THE CURRENT STATE OF ARTIFICIAL INTELLIGENCE IN NEURO-OPHTHALMOLOGY. A REVIEW

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SUMMARY
This article presents a summary of recent advances in the development and use of complex systems using artificial intelligence (AI) in neuro-ophthalmology. The aim of the following article is to present the principles of AI and algorithms that are currently being used or are still in the stage of evaluation or validation within the neuro-ophthalmology environment. For the purpose of this text, a literature search was conducted using specific keywords in available scientific databases, cumulatively up to April 2023. The AI systems developed across neuro-ophthalmology mostly achieve high sensitivity, specificity and accuracy. Individual AI systems and algorithms are subsequently selected, simply described and compared in the article. The results of the individual studies differ significantly, depending on the chosen methodology, the set goals, the size of the test, evaluated set, and the evaluated parameters. It has been demonstrated that the evaluation of various diseases will be greatly speeded up with the help of AI and make the diagnosis more efficient in the future, thus showing a high potential to be a useful tool in clinical practice even with a significant increase in the number of patients.
Key words: artificial intelligence, deep learning system, neuro-ophthalmology, eye movement disorders

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INTRODUCTION

Artificial Intelligence (AI) is defined as critical thinking and intellectual performance extended by the technology of synthetic intelligence, which is used today in practically all spheres of human activity. Since its introduction, AI has progressively spread from areas such as travel and transport, finance, purchasing and healthcare technology, up to medicine. In order to understand the application of AI, not only within the field of ophthalmology, it is necessary to be aware of the mechanisms upon which it is built. Through the sequence of data processing, AI is capable of evaluating its previous operations, and by doing so improves its predictive skills and accuracy. The capacity for performing millions of calculations and tasks without the need for pauses represents an insurmountable advantage of AI over its human counterparts [1]. Within the framework of AI we operate in 2 subsets: machine learning and deep learning. Machine learning requires manually created functions on the part of the programmer, which use this model to optimize the process of learning and to automate the prediction of results with a limited set of data. By contrast, deep learning is capable of automating extractions, but in order to attain virtually perfect accuracy it requires an immense quantity of data. The deep learning system (DLS) improves upon previous approaches based on machine learning by incorporating multilevel mechanisms of learning for the purpose of extracting diverse models in order to attain a better result. This module is composed of several small and large receptive fields which are interconnected and superimposed on each other, similarly to the connection between neurons in the human brain. An understanding and harnessing of the power of AI and neural networks represents an attractive prospect for several fields of activity with respect to the fact that it has the potential to make substantial advances within a relatively short time. AI has already made inroads into several fragmentary disciplines within the framework of ophthalmology, which we shall present a brief review of below [2].

In ophthalmology AI algorithms already exist for the detection of diabetic retinopathy [3], glaucoma [4], age related macular degeneration [5] and retinopathy of prematurity [6]. The sub-specialization focusing on glaucoma is one of the most rapidly developing areas. The first implementation of AI within the area of glaucoma is an analysis of measurement of intraocular pressure (IOP), in which the level of IOP is one of the most significant risk factors in the progression of changes on the optic nerve papilla. For continuous monitoring of IOP, a contact lens has been developed thanks to which we can identify even minor fluctuations of IOP during the course of the day, which would otherwise have eluded us [4]. In addition, several deep learning algorithms have been developed in order to record the size and shape of the disc, the size and shape of excavation, the cup/disc ratio, and the thickness of the neuroretinal rim. It is important to state that one DLS was able to outperform 5 out of 6 ophthalmologists in identifying glaucoma with the aid of these criteria. AI has also found application in imaging methods such as optical coherence tomography (OCT) and testing of the visual field, attaining 93% sensitivity in detecting glaucoma in both of these methods [7].

The three main themes of AI in retinal specialization include diabetic retinopathy (DR), retinopathy of prematurity (ROP) and age-related macular degeneration (ARMD).

In the case of DR, AI was trained to search, among other conditions, for clinically significant macular edema, which enables timely diagnosis and treatment. More practical is the impact of AI on screening for the initial stages of diabetic retinopathy, when patients do not yet perceive any complaints but pathological changes are already manifested.

ROP, or abnormal changes on the retina, and in advanced stages growth of a neovascular retina as a consequence of hypoxia upon a background of premature birth, has also been influenced by advances in the field of AI. Computer algorithms and systems of machine learning have recently been developed which enable the development of scores for quantifying the onset and progression of ROP.

