

# Noncommunicable Eye Diseases Trend Related to Artificial Intelligence: A Bibliometric and Visualization Analysis

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**Abstract**—In recent years, artificial intelligence (AI) has transformed numerous sectors, including healthcare, and ophthalmology is no exception. The field has seen remarkable progress in using AI to detect, diagnose, and manage noncommunicable eye diseases (NCEDs), such as cataract, keratoconus, glaucoma, diabetic retinopathy, and age-related macular degeneration. This study presents a comprehensive bibliometric analysis of 4,280 articles between 2004 and 2026, revealing significant trends in AI-based NCED research. The literature search focused on a highly reputable database: Scopus. The selection of this database ensured a thorough exploration of the field, given its broad coverage of both technical and medical literature. The search strategy employed a carefully curated set of keywords to capture relevant articles and reviews. The field has experienced robust growth, with an average annual increase of 19.41% in publications, peaking in 2023 with 516 articles. Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as the leading approach, surpassing traditional image processing techniques. Research in medical image analysis has primarily focused on age-related macular degeneration, glaucoma, and diabetic retinopathy, with an increasing emphasis on automated screening systems for early detection. Future trends may include a focus on explainable AI and attention mechanisms, integration with telemedicine, and development of more robust, generalizable models, highlighting its potential to revolutionize early diagnosis and management of eye diseases.

**Keywords**—Artificial intelligence; noncommunicable eye disease; cataract; keratoconus; glaucoma; diabetic retinopathy; age-related macular degeneration

## I. INTRODUCTION

Noncommunicable eye diseases (NCEDs) are a global health challenge, encompassing chronic vision-impacting conditions that are non-transmissible. Disorders such as cataracts, glaucoma, diabetic retinopathy, and age-related macular degeneration (AMD) are increasingly prevalent with aging populations and lifestyle changes [1]. According to 2023 WHO data, cataracts lead as the top cause of blindness or vision impairment (94 million), followed by refractive errors (88.4 million), AMD (8 million), glaucoma (7.7 million), and diabetic retinopathy (3.9 million) [2]. This study also includes keratoconus as an NCED, given its impact on the eye's anterior segment. Research on AI applications in eye disease

management, particularly in developing countries, has been widely published in academic journals and conferences. Bibliometric analysis of these trends can reveal AI's role in advancing eye care. To our knowledge, no existing literature specifically addresses NCEDs, including keratoconus, from this perspective. Fig. 1 provides NCED image samples. NCEDs pose significant challenges in ophthalmology, involving complex pathophysiology and potentially severe outcomes. Cataracts occur when the normally clear crystalline lens becomes opaque, reducing light entry into the eye [3]. Diabetic retinopathy, a result of diabetes and chronic hyperglycemia, involves microvascular changes and retinal lesions such as exudates, microaneurysms, and retinal thickening with fluid buildup, leading to visual impairment [4]. Glaucoma is marked by the progressive loss of retinal ganglion cells and their axons, which, if untreated, causes irreversible vision loss [5]. AMD is a multifactorial condition involving progressive damage to the macula, essential for central vision [6]. Keratoconus, a progressive inflammatory disorder, causes corneal thinning and irregular astigmatism, resulting in myopia, reduced visual acuity, and a cone-shaped cornea [7], [8]. Each of these disorders presents unique diagnostic and therapeutic challenges, underscoring the need for continued research and clinical advancements.

The early history of AI in medical imaging, dating back to the 1960s, initially focused on automated computer diagnosis with the ambitious goal of replacing radiologists [9]. However, this approach proved unsuccessful due to technological limitations and unrealistic expectations. In the 1980s, a shift occurred towards computer-aided diagnosis (CAD), where computers assist rather than replace radiologists, leading to widespread adoption despite initial skepticism. The debate between automated diagnosis and CAD continues, with some researchers still pursuing fully automated systems, while others focus on enhancing CAD capabilities, reflecting ongoing discussions about the future role of AI in radiology [9]. The 1980s saw the emergence of rule-based expert systems, followed by the development of CAD systems in the 1990s, particularly in mammography [10]. The early 2000s marked a significant shift with the rise of sophisticated machine learning algorithms applied to various medical imaging modalities [11]. A major paradigm shift then took place in the 2010s with the rapid

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development of deep learning, especially convolutional neural networks (CNNs). The breakthrough performance of CNNs in the 2012 ImageNet competition, demonstrated by AlexNet,

quickly influenced medical image analysis research [12]. More broadly, deep learning soon became a dominant methodological framework in medical image analysis [13].

