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ARTIFICIAL INTELLIGENCE IN EYE DISEASE: AN UPDATE SYSTEMATIC REVIEW

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ABSTRACT

Background: *In recent years, AI has significantly revolutionized the healthcare industry, with deep learning applications being used to identify various illnesses, evaluate cancerous lesions, and determine stroke onset. AI-based systems also have been applied in ophthalmology to address leading eye diseases.*

The aim: *This study aims to determine the role of artificial intelligence (AI) in eye disease.*

Methods: *By comparing itself to the standards set by the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020, this study was able to show that it met all of the requirements. So, the experts were able to make sure that the study was as up-to-date as it was possible to be. For this search approach, publications that came out between 2014 and 2024 were taken into account. Several different online reference sources, like Pubmed and ScienceDirect, were used to do this. It was decided not to take into account review pieces, works that had already been published, or works that were only half done.*

Results: *In the PubMed database, the results of our search brought up 157 articles, whereas the results of our search on ScienceDirect brought up 256 articles. The results of the search conducted by title screening yielded a total of 34 articles for PubMed and 28 articles for ScienceDirect. We compiled a total of 16 papers, 10 of which came from PubMed and 6 of which came from ScienceDirect. We excluded 4 review articles, 2 non-full text articles, 3 articles having insufficient outcomes, and 1 article having ineligible subjects. In the end, we included six research that met the criteria.*

Conclusion: *Our systematic study suggests that AI has a role in the diagnosis or screening of eye disease. AI can be a valuable tool for diabetic retinopathy (DR) screening, glaucoma screening, myopia screening, and diagnosis of dry eye syndrome.*

Keywords: *Artificial intelligence, eye disease, ophthalmology, role*

INTRODUCTION

Numerous eye diseases, including diabetic retinopathy, cataracts, and glaucoma, are among the world's leading causes of blindness. Delays in seeking medical attention reduce the likelihood of early intervention and prevention as well as the health awareness of these disorders and their repercussions. Early detection and management of these conditions are needed to reduce the impact of visual impairment.[1] The increased processing power of modern computers and the abundance of digital data that can be collected and used have led to a recent rise in interest in and advancements in medical artificial intelligence (AI) applications.[2]

Most people agree that the Dartmouth Summer Research Project in 1956 is where the idea of AI first appeared. AI usually involves a hardware-software system. AI is especially interested in algorithms from a software standpoint. A conceptual framework for implementing AI algorithms is called an artificial neural network, or ANN. It is a simulation of the human brain, which consists of a network of connected neurons with weighted communication channels between them.[3] Although the terms machine learning (ML) and deep learning (DL) are commonly used interchangeably, artificial intelligence (AI) is actually an umbrella term that comprises ML, which also includes DL. While data analysis in artificial neural networks (ANNs) occurs through networked nodes with programmable weights, machine learning (ML) is an extension of statistical modelling. With the use of deep neural networks (DNNs), DL is a contemporary expansion of the traditional neural network technique. The advantage of DL is that more complex inputs, such as an entire image, can be used, however, this requires a much larger training dataset.[4]

The healthcare sector has seen a change in recent years because of AI-based technology.[5] In the medical field, deep learning has been applied to identify various illnesses, evaluate cancerous lesions and metastases, and determine the time of stroke start.[6] Their estimation-based medical application in ophthalmology is a potential strategy that may improve clinical exams.[7] Applications of DL in ophthalmology help identify retinopathy of prematurity, age-related macular degeneration, glaucoma, and diabetic retinopathy (DR).[6] Significant progress has been made in AI-based DR screening in recent years, providing an effective, economical, and labor-saving method for enhancing DR screening on a broad scale. AI-based tools have been shown to perform on par with human specialists in several prospective experiments carried out in real-world situations, indicating that they have the potential to improve screening efforts.[8] The purpose of this study is to determine the role of artificial intelligence (AI) in eye disease.

METHODS

Protocol

By following the rules provided by Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) 2020, the author of this study made certain that it was up to par with the requirements. This is done to ensure that the conclusions drawn from the inquiry are accurate.

Criteria for Eligibility

For the purpose of this systematic review, we investigate the role of artificial intelligence (AI) in eye disease. As the primary purpose of this piece of writing, demonstrating the relevance of the difficulties that have been identified will take place throughout its entirety.