OCT and ocular fundus photography are regularly used technologies in the detection of ARMD, which is the main cause of loss of sight in developed countries. Both technologies of detection are the main target of AI. Studies have demonstrated that diagnosis of ARMD with the aid of OCT scans and ocular fundus photographs with the aid of AI is comparable with that conducted by clinical evaluators, while some studies have in fact demonstrated better performance on the part of AI.

It was recently published that a deep learning model was able to differentiate between macular edema upon a background of ARMD, diabetic macular edema, optic disc drusen and choroidal neovascularization with 99.8% and 100% accuracy [8].

Other applications of AI in ophthalmology include detection of ocular malignancies. Machine learning algorithms have been developed for the detection of basal cell and squamous cell carcinomas, and for assisting in the preoperative demarcation of edges and planning of resection of these formations [9]. Furthermore, studies demonstrate that AI has been successful in detecting cataracts, as well as comparison and above all calculation of the power of intraocular lenses (IOL) [10]. The newly emerging technology in AI referred to as a generative adversarial network has demonstrated an ability to convert scans between 2 different imaging methods with high precision. For example, recent studies have shown that it is possible to use this method to synthesize scans of fluorescence angiography from ocular fundus photographs [11]. It is clear that AI has penetrated into several sub-disciplines within the field of ophthalmology, and in the near future we can therefore expect incredible advances. The aim of this article is to present the currently used systems of artificial intelligence in the field of neuro-ophthalmology.

METHOD

For the purposes of this article, literary research was conducted focusing on an assessment and if applicable comparison of the evaluations of individual indications within the field of neuro-ophthalmology. The scientific databases PubMed, Scopus, and Medline were used in the research, as well as the website ClinicalTrials.gov, in order to search for target articles using the key terms "artificial intelligence", "deep learning", "optic nerve head", "papilledema", "retinal", "optic disc", and "neuro-ophthalmology". Of the articles found, we used only those that described a comparison of evaluations with experts, demonstrated qualitative sensitivity and other parameters above 80%, and in which an impact on clinical practice could be expected. For the same reason we excluded articles dealing with an evaluation of the function of the optic nerve.

RESULTS

Current imaging methods in neuro-ophthalmology

Before describing the options for the application of AI in neuro-ophthalmology, it is important to mention the current imaging methods that are already available within this area. The basis of imaging methods in neuro-ophthalmology are constituted by computer tomography (CT), and magnetic resonance (MR), each of which has its own characteristics. CT angiography (CTA) and MR angiography (MRA) offer a fundamental benefit in highlighting vascular abnormalities potentially contributing to the diagnosis of neuro-ophthalmological disorders. Another important diagnostic tool is examination of the visual field with the aid of perimetry, e.g. Humphrey visual field (HVF). As in other sub-disciplines, in neuro-ophthalmology also fundus photography and optical coherence tomography (OCT) of the optic nerve are commonly used to detect changes of the optic nerve [12].

Use of artificial intelligence in neuro-ophthalmology

Evaluation of the optic nerve

Nerve signals generated upon phototransduction of light by the retina are transmitted to the central nervous system by means of the optic nerve. The appearance of the papilla, the proximal end of the optic nerve, depends on its structural integrity. Deformities of axons may cause discoloration (or even atrophy), or swelling in different neuropathies [13]. There are several neurological conditions, e.g. intracranial hypertension, which require quick diagnosis and intervention. Digital fundus cameras provide high quality photographs of the papilla and retina, and offer an alternative to ophthalmoscopy

[12]. As an alternative to trained neuro-ophthalmologists, AI algorithms may offer a solution for a fast, automated and accurate interpretation of the papilla, as well as determination of the basic diagnosis. A review of studies using AI to detect papilla abnormalities is presented in Table 1.

Although glaucoma, retinal pathologies and neuro-ophthalmology overlap considerably, there are certain conditions which have a special status within the framework of neuro-ophthalmology. This concerns papilledema, anterior ischemic optic neuropathy (AION) and nonarteritic anterior ischemic optic neuropathy (NAION), as well as their differentiation from glaucomatous optic neuropathy (GON). Liu et al. developed a DLS which in this respect attained 98.8% accuracy, thereby competing with a far greater set of data from other authors, and demonstrating that a DLS can be accurate also in a small data set [14].

