· Bibliometric Research ·

Artificial intelligence applications in ophthalmic optical coherence tomography: a 12-year bibliometric analysis

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Abstract
● **AIM:** To explore the current application and research frontiers of global ophthalmic optical coherence tomography (OCT) imaging artificial intelligence (AI) research.
● **METHODS:** The citation data were downloaded from the Web of Science Core Collection database (WoSCC) to evaluate the articles in application of AI in ophthalmic OCT published from January 1, 2012 to December 31, 2023. This information was analyzed using CiteSpace 6.2.R2 Advanced software, and high-impact articles were analyzed.
● **RESULTS:** In general, 877 articles from 65 countries were studied and analyzed, of which 261 were published by the United States and 252 by China. The centrality of the United States is 0.33, the H index is 38, and the H index of two institutions in England reaches 20. Ophthalmology, computer science, and AI are the main disciplines involved. Hot keywords after 2018 include deep learning (DL), AI, macular degeneration, and automatic segmentation.
● **CONCLUSION:** The annual number of articles on AI applications in ophthalmic OCT has grown rapidly. The United States holds a prominent position. Institutions like the University of California System and the University of London are spearheading advancements. Initial researches centered on the automatic recognition and diagnosis of ocular diseases leveraging traditional machine learning (ML) technology and OCT images. Nowadays, the imaging process algorithm selection has shifted its focus towards DL. Concurrently, optical coherence tomography angiography (OCTA) and computer-aided diagnosis (CAD) have emerged as key areas of contemporary research.
● **KEYWORDS:** artificial intelligence; optical coherence tomography; bibliometric analysis; deep learning
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INTRODUCTION

Optical coherence tomography (OCT) is a rapidly developing new tomography technology, which has attracted wide attention in recent years[1]. Ophthalmic OCT technology has the ability to characterize the optic nerve papilla, the peripapillary retinal nerve fiber layer, and the macular cell layer, including the ganglion cell layer. This enables it to perform qualitative and quantitative evaluation in the diagnosis of optic nerve disease[2]. Ophthalmic OCT can be used to diagnose and manage a variety of eye diseases, including retinal diseases such as diabetic retinopathy (DR)[3], macular diseases such as macular degeneration[4], optic nerve diseases and glaucoma[5]. However, the OCT technique sometimes requires manual modification of the position of the measured area during accurate analysis[6], and error in scan results may occur under certain ocular pathologic conditions. Therefore, ophthalmic OCT technology still has a lot of room for improvement.

Artificial intelligence (AI) is a field of science and technology that studies how to enable computers to simulate and perform tasks of human intelligence[7]. AI is widely used in the medical field, mainly through machine learning (ML) and deep learning (DL) to develop AI applications in medical imaging[8]. The field of ophthalmology is currently witnessing thriving AI research[9]. In the field of ophthalmology, an image-based diagnostic system, traditional ML and DL has a very high degree of application[10]. These technologies have been used in imaging segmentation and feature extraction of OCT, anomaly detection and screening, 3D reconstruction and visualization, data analysis and prediction model. For example, DL has achieved excellent accuracy in automatic detection and quantification of macular fluid in OCT images[11]. In terms of identifying the characteristics, progression and treatment of retinal diseases, such as neovascular age-related macular degeneration (AMD) and diabetic macular edema, the application of OCT technology in combination with AI and DL systems is gradually attracting wide attention[12]. The deep integration of AI (including traditional ML and DL) and ophthalmic OCT is expected to change the existing disease diagnosis system and produce significant clinical effects in ophthalmic medical services[13].

This study aims to conduct the latest bibliometrics research on the application of AI in ophthalmic OCT imaging by analyzing articles retrieved in the Web of Science Core Collection (WoSCC) database. Combined with general data, countries or regions, institutions, research categories, keywords and other relevant data, as well as the 10 most influential articles in the field, to evaluate the global application of AI OCT in ophthalmology. An important aim of this study is to develop a repeatable and unbiased strategy for analyzing research hotspots and trends, exploring the dynamic frontier of knowledge in this research area. In particular, this study examines the active fields, prospective development and potential obstacles of AI application in ophthalmic OCT imaging, and provides guidance and advice for AI professionals, ophthalmologists, and medical imaging researchers.

MATERIALS AND METHODS

On February 17, 2024, citation data published between January 1, 2012 and December 31, 2023, acquired from the WoSCC, were verified independently. The search formula was TS=(AI or “artificial intelligence” or “neural network” or “transfer learning” or “machine learning” or “deep learning”) AND TS=(OCT or optical coherence tomography).

The search selected articles written in English and excluded early access, proceedings papers, book chapters, data papers, and retracted publications.

We manually deleted data after reading the title and abstract of each article to obtain the most accurate analysis results. The criteria for manual exclusion are as follows: 1) the research subject is not ophthalmology; 2) the research object is not OCT; 3) the research method doesn’t include AI. The details of the filtering process are shown in Figure 1. The data included in the study are all about the application of AI in ophthalmic OCT. We analyzed the general data, countries or regions, institutions, subject categories, and keywords using the analysis function of Web of Science and CiteSpace 6.2.R2 Advanced. Simultaneously, high-impact articles were analyzed thoroughly and comprehensively. All citation features are included in this article.

