM model during training to provide a reference plane for computing the CDR (80) by approximating the coarse disc margin using a spatial correlation smoothness constraint. As glaucoma worsens, defects in the VF play a major role in the deterioration of visual function. Early in the disease, changes in the central VF may manifest, which is consistent with findings from imaging studies (81). Therefore, early detection of glaucomatous changes in the VF is essential for both the diagnosis and management of glaucoma.

Challenges and Future Research

AI utilization and contemporary applications in research represent significant advances in optimizing and enhancing efficiency. As the number of electronic medical record increases, healthcare providers and medical facilities find themselves with an extensive patient data repository. AI plays a crucial and central function in this context, as creating computer-generated algorithms or the appropriate training of automated systems for bulk processing of patient information results is a substantially faster data collection process than manual methods. Ophthalmology, a medical discipline characterized by swift access to ophthalmic imaging and objective markers, is particularly well-suited for managing vast datasets. The Smart Eye Database is a database that holds electronic health information about patients with ophthalmology, arranged according to the conditions that affect each patient's eyes (82). IRIS and the Smart Eye Database are two instances of datasets, which enables the identification of subtle correlations, the execution of multicenter studies, the integration of multimodal analyses, the discovery of novel imaging patterns, and increased statistical power in research. These capabilities are challenging to achieve with smaller datasets (83). Modifications to these machines were confined to those foreseen and considered during pre-programing. Since humans programed the machine, its capabilities were restricted by the technological knowledge of the individuals who drafted the programing. The caliber of the dataset that an AI algorithm uses for training and validation determines the effectiveness of the program will be estimating the optimal number of training images within a dataset poses a challenge, as there is a common belief that a larger number of images leads to better outcomes. However, an excessively large dataset can impede the efficiency of the training process and potentially result in overfitting the MLC to the training dataset. Variations between machines from different brands may introduce subtle differences that can impact assessment accuracy. Restricting the number of categories in a program to those with significant predictive importance may be beneficial given the size of the dataset and the complexity of the algorithm (84). Establishing standards for reporting in future research is crucial for minimizing heterogeneity across studies. If AI improves medical care, it becomes imperative to ensure that these improvements reach populations facing financial constraints. A significant obstacle in deploying proven, the need for AI solutions is essential for a complete solution designed for practical use. Achieving this goal may involve integrating DL, implementing solutions that demonstrate satisfactory performance in a clinical setting, and ensuring that the solution can effectively handle pictures of different quality levels from regularly used equipment. There is a requirement for developing clinical guidelines that support the provision of patients with the DL system classifications and supporting their choice of patient. It is important to remember that the majority of DL systems in use today have only been independently validated for the classification of one eye condition at a time. For providers without technical AI or software skills, maintaining and switching between different DL systems for every possible eye condition is impractical and represents a considerable challenge. It is crucial to establish supportive systems and processes to rectify misclassifications among patients, including instances of incorrect classifications or errors in either direction. This emphasizes the importance of adopting standardized practices in the entire lifecycle of AI, encompassing development, validation, reporting and implementation. Such measures are essential to prevent misclassification issues, especially when AI is applied to diverse target populations. Ethical and legal dilemmas arise when employing DL systems to classify clinical data, particularly due to their lack of ability to explain. Addressing these challenges requires a focus on appropriate training data and external validation. Overcoming this obstacle is essential for ensuring the generalizability and practical application of these solutions. The challenge lies in the arduous task of labeling collected data throughout the training process, which requires the participation of skilled practitioners. By carefully selecting patients, the imaging datasets are repetitively labeled to calibrate the DL system, with each new set population potentially causing delays in adoption and contributing to setup costs. The inherent characteristics of AI and the absence of comprehensibility in DL methods provide substantial technical obstacles that must be resolved. Advancements in AI development for picture classification include using techniques like "soft attention" (85). New approaches like "weighted error scoring" are being created to compare the effects of inaccurate automated classification AI decisions to human grading (86). AI techniques have proven effective in the healthcare industry for identifying a range of illnesses. By easing the sharing of specialist expertise and optimizing limited resources, AI applications can greatly aid in the support of patients in remote areas. However, model accuracy frequently decreased as the frequency of disease increased. In order to enhance the use of AI in clinical settings, funding must be allocated toward developing intelligent systems capable of accurately diagnosing a broad spectrum of illnesses.

Reliance on a small number of abnormalities identified by a single imaging method may not guarantee accurate diagnosis of certain retinal diseases in clinical practice, such as glaucoma or DR. including a number of clinical images, including fundus, angiography, OCT, and VF imaging, is essential for constructing a robust AI system that ensures more reliable diagnostic outcomes. Despite the availability of various datasets, the fundamental challenge lies in the insufficient representation of the multitude of diseases that humans experience. Images depicting severe or rare diseases are notably lacking in these datasets. Therefore, when selecting input data, factors such as demographic features, the existence of various systemic illnesses, and the numerous physical traits of diseases should be considered. For more robust validation, larger datasets from diverse patient cohorts encompassing different settings, conditions, ethnicities, and environments are imperative for some automated diagnosis systems that have shown promising outcomes. Significant reliance on data quality should not be overlooked. The diversity of imaging devices, imaging procedures, and inherent noise in the data can substantially impact data quality, thereby exerting considerable influence on model performance. AI faces challenges in ophthalmological dyslexia by needing nuanced data for accurate recognition, understanding, and aiding dyslexic individuals (87). AI confronts significant challenges when it comes to enhancing wearable eye sensor gadgets tailored for eye-related diagnostic applications (88). The challenges lie in refining sensor precision, minimizing device size while maximizing data accuracy, addressing connectivity issues, ensuring seamless integration with AI algorithms, and fostering user trust regarding data security and privacy. AI confronts significant hurdles when it comes to enhancing wearable sensor gadgets tailored for eye-related applications. The challenges lie in refining sensor precision, minimizing device size while maximizing data accuracy, addressing connectivity issues, ensuring seamless integration with AI algorithms, and fostering user trust regarding data security and privacy. AI must overcome variability in symptoms, adapt to diverse language patterns, and provide personalized interventions. Ensuring inclusivity, privacy and ethical use while enhancing accessibility remain pivotal challenges in AI for dyslexia support. AI needs to revolutionize cancer diagnosis (89) for eye diseases, employing advanced algorithms to analyze medical images swiftly and accurately. In radiology, AI helps interpret complex optic scans, enhancing early detection and personalized treatment for ophthalmology.

CONCLUSION

AI and DL capabilities are advancing swiftly, presenting potential solutions to technical challenges. In the realm of ophthalmology, research on AI has moved away from creating and validating tools to their practical implementation. This crucial transition aims to identify and address practical and sociocultural challenges, tailoring solutions to the specific needs of users, including patients and healthcare providers. In conclusion, AI exhibits great promise in enhancing the capacity of health systems for eye screening in well-defined areas. This involves automating the classification of diseases, such as DR, across various clinical applications. There is a growing degree of preparedness as technology advances from clinical validation to translation; however, new difficulties arise when incorporating AI solutions into clinical care pathways and healthcare infrastructures. Current studies are in progress to tackle the issues mentioned and provide focused remedies.

Ethics

Author Contributions

Concept: L.S., Design: L.S., Analysis or Interpretation: A.S., Literature Search: A.S., A.M., Writing: A.S.

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