In a groundbreaking retrospective study from 2020 using 14 341 photographs of the ocular fundus, Milea et al. described how deep learning systems using retinal cameras were able to differentiate a normal ocular fundus from scans with edema of the optic nerve papilla, or with other abnormalities which were not connected with papilledema [15,16]. Following a cross-comparison with 4 experienced neuro-ophthalmologists, it was determined that the DLS had 96.4% sensitivity and 84.7% specificity for detection of papilledema, and produced results that were at minimum comparable with those of the experts. The DLS was also tested against 2 experienced neuro-ophthalmologists in an evaluation of 800 fundus photographs. The classification was divided into normal optic fundus, papilledema or other abnormalities. In this study the DLS correctly classified 678 out of 800 scans (84.7%), whereas expert 1 correctly classified 675 out of 800 (84.4%) and expert 2 correctly classified 641 out of 800 (80.1%) [17]. Another study assessed a significant factor influencing the accuracy of evaluation of the optic nerve, namely the quality of scans. The validated DLS evaluated an international, multicentric, multiethnic data set of 5 015 scans of the ocular fundus from 31 centers in 20 countries, with an overall accuracy of 90.6%, including poor quality scans, in an evaluation several times faster than those of 3 independent experts [18].

Another study described how the performance of a deep learning system in classifying abnormalities of the optic disc was at least as good as that of 2 independent neuro-ophthalmologists [19]. Akbar et al. developed an automated system for detecting the severity of papilledema from 160 fundus photographs with the aid of AI. This system attained 92.9% and 97.9% accuracy in the detection and classification of edema [20]. Other studies using various different combinations of extraction of algorithm features have also demonstrated good accordance for classification of papilledema in comparison with a neuro-ophthalmologist (Kappa score = 0.71), and comparison in evaluation by OCT (Pearson correlation coefficient, r = 0.77) [21]. Ahn et al. used a DLS to differentiate normal papilla scans from abnormalities caused by other neuropathies and edema. With the aid of data expansion and a classical convolutional neural network (CNN) with Tensorflow and transfer learning, they differentiated actual edema from pseudo-edema with high precision (95%). Unfortunately, the study suffered from a number of methodological limitations such as insufficiently stringent clinical inclusion criteria and external testing of the data file [22].

The results of these studies thus emphasize the possibility of faster and more accurate determination of papilledema for timely commencement of treatment. However, the fundamental question as to whether AI may provide a more accurate classification in comparison with experts still remains. In a study which addressed this question, the overall accuracy of classification of the BONSAI-DLS system (84.7%) was at least as good as that of 2 neuro-ophthalmologists with more than 25 years of clinical practice behind them (80.1% and 84.4%), who similarly to the DLS diagnosed the appearance of the ocular fundus based on digital fundus photographs without other clinical information [19]. The robustness of a DLS for detecting papilledema and other abnormalities was also confirmed by 2 further studies, even if with smaller groups of validation and evaluation datasets [14,23].

Glaucomatous and non-glaucomatous optic neuropathy

AION and NAION are sight-threatening conditions, in which timely diagnosis is of vital importance. A retrospective study in comparison with experienced clinicians demonstrated that their neural network was able to detect AION in 94.7% of cases [24]. It is very important to differentiate glaucomatous optic neuropathy from non-glaucomatous optic neuropathy (NGON), such as AION or NAION. Jang et al. applied the neural network ResNet-50, DLS MATLAB, to 3 815 color fundus scans, and demonstrated 93.4% sensitivity and 81.8% specificity in differentiating between NGON and GON [24]. It therefore has the potential to provide a clear diagnostic differentiation between these 2 pathologies, which could enable greater effectiveness and better utilization of time and resources.

A study by Feldon et al. from 2006 describes the ability of a computer classification system to characterize the severity of NAION on the basis of evaluation of HVF. However, the study was not clinically usable and was focused rather for research purposes [25]. Glaucoma is typically manifested in the excavation of the optic nerve papilla. It is nevertheless very important to correctly identify compressive neuropathy, which may imitate glaucoma. Yang et al. used DL in order to differentiate GON from non-glaucomatous optic neuropathy (NGON) caused by compression, hereditary disorder, chronic ischemia, inflammation, trauma or toxicity with the aid of an analysis of fundus photographs using the CNN architecture ResNet-50. The diagnosis of the cause of neuropathy was evaluated by 2 specialists, who supported it with evidence from an evaluation of the visual field and OCT. The overall accuracy of the DLS reached 99.1%. The diagnostic precision of the DLS for specific differentiation of GON from images of NGON demonstrated sensitivity of 93.4% and specificity of 81.8% [26].