RESULTS

Distribution of Articles by Publication Year In total, 877 studies focusing on AI application in ophthalmic OCT, published between January 1, 2012, and December 31, 2023, were analyzed. The data collected and counted from WoSCC were deduplicated using the duplication removal function of CiteSpace software.

Between 2012 and 2019, the number of annual articles grew steadily. This number began to grow rapidly in 2020 and almost doubled that of the previous year. The number of articles published exceeded 200 for the first time in 2022. Figure 2 showed the annual number of publications.

Countries or Regions The default settings of CiteSpace software were used to count the number of articles of each country and analyze the cooperation relationships between countries and regions. The citations involve 65 countries and regions in total. In Figure 3, the size of each yellow node area represents the number of citations. The top three countries with large yellow nodes are the United States, China, and England, with 261, 252, and 96 articles respectively. The links between nodes represent cooperation relationships between countries. Countries with more links are much more influential. The centrality of a country represents in Figure 3 as the dimension of the purple circle. According to the data calculated by the CiteSpace software, the centrality of the United States is the largest (0.33), which is significantly higher than that of England (0.25). The data in Table 1 can confirm this result objectively. The H-index can accurately reflect the academic achievement of a country. The three countries with the highest H-index are the United States, China and England. Overall, the United States has the largest number of publications in this field and the highest reference value of research.

Institutions Table 2 lists the 10 institutions that have done the most research on AI OCT in the selected articles. The data displayed was processed under the default settings of CiteSpace. The top three institutions with the highest number of publications are all from England, and their H-index also ranks the top. The University of London in England had the highest participation in relevant studies, with 58 articles included in the statistics. England has three institutions on the list, while the United States, China and Singapore each have

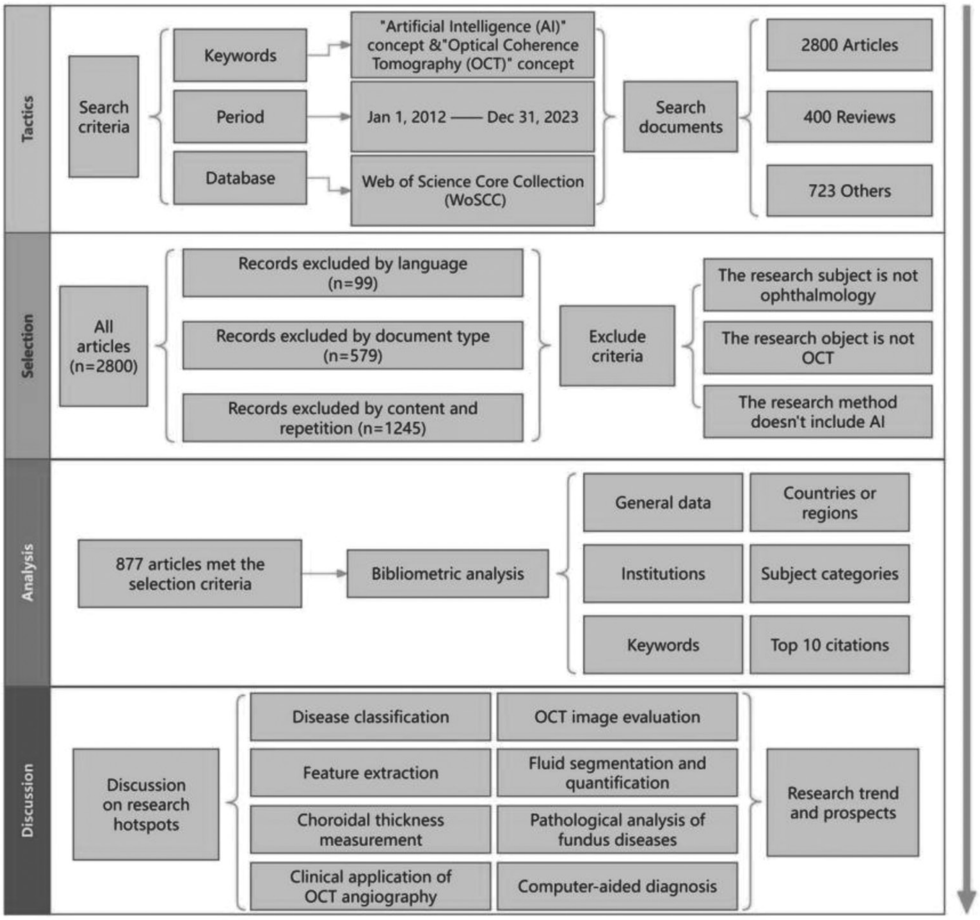

Figure 1 Frame flow diagram showing the detailed selection criteria and bibliometric analysis steps for the study of AI application in ophthalmic OCT AI: Artificial intelligence; OCT: Optical coherence tomography.