In order for researchers to take part in the study, they needed to fulfil the following requirements: 1) The paper needs to be written in English, and it needs to determine artificial intelligence (AI) in eye disease. In order for the manuscript to be considered for publication, it needs to meet both of these requirements. 2) The studied papers include several that were published after 2014, but before the time period that this systematic review deems to be relevant. Examples of studies that are not permitted include editorials, submissions that do not have a DOI, review articles that have already been published, and entries that are essentially identical to journal papers that have already been published.

Search Strategy

We used "artificial intelligence"; "eye disease"; “ophthalmology”; and "role" as keywords. The search for studies to be included in the systematic review was carried out from February, 19th 2024 using the PubMed and ScienceDirect databases by inputting the words: "artificial intelligence"[MeSH Terms] OR "artificial"[All Fields] AND "intelligence"[All Fields] OR "artificial intelligence"[All Fields] AND "eye diseases"[MeSH Terms] OR "eye"[All Fields] AND "diseases"[All Fields] OR "eye diseases"[All Fields] OR("eye"[All Fields] AND "disease"[All Fields] OR "eye disease"[All Fields] AND "ophthalmologie"[All Fields] OR "ophthalmology"[MeSH Terms] OR "ophthalmology"[All Fields] OR "ophthalmology s"[All Fields] AND "role"[MeSH Terms] OR "role"[All Fields] AND (y_10[Filter]) AND (english[Filter]) used in searching the literature.

Data retrieval

After reading the abstract and the title of each study, the writers performed an examination to determine whether or not the study satisfied the inclusion criteria. The writers then decided which previous research they wanted to utilise as sources for their article and selected those studies. After looking at a number of different research, which all seemed to point to the same trend, this conclusion was drawn. All submissions need to be written in English and can't have been seen anywhere else.