A further study on a DLS in relation to HVF was conducted in relation to glaucomatous changes. With the use of 32 443 HVF, Wen et al. demonstrated that their algorithm

Table 1. Summary of studies evaluating classical machine and deep learning to detect structural and functional abnormalities of the optic nerve and papilla

Assessment specifications					AI characteristics			Source
AI	**Assessment**	**Model**	**Aim**	**Dataset**	**Sensitivity**	**Specificity**	**Accuracy**	
ML	Colour picture of the fundus	Image processing and extraction of vasculature features, blurring and disc colour. Extraction of textural features using GLCM. Classification using SVM with RBF.	Detection of papilledema. Classification of the severity of papilledema into mild (MFS 1 and 2) and severe (MFS 3 to 5).	160 images, 50 normal and 40 with papilledema from the STARE database and 40 normal and 30 with papilledema from the local database.	90.09	96.49	92.99	Akbar et al, 2017
ML	Colour picture of the fundus	Analysed parameters of optical disc pallor.	Assessment of optic disc pallor.	230 images, 107 with disc pallor and 123 normal from the local database.	95.3	96.7	96.1	Yang et al, 2019
ML	Colour picture of the fundus	NA.	Differentiate papilledema from a normal finding or other abnormalities. To compare the performance of DLS against 2 neuro-ophthalmologists.	Training dataset: 14341 images (2148 with papilledema, 3037 with other abnormalities, 9156 with normal findings). 800 images were evaluated (201 with papilledema, 199 with other abnormalities, 400 with normal findings).	83.17	94.39	91.59	Biousse et al, 2020
DL	Colour picture of the fundus	CNN using Google's Tensorflow framework, Inception V3, on ResNet and VGG.	Detection of papilla swelling accuracy.	1 396 images (295 with neuropathy, 295 with pseudopapilledema, 779 normal) from a local database. Training dataset: 876 images.	95.99			Ahn et al, 2019
DL	Colour picture of the fundus	BONSAI DLS: DenseNet-121 classification network.	Distinguishing papilledema from normal images and other abnormalities.	Test dataset: 14341 images (2148 with papilledema, 3037 with other abnormalities, 9156 with normal findings). 1505 images evaluated (360 with papilledema, 532 with other abnormalities, 613 with normal findings).	96.49	84.78	87.58	Milea et al (2020)
DL	Colour picture of the fundus	U-net segmentation network, VGGNet classification network.	Classification of the severity of papilledema into mild (MFS 1 and 2) and severe (MFS 3 to 5).	Training dataset: 2103 images (1052 with mild/moderate oedema, 1051 with severe papilledema). Test dataset: 214 images (92 with mild/moderate oedema, 122 with severe oedema).	91.8	82.6	87.9	Vasseneix et al, 2021
DL	Colour picture of the fundus	Classification using ResNet-152.	Differentiating between normal and abnormal smartphone images.	Training dataset: 944 images (364 abnormal, 580 normal) from the local database. Test dataset: 151 images (71 abnormal, 80 normal) from a local database.	94.01	96.05		Liu et al, 2021

CNN – convolutional neural network, DL – deep learning, GLCM – co-occurrence matrix, MFS – modified Frisén grade scheme, ML – machine learning; NA – not Applicable, RBF – radial basis function, SVM – support vector method

Table 2. Summary of studies evaluating classical machine and deep learning on eye movement disorders

Assessment specifications					AI characteristics			Source
Aim	**Dataset**	**Sensitivity**	**Aim**	**Dataset**	**Sensitivity**	**Aim**	**Dataset**	
ML	Face photo.	Classification using the detection and calculation of the corneal light reflex ratio.	Eye misalignment detection in primary gaze facial photographs using the corneal light reflex.	103 subjects.	97.2	73.1	94.2	Khumdat et al (2013)
ML	Digital video recordings of eye movements with cover test.	Classification using automatic eye deviation. The model was not further specified.	Identification of strabismus in digital video recordings using the cover test.	15 patients with exotropia.	80.0	100.0	93.3	Valente et al, 2017
DL	Retinal birefringence scan.	Classification using the Neural Network toolbox for MATLAB.	Detection of eye disorders using retinal birefringence sensing.	Validation: 10 eyes in 5 subjects with different fixations. Test: 39 subjects (19 with strabismus, 20 controls).	98.5	100		Gramatikov et al, 2017
DL	Photographs of eyes taken by patients.	Segmentation using ResNet-101. Classification using CNN.	Strabismus detection using autoscreening.	Validation: 3409 images (701 strabismus, 2708 controls). Test: 2276 images (470 strabismus, 1 806 controls).	93.3	96.2	93.9	Lu et al, 2018
DL	Face photo.	Area localization using faster R-CNN. Classification using Inception-V3 pretrained on ImageNet.	Screening for horizontal strabismus in primary gaze using facial photographs.	Validation: 7026 images (3829 strabismus, 3197 controls). Test: 277 frames.	94.0	99.3	95	Zheng et al, 2021