Table 1 Top 10 countries or regions with the highest publication volume in the field of AI ophthalmic OCT from 2012 to 2023

Rank	Countries or regions	Counts	Centrality	H-index
1	USA	261	0.33	38
2	China	252	0.09	30
3	England	96	0.25	25
4	South Korea	75	0.08	18
5	Germany	71	0.07	17
6	Japan	64	0.01	22
7	India	60	0.12	16
8	Singapore	49	0.07	17
9	Austria	49	0.04	19
10	Switzerland	44	0.05	15

AI: Artificial intelligence; OCT: Optical coherence tomography.

two institutions on the list. In addition, an institution from Austria was included. The nodes' size positively correlated with the number of articles published by institution (Figure 4). The link between the nodes reflects the collaborative relationship between institutions. The University of California System in the United States had the highest centrality, followed by institutions in England and Austria.

Research Categories Figure 5 showed the category-based clustering generated by the CiteSpace software. The overlap of the clustering color blocks represents the connection between the subject areas. The eight clusters are "ophthalmology", "endocrinology & metabolism", "surgery", "multidisciplinary sciences", "computer science, artificial intelligence", "mathematical & computational biology", "clinical neurology", and "physics, applied".

Keywords In order to better understand the application of AI in the ophthalmic use of OCT in the past decade, the emerging keywords developed over time were analyzed based on the keyword co-occurrence cooperative network analysis chart. This reflects the shift of research hotspot. The default setting of CiteSpace is changed to the following mode: "Year Per Slice"=1, "γ"=0.5, and "Minimum Duration"=1. Our results were depicted in Figure 6. The Burstness detection analysis can detect the situation of great changes in the number of references in a certain period of time, so as to find the fading or rising of a certain subject word or keyword. The emerging keywords for the investigated timeline are depicted as the red square in Figure 6. The emerging keywords during 2012-2023 include machine learning classifiers (2012-2018), nerve fiber layer (2012-2014), feature selection (2012-2016), parameters (2012-2015), coherence tomography (2013-2016), drusen (2015-2019), AMD (2018-2019), diabetic retinopathy (2018-

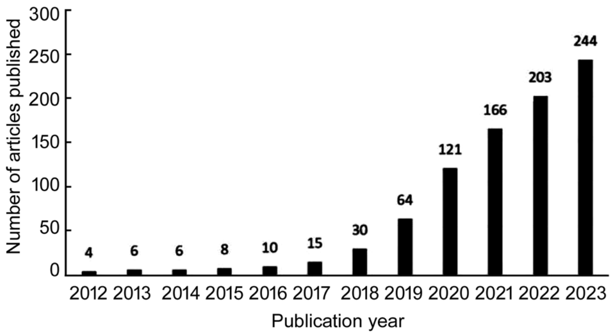

Figure 2 The annual number of publications on AI application in ophthalmic OCT between 2012 and 2023 AI: Artificial intelligence; OCT: Optical coherence tomography.

Figure 3 Collaboration of countries or regions that contributed to publications on AI application in ophthalmic OCT between 2012 and 2023 AI: Artificial intelligence; OCT: Optical coherence tomography.

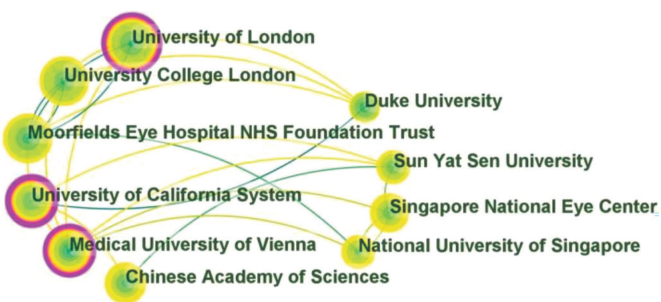

Figure 4 Cooperation of institutions that contributed to publications on AI application in ophthalmic OCT between 2012 and 2023 AI: Artificial intelligence; OCT: Optical coherence tomography.

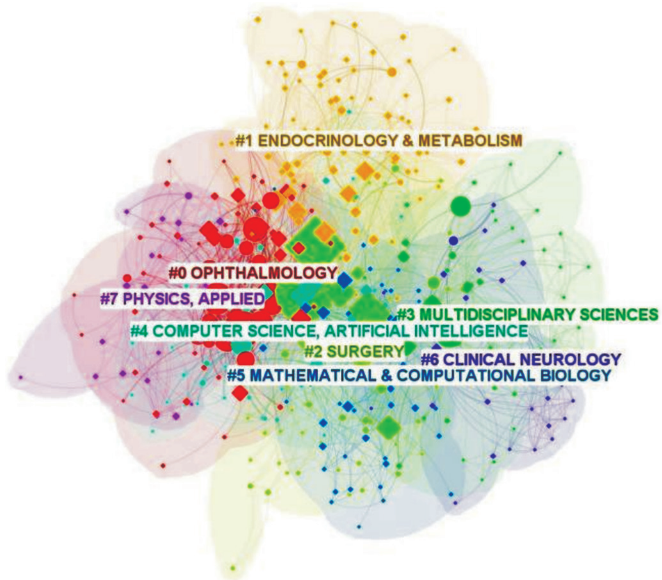

Figure 5 Category-based clusters of publications on AI application in ophthalmic OCT between 2012 and 2023 AI: Artificial intelligence; OCT: Optical coherence tomography.