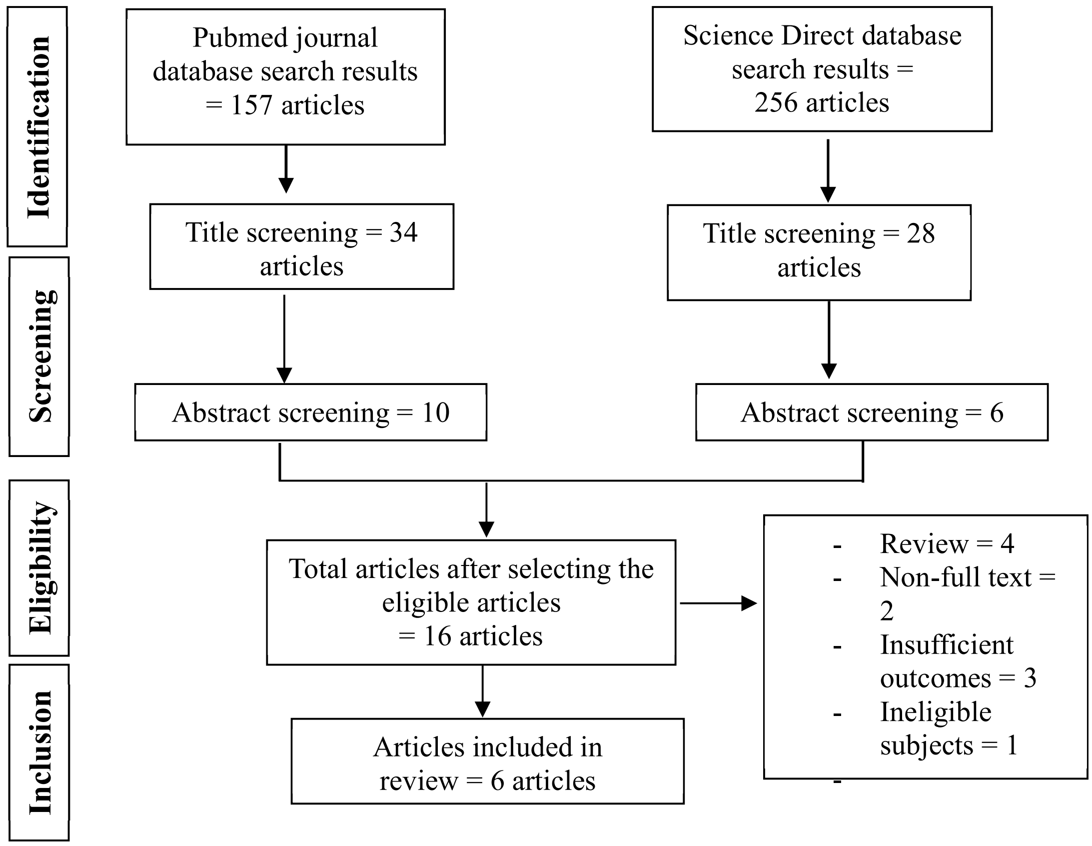

Figure 1. Article search flowchart

Only those papers that were able to satisfy all of the inclusion criteria were taken into consideration for the systematic review. This reduces the number of results to only those that are pertinent to the search. We do not take into consideration the conclusions of any study that does not satisfy our requirements. After this, the findings of the research will be analysed in great detail. The following pieces of information were uncovered as a result of the inquiry that was carried out for the purpose of this study: names, authors, publication dates, location, study activities, and parameters.

Quality Assessment and Data Synthesis

Each author did their own study on the research that was included in the publication's title and abstract before deciding on which publications to explore further. The next step will be to evaluate all of the articles that are suitable for inclusion in the review because they match the criteria set forth for that purpose in the review. After that, we'll determine which articles to include in the review depending on the findings that we've uncovered. This criteria is utilised in the process of selecting papers for further assessment to simplify the process as much as feasible when selecting papers to evaluate. Which earlier investigations were carried out, and what elements of those studies made it appropriate to include them in the review, are being discussed here.

RESULT

In the PubMed database, the results of our search brought up 157 articles, whereas the results of our search on ScienceDirect brought up 256 articles. The results of the search conducted by title screening yielded a total of 34 articles for PubMed and 28 articles for ScienceDirect. We compiled a total of 16 papers, 10 of which came from PubMed and 6 of which came from ScienceDirect. We excluded 4 review articles, 2 non-full text articles, 3 articles having insufficient outcomes, and 1 article having ineligible subjects. In the end, we included six research that met the criteria.

Table 1. The literature included in this study

Author	Origin	Method	Sample Size	Result
Jing, 2022[9]	China	Prospective study	229 eyes of 155 patients with DED	This study established a thorough method for assessing each dry eye syndrome (DED) patient's unique ocular health by integrating ocular indicators, symptoms, and precise tools including Pentacam, IVCM, and Oculus keratography. This would enable further research into the mechanism behind DED and facilitate the implementation of a combination treatment plan.
Lemij, 2023[10]	USA	Cross-sectional study	113,893 eyes of 60,357	The results showed that a sizable collection of high-quality Color fundus photos (CFPs) was assembled in order to create artificial intelligence screening tools for glaucoma. The inferior and superior appearance of the NRR were the most prevalent characteristics of RG. Disc hemorrhages were an uncommon RG symptom. Future screening programs may benefit from the development and improvement of these data and results.
Pei, 2022[11]	China	Cross-sectional study	1,768 retinal images from 563 patients with T2DM	These findings suggested that screening for diabetic retinopathy (DR) can be done effectively with EyeWisdom®DSS, and identifying patients without DR was more accurately done using EyeWisdom®MCS. AI-based DR screening has a place in less developed areas.

Shimizu, 2023[12]	Japan	Retrospective study	158 eyes from 79 patients	An innovative AI-based DED diagnostic model was effectively built in this study. It may be possible to do ophthalmology examinations outside of clinics and hospitals with the help of this diagnostic model.
Tan, 2021[13]	Singapore	Retrospective study	226,686 retinal images from 112110 patients	These algorithms may prove to be useful screening instruments for identifying myopic people who are most likely to experience issues in the future. Addressing the prevalence of myopia worldwide is expected to benefit from this approach. Furthermore, we demonstrated for the first time how deep learning algorithms and blockchain technology may be combined to enhance security, auditability, and transparency in AI-based medical research.
Vought, 2023[14]	USA	Cross-sectional study	62 patients	The results of this investigation provide light on the application of Al in diabetic screenings and the important part it will play in automated DR identification. With a few restrictions, the EyeArt readings were helpful in a community screening setting.

Jing, et al. (2022)[9] investigated the patterns of morphological changes in the corneal sub-basal nerve and the intrinsic abnormalities in the cornea associated with dry eye disease (DED). The characteristics of the sub-basal nerve fiber were produced by a deep learning model using artificial intelligence (AI). Contrary to anterior, posterior, and total corneal aberrations, the average density of the corneal nerve exhibited a negative correlation. The maximum length and the previously indicated characteristics also showed a negative correlation. Yet, the LC number and total corneal aberrations were found to be significantly and favorably correlated in this investigation. The quantity of corneal endothelial cells and aberrations, however, did not significantly correlate. We performed distinct hierarchical multiple regressions (age <60 years, 60–70 years, and >70 years) to rule out the possibility that aging changed the aberration and hence affected our results. Following a stepwise regression process, the corneal nerve average density was determined to be a determinant of the total corneal RMS HOA (R2increment = 0.15 0.10 0.05; $P < 0.05$).