CNN – convolutional neural network, DL – deep learning, GLCM – co-occurrence matrix, MFS – modified Frisén grade scheme, ML – machine learning; RBF – radial basis function, SVM – support vector method

was capable of providing predictions of development of the visual field in glaucoma on the basis of a single initial HVF. The accuracy of prediction was within the range of 0.5 to 5 years, which provided clinical doctors with a tool for creating more precise plans for treatment [27].

Detection of eye movement disorders

The deviation in childhood and acquired strabismus may be connected with muscle restriction, convergent or divergent insufficiency or refractive errors. It can be clinically determined among other matters by a Hirschberg and Krimsky test, in which the gold standard is a prism cover test (PCT). AI systems have been developed which model data on the motor activity of the eye in order to predict signs in connection with infantile nystagmus and to detect strabismus. In future these systems could be extended also to other causes of ocular asymmetry, such as cranial nerve palsy [28,29].

Strabismus and similar abnormalities

The detection of squinting or strabismus with the aid of AI has been described predominantly in technical studies using photographs of patients, video recordings of eye movements, cover tests, retinal birefringence scanning or measurement by PCT. These studies are summarized in Table 2.

Facial photographs have been used to detect strabismus with the aid of various different AI methods. Sousa et al. designed a system on the basis of the Hirschberg reflex from photographs of 40 adult patients in 5 positions (primary gaze, upward gaze, downward gaze, left gaze and right gaze). The authors used 5 steps: segmentation of the face, detection of the ocular region, localization of the eyes, limbus and glare, and finally diagnosis based on the distance of the center of the cornea from the detected light reflex. The accuracy of identification of ocular asymmetry was 100% in exotropia, 88% in esotropia, 80% in hypertropia and 83% in hypotropia. A similar study, which used analysis of corneal light reflex, but only in children, attained accuracy of 94.2%, sensitivity of 97.2% and specificity of 73.1% [30]. Zheng et al. also developed a DL approach for screening of referable horizontal strabismus in children based on photographs in primary gaze. A total of 7026 images were used to train the model, 277 of which were tested. The algorithm attained accuracy of 95%, which was superior to the result of the resident ophthalmologists (accuracy within the range of 81–85%). However, before confirmation of usefulness it is necessary to conduct more extensive clinical validation trials, ideally performed prospectively [31].

Some studies have analyzed video recordings of eye movements from different gazes. Chen et al. developed AI which used various different CNN models and achieved accuracy of 95%, sensitivity of 94% and specificity of 96% in testing on a small sample of 17 adult patients with strabismus and a control group of 25 individuals [32]. In the study by Yang et al., an infrared camera with a special occlusor that blocked the subject's gaze and selectively let in infrared light was used. This program achieved strong correction with manual measurement by PCT, performed by 2 independent ophthalmologists. Valent et al. attempted to dispense with the need for a special camera or filters in the analysis of video recordings of a cover test with the aid of a different program which incorporated identification of the limbus, observation of the eye and detection of the occlusor. This method attained 93.3% accuracy, 80.0% sensitivity and 100% specificity for the detection of exotropia [26].

In order to overcome a number of methodical errors, Gramatikov et al. embarked upon retinal birefringence scanning for the purpose of determining central fixation according to changes of polarization of light refracted from the eye. In combination with an analysis with the aid of a specially designed ANN, in testing on 39 subjects the system attained 98.5% sensitivity and 100% specificity for the detection of ocular shift [33]. The use of AI for the detection and diagnosis of ocular asymmetry or other disorders is promising, both for its use in pediatric ophthalmology and in neuro-ophthalmology [34].