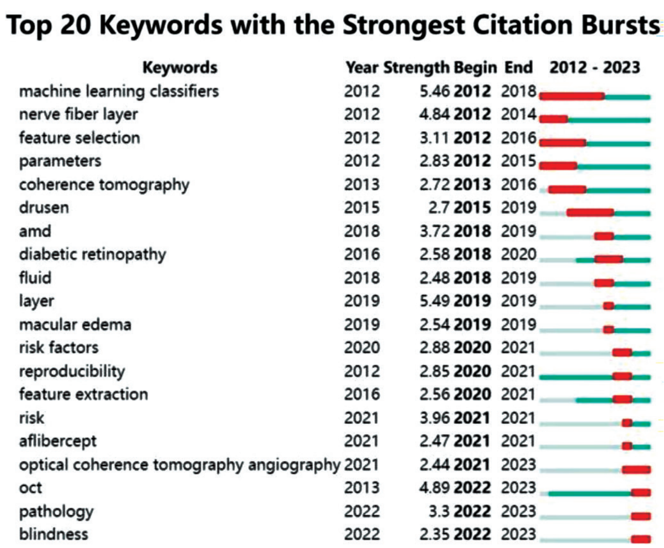

Figure 6 Keywords with the strongest citation bursts for publications on AI application in ophthalmic OCT between 2012 and 2023 AI: Artificial intelligence; OCT: Optical coherence tomography.

2020), fluid (2018-2019), layer (2019-2019), macular edema (2019-2019), risk factors (2020-2021), reproducibility (2020-2021), feature extraction (2020-2021), risk (2021-2021), aflibercept (2021-2021), optical coherence tomography angiography (2021-2023), OCT (2022-2023), pathology (2022-2023), blindness (2022-2023).

Timezone The role of keyword-based timezone map highlights the emerging research hotspots in the field. Each node in the graph represents a keyword that is the year of first appearing in the dataset analyzed. Once a keyword appears, it will be fixed in the year when it first appears, then the frequency of the keyword will be increased by 1 in the position where it first appears, and the frequency will be increased several times if it appears several times. If they appear in the same article with the previous keywords, the two nodes will be linked by lines. Figure 7 showed the top-ranked keywords in each timezone according to the frequency of occurrence.

Hot Knowledge Base Table 3[11,14-22] elaborates the top 10 citations in the articles on AI application in ophthalmic OCT.

DISCUSSION

Principal Results The results indicated a rapid increase in publications focusing on AI application in ophthalmic OCT over the past four years. This trend highlights the growing recognition of OCT as a high-precision screening technology when combined with AI.

As a rapidly evolving imaging technology in recent decade, the integration of OCT with AI represents one of the cutting-

Figure 7 Top-ranked keywords in each timezone according to the frequency of occurrence for publications on AI application in ophthalmic OCT between 2012 and 2023 AI: Artificial intelligence; OCT: Optical coherence tomography.

Table 2 Top 10 institutions with the highest publication volume in the field of AI ophthalmic OCT from 2012 to 2023

Rank	Institution	Counts	Centrality	H-index	Countries or regions
1	University of London (UoL)	58	0.12	20	England
2	University College London (UCL)	56	0.04	20	England
3	Moorfields Eye Hospital NHS Foundation Trust	49	0.05	19	England
4	University of California System	44	0.31	16	USA
5	Medical University of Vienna	44	0.10	18	Austria
6	Chinese Academy of Sciences	35	0.06	14	China
7	National University of Singapore	31	0.03	14	Singapore
8	Singapore National Eye Center	30	0.03	14	Singapore
9	Sun Yat Sen University	26	0.09	12	China
10	Duke University	24	0.02	13	USA

AI: Artificial intelligence; OCT: Optical coherence tomography.

edge research areas in medicine. Ophthalmology is the primary application field for OCT. Numerous studies have confirmed that DL algorithms exhibit high sensitivity and specificity in the screening and diagnosis of eye diseases with OCT images, making it a highly promising research domain[23].

In terms of national document output, the United States leads in both the number of articles and the influence, indicating its dominant position in this research field. Although China's publication volume is similar to that of the United States, its centrality is relatively lower. Additionally, England, and South Korea hold significant centrality and influence. The top three research institutions by publication count are all situated in England. As for the H-index of institutions, the University of California System and University of London exert considerable influence in this area. The advent of AI has led to an explosion of research in ophthalmic OCT, with increasing applications of AI in disease classification and differentiation[22], lesion identification[24], OCT layering[25], fluid segmentation[26], measurement of choroidal thickness[27], and computer-assisted diagnosis (CAD)[28] in the field of ophthalmic OCT research. Currently, the focus of AI research is primarily on advancing traditional ML and DL algorithms and the construction of diagnostic and referral systems.