Lemij, et al. (2023)[10] assembled a sizable, labeled data set of CFPs to create an AI system that would enable low-cost, multi-ethnic population-based glaucoma screening. Prospective screening programs could benefit from the data and results in the future. According to the estimated sensitivity and specificity, which were higher than the desired levels of 80% and 95%, respectively, the annotated data set ought to be of adequate quality for creating AI screening solutions.

Pei, et al. (2022)[11] showed that in 549 DM patients, EyeWisdom ®DSS software identified 337 (61.4%) cases of DR, and EyeWisdom ®MCS software identified 264 (48.1%) DR cases in these individuals. According to EyeWisdom®DSS's automatic grading, 68 patients (12.4%) had mild NPDR, 79 patients (14.4%) had moderate NPDR, 71 patients (12.9%) had severe NPDR, and 119 patients (21.7%) had PDR. 295 (91.0%) and 247 (76.2%) of the 324 DR patients received the accurate diagnosis of DR with EyeWisdom®DSS and EyeWisdom®MCS, respectively. Of the 225 patients with diabetes mellitus who did not have diabetes, 83 (81.3%) had an accurate diagnosis made by EyeWisdom ®DSS, and 208 (92.4%) had an accurate diagnosis made by EyeWisdom ®MCS. The kappa data showed that the degree of agreement between EyeWisdom®DSS and the ophthalmologist grading for DR was 0.730 ($P < 0.001$), for NPDR it was 0.527 ($P < 0.001$), and for PDR it was 0.608 ($P < 0.001$). The kappa value for the ophthalmologist's DR grading and EyeWisdom®MCS was 0.660 ($P < 0.001$).

Shimizu, et al. (2023)[12] showed that the diagnostic performance for DED was assessed using tear film breakup time (TFBUT) and the ocular surface disease index (OSDI). This model has the following characteristics: sensitivity, specificity, PPV, and NPV were, in order, 0.778 (95% CI 0.572–0.912), 0.857 (95% CI 0.564–0.866), 0.875 (95% CI 0.635–0.975), and 0.750 (95% CI 0.510–0.850). In addition, the AUC was 0.813 (95% CI 0.585-1.000). There was a moderate correlation (r = 0.791, 95% CI 0.486–0.924) between the TFBUT obtained from the EMR and that calculated using the machine learning approach. Furthermore, the anterior-segment video input takes an average of 2.38 seconds to process before the TFBUT output is produced by this AI model. With a 95% confidence interval (CI) of 0.769–0.809, the tear film breakup time estimation accuracy was 0.789. The AI model's area under the receiver operating characteristic curve was 0.877 (95% CI 0.861–0.893). This AI model's DED diagnostic accuracy was 0.778 (95% CI 0.572–0.912) and 0.857 (95% CI 0.564–0.866) in terms of sensitivity and specificity, respectively.

Tan et al. (2021)[13] showed that specificities were from 80.8% to 95.5%, sensitivities from 85.3% to 92.7%, and AUCs from 0.913 to 0.966 for the SE criterion-based identification of high myopia. The first AUC for external test dataset 5 was 0.746 (95% CI 0.740–0.753), with a 90.5–46.2% specificity and a 90.0–90.8% sensitivity. The AUCs for external test datasets 1 and 2 were 0.969 (95% CI 0.947–0.984) and 0.956 (0.930–0.977) respectively, indicating that only these two test datasets have available AL data for the purpose of detecting high myopia using the AL criterion.

Vought, et al. (2023)[14] showed that there was an overall 79% agreement between the retina specialist, the onsite grader, and the EyeArt results about the diagnosis of DR. In 27% of patients, the onsite grader and 24% of patients, the retina specialist, respectively, discovered DR. Comparatively speaking, 2% of the patients' images were ungradable by EyeArt, while 15% of patients had images that could not be graded by the retina specialist. Indicating strong agreement, the kappa score for concordance on a diagnosis was 0.69 (95% CI: 0.61-0.77). There was an overall 85% agreement among the ophthalmologist, EyeArt, and the on-site grader about referral trends. Significant agreement was indicated by the concordance kappa score of 0.70 (95% CI: 0.60-0.80) for "whether to refer."