DISCUSSION AND LIMITS OF ARTIFICIAL INTELLIGENCE

The visual pathway begins with photoreceptors, and after switching to various different levels ends in the occipital lobe of the brain. As a consequence of this, intracranial pathologies may lead among other factors to disorders of the visual apparatus. Neuro-ophthalmology is an integrating medical discipline that incorporates the study of pathologies along the entire visual pathway. The most commonly occurring disorders affect the afferent visual system and the efferent pathway, which leads to central motor disorders, cranial neuropathies, instability of gaze and disorders of the pupils. These changes may have their origin in a broad range of pathologies, from autoimmune, infectious, inflammatory, ischemic, traumatic, compressive, congenital or degenerative disorders. It frequently occurs that neuro-ophthalmic dysfunction may be the first manifestation of a neurological disorder (e.g. multiple sclerosis). Similarly, optic nerve hypoplasia (ONH) may represent the sole manifestation of increased intracranial pressure [35]. Up to now neuro-ophthalmology has not benefitted substantially from advances in the field of artificial intelligence. The probable reasons are: (1) low prevalence and heterogeneity of disorders, which means that there is insufficient available data necessary for effective practice and training of systems; (2) relatively small community of specialists in comparison with other specializations; and (3) lack of uniformity in determination of final diagnosis between individual centers, especially when neurologists may enter the process. This may then lead to a loss of basic data and a decrease in the reliability of sufficient training before validation of the artificial intelligence algorithms. Despite this, the article has attempted to summarize and discuss the knowledge we have so far relating to systems of machine and deep learning for the purpose of detecting abnormalities within the neuro-ophthalmological environment [36].

One of the most limiting factors in the introduction of artificial intelligence (AI) is costs. In the literature there is only a negligible quantity of studies that address the impact of costs on the practical usability of AI. There are even fewer of those that deal with specific conditions, while the largest amount of literature focuses on the implementation of screening for diabetic retinopathy. With reference to this situation, Ruamviboonsuk et al. found 5 studies that addressed the cost-effectiveness of AI. The authors reached the conclusion that AI is more cost-effective than manual screening of diabetic retinopathy [37], though the studies nevertheless lack generalization in other indications. With regard to this insufficiency, it is difficult to determine the overall impact which AI is capable of having.

From this there ensures a further problem faced by AI, namely the methodology of clinical trials. With reference to the time and finances required for the creation of the technology, it is a particularly laborious process to obtain approval from the American FDA for testing of a research hypothesis. However, this approval is essential within the framework of the payment process. Without financial coverage, the costs are otherwise too high to justify the use of AI [24]. Another limitation of AI consists in the collection of extensive and complete data files for the creation and validation of algorithms. The "garbage in, garbage out" rule clearly states that if AI receives incomplete or insufficient data, the result will be incomplete and insufficient predictions. The supply of such data files requires either a large private practice or a hospital environment with patients who are willing to participate [38]. Large data files containing clearly categorized images with pronounced clinical features on color fundus photographs are not common. As a consequence, greater endeavors on the part of developers are required in order to develop AI solutions capable of detecting multiple papilla conditions in clinical practice.

It appears that the majority of research up to now has focused on fundus scans in the detection of neuro-ophthalmological disorders. However, in order for AI to have a greater impact in this field, it must penetrate far deeper into these imaging methods. Similar studies have already been conducted in other fields of medicine, including cardiology, pneumology and neurology [16,24]. Most studies in this article use a retrospective design [8,9,11,39,40]; nevertheless, a prospective evaluation would manifest far greater clinical validity. We can only hope that the advance of AI in medicine will contribute to a greater availability of literature and other sources which demonstrate the cost-effectiveness of AI, thereby leading to easier use of the technology in practice.

CONCLUSION

Thanks to technological advances, artificial intelligence (AI) can now boast the ability to process large sets of data quickly and consistently, which may help doctors determine a more accurate diagnosis within a shorter time. It is necessary to note that within the current configuration, AI rather plays the role of a "seconder" than an equal partner alongside the clinician. At present AI is used in several fields of medicine, including dermatology and radiology, and ophthalmology also has good prerequisites for the harnessing of its efficacy. With reference to the routine gathering of data from various methods of clinical evaluation, AI may serve as a tool for analyzing a huge quantity of data and assisting in clinical decision-making. AI systems already exist in ophthalmology for detecting diabetic retinopathy, glaucoma, age-related macular degeneration and other conditions. This article has attempted to describe advances in the use of AI in neuro-ophthalmology.

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