Research Categories According to the category-based clusters of publications selected, it is evident that the integration of AI in ophthalmic OCT encompasses a diverse range of disciplines, including emerging technologies like computer science and AI. This integration aims to further elucidate the potential of AI in screening, diagnosing, and grading diseases using OCT images[29-31], and to revolutionize the existing diagnostic system and yield substantial clinical benefits in ophthalmic medical services. In the realm of endocrinology and metabolism, AI-assisted OCT can help non-ophthalmic doctors in diagnosing retinal diseases, such as DR[32]. Furthermore, in surgical procedures, AI-assisted OCT can enhance doctors' understanding of disease etiology and

Table 3 Top 10 cited articles on the use of AI ophthalmic OCT from January 2012 to December 2023

Rank	Title of citing documents	Times cited	Interpretation of the findings	Research limitations
1	Identifying medical diagnoses and treatable diseases by image-based deep learning[14]	1684	An AI platform based on DL framework was established to screen choroidal neovascularization in the diagnosis and referral of DME and neovascular AMD, and it was widely used in medical imaging technology.	The research involves relatively few applications.
2	Clinically applicable deep learning for diagnosis and referral in retinal disease[15]	1315	Researchers have proposed a new framework capable of providing expert-level referral recommendations for OCT scans in the diagnosis of retinal diseases.	Currently, there are relatively few types of medical imaging
3	CE-Net: context encoder network for 2D medical image segmentation[16]	1165	Researchers have proposed an end-to-end DL framework known as CE-Net, which is capable of performing segmentation on multiple images.	Limited to 2D images, 3D image processing has not been realized yet.
4	Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices[17]	657	A self-diagnostic AI system named mtmDR, which automatically detects DR and DME, is the first self-diagnostic AI system in the medical field to be authorized by the FDA.	Certain conditions must be met to obtain images of sufficient quality. The targeted diseases are relatively limited in scope.
5	F-AnoGAN: fast unsupervised anomaly detection with generative adversarial networks[18]	588	A unsupervised learning method, based on generative adversarial networks and encoder training, accurately detects and localizes anomalies in retinal imaging data without the need for annotations, making it a feasible and efficient approach for anomaly detection in clinical practice.	There are limitations in the quantitative evaluation of segmentation accuracy and the coverage of abnormal annotations, which leads to the potential unreliability of false positive estimation and quality measurement.
6	Joint optic disc and cup segmentation based on multi-label deep network and polar transformation[19]	575	A DL architecture, M-Net, for joint optic disc and cup segmentation was proposed, achieving state-of-the-art results on the ORIGA dataset and satisfactory glaucoma screening performance on both ORIGA and SCES datasets.	The rim error is larger than cup error. It is difficult to automatically outline the optic disc area horizontally, and the accuracy is lower when compared to vertical.
7	Deep learning is effective for the classification of OCT images of normal versus age-related macular degeneration[20]	370	For the first time in ophthalmic OCT classification, DL algorithms were used to train and validate images from large-scale electronic medical records extraction.	The study only included images from patients who met specific criteria. The neural network was only trained on images meeting the study criteria. Training was done on images from a single academic center, so external generalizability is unknown. Future studies should expand the number of diagnoses, use all images from a macular OCT scan, include images from different OCT manufacturers, and validate on OCT scans from other institutions.
8	Fully automated detection and quantification of macular fluid in OCT using deep learning[11]	326	The paper presents a highly robust and sensitive automated method using DL to detect, differentiate, and quantify macular fluid in OCT images across various exudative macular diseases and OCT devices.	Training on AMD, RVO, and DME cases simultaneously may reduce performance due to differences in label distributions. Need for sufficient ground truth cases.
9	Macular OCT classification using a multi-scale convolutional neural network ensemble[21]	173	A novel CAD system based on a multi-scale convolutional mixture of expert ensemble model for the diagnosis of retinal pathologies in macular OCT images was introduced, aiming to provide an efficient, fast, and reliable diagnostic classifier for macular OCT screening.	The study is limited to a single foveal slice manually selected by expert ophthalmologists. The study does not address the limitations of generalizing the results to other retinal pathologies or different datasets. The study does not discuss potential biases in the dataset or methodology. The study does not provide suggestions for further research beyond improving the proposed multi-scale convolutional mixture of expert model.
10	Early detection of diabetic retinopathy using PCA-firefly based deep learning model[22]	168	This study focuses on the use of DR data set from UCI machine learning repository, and introduces the implementation of deep neural network model and principal component analysis and firefly algorithm.	The study may not perform well on low-dimensional datasets due to the risk of overfitting. Overfitting was observed when using the original dataset, impacting testing accuracy. The model's performance may vary when applied to datasets in other domains. The study suggests further research in other domains and applications, such as healthcare prediction with magnetoencephalography data analysis.

AI: Artificial intelligence; OCT: Optical coherence tomography; AMD: Age-related macular degeneration; DR: Diabetic retinopathy; DME: Diabetic macular edema; FDA: Food and Drug Administration; DL: Deep learning; RVO: Retinal vein occlusion; CAD: Computer-aided diagnosis.

progression by providing precise labeling explanations or high-resolution images, thereby elevating surgical success rates and prognoses[33-34]. Collectively, these capabilities underscore the potential of AI-assisted OCT to foster interdisciplinary collaboration, particularly between ophthalmology, computer science, and AI, paving the way for more intelligent and precise OCT technologies in the future.