DISCUSSION

The purpose of this research was to review studies published after January 2014 and up to February 2024 that investigated the role of AI in eye disease, systematically. This review included three cross-sectional studies, two retrospective studies, and one prospective study. Overall, the studies showed that AI is a valuable tool for screening or diagnosis of eye diseases including diabetic retinopathy (DR), glaucoma, myopia, and dry eye syndrome (DED).

The most prevalent microvascular consequence of diabetes mellitus that causes vision loss in the elderly is diabetic retinopathy (DR). Between 2005 and 2014, Taiwan had a range of 3.75 to 3.95% for the prevalence of diabetic eye illness and 0.29 to 0.35% for the prevalence of poor vision and blindness. From 14.3% in 2006 to 15.9% in 2013, diabetic retinopathy became more common in Korea. Diabetic retinopathy screening is crucial to early detection of preventable blindness because it is still the primary cause of visual impairment. The next steps in the patient's care can be promptly determined with the use of the AI DR tool, which can help the doctor with fundus picture analysis.[15]

In England, screening for DR and disorders that could impair vision has been shown to be highly successful. Since its launch in 2003, the National Health Screening (NHS) Diabetic Eye Screening Program has been administered by trained clinical and non-clinical personnel who are enrolled in approved continuous professional development and quality assurance programs. With a 79% countrywide acceptance, the UK National Screening Committee has proposed a comprehensive population screening program for those with diabetes aged 12 and above. The AUC, specificity, and sensitivity of referable DR detection were 97%, 87%, and 97%, respectively. The identification of DR that posed a hazard to vision showed a 100% sensitivity and 91% specificity. No DME cases were overlooked, and the AUCs were all above 0.95.[16]

A set of progressive optic neuropathies known as glaucoma are defined by alterations in the optical nerve head brought on by the degradation of retinal ganglion cells and retinal nerve fiber layers. The primary cause of permanent blindness in the globe, glaucoma is linked to a lower quality of life.[17] The diagnosis of glaucoma is not only subjective and subject to over- or underestimation because it depends on the expertise and experience of a single doctor, but it can also be time-consuming and expensive. As an alternative, automated AI models that analyze and quantify images of the retina and optic nerve could reduce subjectivity. There are numerous further uses of AI for glaucoma. AI, for example, can be used to streamline workflows and procedures in glaucoma clinics, thereby freeing up more time for doctors to spend with patients thus enhancing overall care.[18] Based on SD-OCT and SAP (24–2) data gathered from 62 glaucomatous patients and 48 healthy people, Silva et al. built models for glaucoma diagnosis. With a sensitivity of 95.16% (at 80% specificity) and a sensitivity of 82.25% (at 90% specificity) using 10-fold CV, RF obtained the best AUC of 0.946 based on four characteristics.[19]

One of the most prevalent refractive errors in the general population is myopia. Due to its severity, blindness may ensue. Myopia is becoming more common and is now a significant public health concern. East Asian children have a high myopia development rate of almost −1 diopter (D) every year, and about 24% of the myopic population develops high myopia in adulthood. Myopia has emerged as a serious public health issue in recent years. In East Asia, myopia maculopathy, a myopia complication, is now the most common cause of irreversible vision loss.[11] Although ophthalmologists typically find it challenging to assess refractive error from a retinal fundus picture, DL methods can rather accurately predict it. A DL system trained by Yang et al. to automatically identify myopia from ocular appearance photos achieved an AUC of 0.9270. The study showed that children with myopia in remote locations might have their refractive status checked and monitored.[20]

Throughout the world, (DED) is a common ocular illness. Approximately 25% of patients who attend an ophthalmology clinic report having dry eye symptoms. DED has evolved into an unavoidable public health issue in recent years.[21] In 2017, the definition of dry eye disease that was first presented in 2007 was evaluated by the Tear Film and Ocular Surface Society (TFOS) Dry Eye Workshop (DEWS) II.[22] AI has great promise for use in a wide range of DED-related applications, such as the automatic detection and categorization of DED, the study of the etiology and risk factors for DED, and the identification of putative biomarkers.[23]

CONCLUSION

Our systematic study suggests that AI has a role in the diagnosis or screening of eye disease. AI can be a valuable tool for diabetic retinopathy (DR) screening, glaucoma screening, myopia screening, and diagnosis of dry eye syndrome.

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