The integration of AI into OCT technology has revealed remarkable possibilities. By fostering close cooperation and deep integration with ophthalmology, we can consistently enhance the role of AI in OCT imaging analysis and diagnosis, thereby elevating the precision and efficiency of ophthalmic disease detection. Simultaneously, the utilization of AI facilitates the optimization of medical resource allocation, permitting ophthalmologists to process large amounts of imaging data more quickly and providing more accurate medical services to patients. This undertaking is pivotal in bolstering the overall quality of ophthalmic healthcare and fostering the development of an efficient and intelligent ophthalmic healthcare system.

Research Hotspots The research of AI applications in ophthalmic OCT between 2012 and 2023 can be broadly categorized into two periods combining the burst keywords and the timezone map.

The first period spanning from 2012 to 2017 focused on automated diagnosis of eye diseases using OCT imaging recognition, predominantly employing traditional ML (not DL) technology. The emergence of keywords such as "machine learning classifiers", "nerve fiber layer", "feature selection", "parameters", "coherence tomography", and "drusen" characterized this phase, showcasing a prevalent trend of harnessing traditional ML in ophthalmology.

One particularly promising utilization of traditional ML in in this field was the evaluation of OCT imaging quality and aiding in the diagnosis of glaucoma. Mounting evidence has confirmed that retinal nerve fiber layer loss precedes detectable visual field loss in early glaucomatous optic neuropathy. While OCT, a non-invasive imaging modality, offers high-resolution cross-sectional visualizations of the retina and can detect these slight changes. Nevertheless, interpreting these images can pose a significant challenge, necessitating a high degree of specialization and practical experience. It is at this junction where traditional ML plays a pivotal role. traditional ML algorithms can be trained to analyze OCT images and automatically detect features indicative of glaucoma. These algorithms can learn from extensive datasets of OCT images, annotated by experienced ophthalmologists, to discern patterns and associations that are difficult for human eyes to detect. Consequently, traditional ML can enhance the precision and efficiency of glaucoma diagnosis. For instance, Kim *et al*[35] developed traditional ML models that can be used for predicting glaucoma against unknown examination records. The models were based on retinal nerve fiber layer thickness and visual field, and had shown high accuracy, sensitivity, specificity, and area under curve (AUC) in classifying among glaucoma and healthy eyes. Another influential study developed a deep feed-forward neural network classifier which can distinguish preperimetric glaucoma visual fields from healthy visual fields accurately[36]. In addition, researchers have also verified the reliability of traditional ML in evaluating spectral domain OCT images and anterior segment OCT images, which will help ophthalmologists make more accurate and timely diagnoses of glaucoma, such as improving the early detection of glaucoma damage and automatically identifying the mechanisms of glaucoma[37-39], thus leading to better patient outcomes. These studies provide strong support for the diagnosis and treatment of glaucoma, and also provide more possibilities for the application of traditional ML in the medical field.

Combining the keywords in the timezone map of this period, such as "age-related macular degeneration", "diabetic retinopathy", and "subretinal fluid", we can conclude that AI technology is widely used in the diagnosis of ophthalmic diseases. In addition to the diagnosis and evaluation of glaucoma, it has also made some progress in the analysis of OCT imaging characteristics of AMD, DR, and other retinal diseases. AMD is a common eye disease that affects central vision, while DR is a serious complication that diabetic patients may face. In the research of Fraccaro *et al*[40], traditional ML analysis considered soft drusen and age as important variables in clinical diagnosis of AMD, providing interpretable support for clinical assisted diagnosis of AMD as a potential automated diagnostic system. Schmitz-Valckenberg *et al*[41] successfully developed and evaluated a software tool that can automatically detect focal hyper pigmentary changes in the eye of patients with intermediate AMD based on the patient's color fundus and autofluorescence photographs, and has achieved satisfactory results in terms of sensitivity and specificity. ElTanboly *et al*[42] established a CAD system that can detect and diagnose DR in patients with type 2 diabetes in OCT images, and verified its high accuracy in early DR detection. In addition, traditional ML has also been applied in evaluating the anti-VEGF therapy of retinal vein occlusion[43].

There is another keyword "multiple sclerosis" on the timezone map during this period. Multiple sclerosis (MS) patients often experience optic nerve changes, with optic neuritis being a common manifestation. This condition is characterized by subacute painful visual loss, color and contrast sensitivity loss, and an afferent pupillary defect. Other ophthalmological abnormalities in MS include impairments of the afferent pathway, efferent pathway, and upper cerebral areas[44]. These changes can significantly impact the quality of life of MS patients. By enhancing diagnostic accuracy, distinguishing between MS eyes with or without antecedent optic neuritis, and monitoring disease progression, the integration of artificial neural network (ANN) technique with OCT can help clinicians provide better care to patients with MS[45-46].

The subsequent period from 2018 to 2023 saw a shift in research focus from traditional ML to DL algorithms for automated diagnosis of eye diseases while addressing challenges in processing OCT images for diseases like glaucoma, AMD, and diabetic macular edema (DME).

Since the advent of DL technology in ophthalmology, the research landscape in this field has experienced a remarkable boom. This revolutionary technology has brought about significant advancements in ophthalmic OCT, and led to a more detailed and comprehensive understanding of ocular diseases and conditions. One significant area of research is disease classification. By training DL models on large datasets of OCT images, researchers have been able to accurately classify different ocular diseases, such as glaucoma[19], AMD[47], DR, epiretinal membranes[48], and macular edema[49]. This will significantly improve the diagnostic accuracy and efficiency, enabling ophthalmologists to make more informed treatment decisions.

According to the bursting keywords, fluid segmentation and quantification, and feature extraction are important areas where DL has made significant progress. In ocular diseases like AMD and DME, accurate segmentation and quantification of retinal fluid is crucial for assessing disease severity and monitoring treatment response. Researches have shown that the new diagnostic mode which utilizes DL to automatically quantify macular fluid to improve the accuracy of macular disease diagnosis, providing ophthalmologists with valuable quantitative data to support clinical decision-making[11,50]. Li *et al*[51] proposed a 3D fully convolutional network for segmentation in the retinal OCT images, and achieved accurate diagnostic data in patients with retinal fluid. Since OCT is the current standard for evaluating the existence and quantity of retinal fluid and managing image-guided therapy, the challenge RETOUCH was organized in 2019 to validate the performance of the retinal OCT analysis methods have been proposed[52]. The findings revealed that in the fluid detection task, the automated methods exhibited performance that was comparable to human graders. However, in the fluid segmentation task, the integration of automated methods resulted in superior segmentation outcomes compared to all individual methods. Meanwhile, feature extraction refers to extracting useful features from raw data for specific tasks. In traditional ML and AI algorithms, it is directly related to the accuracy and effectiveness of subsequent tasks such as classification and regression. Traditional OCT imaging analysis relied heavily on manual interpretation by ophthalmologists, which was not only time-consuming but also prone to interobserver variability. However, with the help of AI algorithms, OCT images can be automatically evaluated and analyzed, reducing the dependency on manual interpretation and improving the consistency and reliability of imaging analysis. Gu *et al*[16] have proposed an end-to-end DL framework known as CE-Net, which is capable of performing segmentation on multiple images. The CE-Net was tested on various 2D medical imaging segmentation tasks, and the results demonstrate that the proposed method surpasses the original U-Net and other leading methods in optic disc segmentation, vessel detection, lung segmentation, cell contour segmentation, and retinal OCT layer segmentation. In 2023, Dutta *et al*[53] developed a fusion model called to detect retinal diseases from foveal cut OCT images, and the weighted average classification accuracy, precision, recall, and F1 score of the model are found to be approximately 94%. Another automatic method for retinal eye disease detection and classification from OCT images using fusion and selection techniques has been proved state-of-the-art performance[54].

In addition, choroidal thickness measurement is another application of AI in OCT research. The choroid, a vascular layer beneath the retina, plays a crucial role in ocular health. Retinal diseases can significantly influence choroidal thickness, with various conditions leading to both increases and decreases in thickness. For instance, conditions such as central serous chorioretinopathy and polypoidal choroidal vasculopathy are associated with increased choroidal thickness[55]. On the other hand, conditions like AMD can lead to decreased choroidal thickness[56]. By using AI algorithms, ophthalmologists can accurately measure choroidal thickness, enabling them to monitor choroidal changes and assess disease progression[57-59].

Notably, a keyword optical coherence tomography angiography (OCTA) emerged in 2021. OCTA is a non-invasive imaging technology that has revolutionized the visualization of retinal and choroidal microvasculature. It is based on the detection of movement or changes that represent moving red cells in sequential OCT scans. This technology has been particularly beneficial in understanding microvascular changes in ocular diseases such as DR[60], AMD[61], glaucoma[62], and retinal vein occlusions (RVO)[63]. In 2015, OCTA technology has proved the ability to accurately detect microvascular changes, thus effectively identifying the risk of diabetic eye lesions, demonstrating the potential of rapid non-invasive diabetes screening before systemic diagnosis[64]. OCTA technology has been instrumental in the pathological examination of retinal disorders, including the detection and segmentation of choroidal neovascularization morphological features[65], vascular impairment in RVO patients[66], diagnosis of central serous chorioretinopathy[67], and quantification of foveal avascular zone[68], attributed to the technology's detection principles. Furthermore, Yang *et al*[69] have observed a notable elevation in deep retinal blood flow density among preclinical DR patients, potentially validating a novel theory on the etiology of DR. As AI technology continues to advance, OCTA will become increasingly significant in the pathological analysis of fundus diseases.

The core essence of OCTA lies in the fusion of OCT with AI. While our research primarily delves into research hotspots and trends on the application of AI in OCT, it's crucial to acknowledge that OCTA represents a distinct intersection of OCT and AI. Unlike the focus of AI applications in OCT, which primarily revolves around retinal layers or local lesions, the application of AI in OCTA predominantly focusses on the artificial intelligence analysis of retinal vasculature, including microvasculature. This distinction underscores the unique perspective and challenges posed by OCTA in leveraging AI for pathological analysis. The next focus of our team will gravitate towards the analysis of research hotspots and trends on the application of AI in OCTA. Meanwhile, computer-aided diagnosis, or CAD, is an emerging area in ophthalmology that has been greatly influenced by DL technology. CAD systems use DL algorithms such as CNN to analyze OCT images and other relevant patient data to assist ophthalmologists in making diagnostic decisions[21,70-72]. These systems can provide objective and quantitative assessments of ocular diseases, reducing diagnostic errors and improving patient outcomes. In brief, the integration of AI technology into ophthalmology has achieved remarkable advancements in OCT research, enhancing the precision and productivity of ophthalmic care, particularly in the prompt detection of blinding ocular disorders. The advancement of these technologies has ushered in fresh research horizons and revolutionized the conventional methods of diagnosis and therapy. As AI continues to evolve and mature, we anticipate achieving further substantial breakthroughs in ophthalmology in the forthcoming years.

Present Limitations and Future Opportunities By summarizing the limitations of the top 10 cited studies listed in Table 3, we found that the application of AI in ophthalmic OCT can be divided into four categories: 1) The training dataset involves relatively few types of diseases, making the established model unable to be applied to other ophthalmic diseases. 2) Some datasets are manually selected and may introduce human error. 3) The imaging results of the diagnostic system may have errors or false positives, and do not have the ability for independent diagnosis. Therefore, the assistance of clinical doctors is still needed for diagnosis. 4) The model's training scenarios differ from actual clinical work, and it cannot be assured that it will seamlessly adapt to clinical practice.

Besides the outlined limitations, a notable research hotspot on anterior segment optical coherence tomography (AS-OCT) wasn't evident in our findings. Although the integration of AI with AS-OCT has gained momentum in recent years[73-74], it has not yet emerged as a predominant research hotspot. This could be attributed to the relatively limited number of publications in this domain currently. As AS-OCT continues to expand its applications in ophthalmology, we anticipate a surge in the application of AI in AS-OCT. Thus, the utilization of AI in AS-OCT presents a significant research trend warranting increased attention.

Hence, it is imperative to prioritize enhancing both the quantity and quality of the datasets, followed by broadening its application scope. This involves enhancing the quality and resolution of OCT images to accurately identify and analyze retinal structures. To minimize human error during data selection, the implementation of a multi-party annotation system is recommended. Additionally, the integration of multimodal imaging data, including OCT, fundus fluorescein angiography (FFA), and magnetic resonance imaging (MRI), can improve the accuracy and comprehensiveness of disease diagnosis. Furthermore, the development of intelligent algorithms and models is essential to automate measurement and analysis, reducing the need for human intervention. And expediting the establishment of auxiliary diagnostic mechanisms for diagnostic systems aims to enhance the efficiency and precision of clinical diagnoses. Lastly, clinical doctors must commit to ongoing learning and avoid solely relying on diagnostic system outputs. Strengthening multinational collaboration is also imperative to promote the advancement and application of OCT technology in ophthalmology.

This study is subject to several constraints. First, it exclusively focuses on articles published between 2012 and 2023. However, this does not include ongoing research that has not been published, which may limit the scope and implication of our research results. Second, our analysis is limited to English-language articles within the WoSCC academic database. Consequently, we may have overlooked relevant studies published in other languages or databases, given the practical difficulties in amalgamating and analyzing diverse data sources. This can also introduce potential bias in the findings, as there may be an underrepresentation of research articles published in countries where English is not the primary language. Finally, despite meticulous attempts to read and analyze all 877 articles encompassed in this study, the possibility of residual researcher bias cannot be completely ruled out.

In conclusions, the training of intelligent algorithms based on imaging analysis has garnered increasing attention in recent years. The application of AI in ophthalmic OCT holds immense potential, with the United States currently leading research efforts in this area. Through continuous technological innovation and extensive research, it is expected to revolutionize eye care services, enhancing patients' quality of life and cure rates. Since the application of DL technology in the field of ophthalmology, the research in this field has shown a booming trend. In particular, the researches on OCT are getting more detailed and have covered many aspects, such as disease classification, feature extraction, OCT imaging evaluation, fluid segmentation and quantification, choroidal thickness measurement, pathological analysis of fundus diseases, clinical application of OCTA, and computer-aided diagnosis. These advancements not only improve the accuracy and efficiency of ophthalmic treatment but also pave the way for new possibilities in ophthalmic research. While initial research emphasized automatic recognition and diagnosis of eye diseases using traditional ML technology and OCT images, the current trend leans more towards intelligent algorithms, particularly DL. Concurrently, OCTA and CAD remain crucial areas of ongoing exploration.

The present research, however, is not without its constraints. Notably, the AI training model is restricted by a limited sample size, and the practical efficacy of its clinical implementation requires further validation. Successful deployment in clinical settings mandates collaboration with ophthalmologists or other relevant experts. Contemporary research is primarily focused on system development and testing, with mature diagnostic systems yet to be realized. To overcome these challenges, it is advisable to implement a multi-party annotation system, integrate multi-modal imaging data, and accelerate diagnostic system development to enhance clinical diagnosis precision and efficiency. Additionally, clinicians must prioritize ongoing professional development and avoid over-reliance on diagnostic system. Simultaneously, fostering cross-disciplinary collaboration and facilitating technological exchange are paramount. In conclusion, ophthalmic OCT technology, in conjunction with AI, holds wide potential to revolutionize eye disease diagnosis and treatment globally.

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