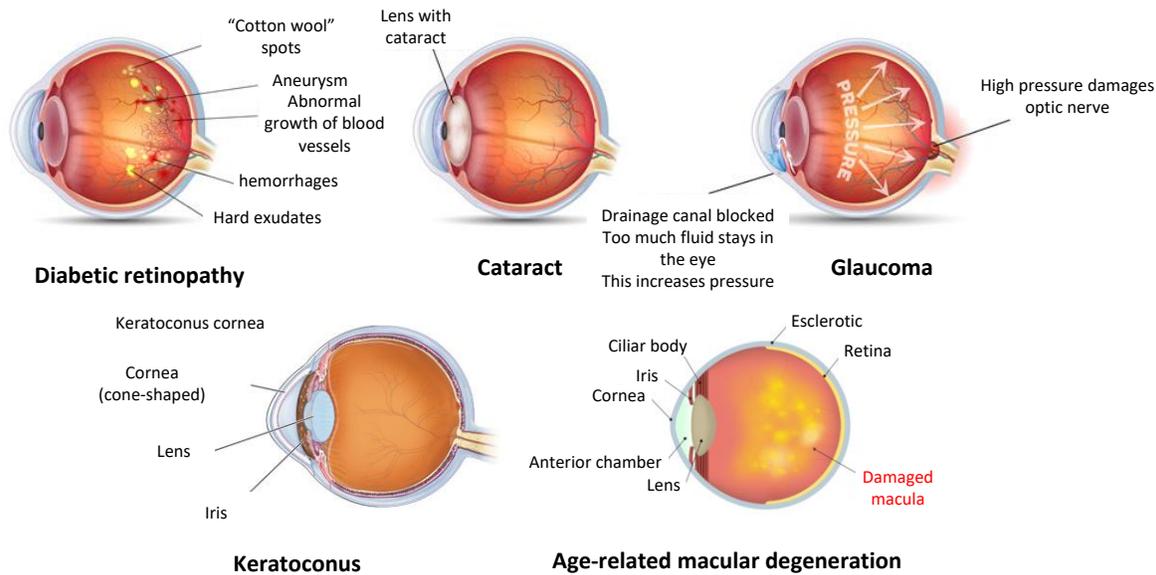


Fig. 1. Sample of NCEDs images [3]-[5].

Furthermore, a lot of research has been done on medical image analysis, including ophthalmology. The evolution of AI in ophthalmology has started with initial efforts focused on basic image processing techniques to detect retinal abnormalities. For instance, early work by Katz et al. [14] used digital image processing for diabetic retinopathy screening. Then, in the era of machine learning in the 2000s, Abramoff et al. [15] demonstrated the feasibility of automated diabetic retinopathy detection using computational image analysis approaches. The subsequent emergence of deep learning, particularly CNNs, markedly improved the accuracy of ocular disease detection. Gulshan et al. [16] reported a landmark deep-learning study for diabetic retinopathy detection that achieved performance comparable to that of human experts. Ting et al. [17] further extended this direction by developing a system capable of detecting diabetic retinopathy and related eye diseases from retinal images. More recently, increasing research attention has been directed toward robust multi-disease systems, clinically deployable models, and real-world validation of autonomous AI-based ophthalmic screening systems [17], [18]. However, important challenges remain, particularly in relation to accuracy, generalizability, and real-time clinical deployment, where multiple disease-specific factors and imaging conditions must still be considered.

Bibliometric analysis has emerged as a powerful tool for mapping the landscape of scientific research across various fields [19], including the rapidly evolving domain of AI in ophthalmology. This quantitative approach offers a bird's-eye view of research trends, helping scholars and policymakers alike to navigate the vast sea of published literature. Bibliometric analysis offers a quantitative approach to understanding the landscape of scientific research. As Aria and Cuccurullo [20] explain, "Bibliometrics is the application of quantitative analysis

and statistics to publications such as journal articles and their accompanying citation counts". This method allows researchers to evaluate the growth and maturity of a field, identify leading authors, and chart the conceptual and intellectual trends within a scientific discipline. In the rapidly evolving domain of AI in ophthalmology, such analysis can provide valuable insights into research patterns and emerging areas of focus. Thus, this study aims to draw bibliometric analysis specifically on NCEDs to conceptualize the trends of AI in medical image analysis. Our study employs a comprehensive approach to analyze the landscape of research in this field:

- To analyze the performance metrics of relevant publications. This includes an in-depth look at annual trends, publication types, research fields, and highly cited works. This analysis provides a bird's-eye view of the field's evolution and impact.
- To identify the key players in the research arena. This includes countries, institutions, and individual researchers who have made significant contributions. We also explore the intricate web of collaborations between these entities, shedding light on the global research ecosystem.
- To capture the dynamic nature of research to pinpoint emerging trends and shifts in focus over time, across various dimensions such as article sources, references, authors, institutions and countries.
- To dive into the heart of the research itself, using keyword analysis to map out the intellectual landscape. This approach helps us identify current hotspots, emerging frontiers, and potential future directions in the field.

- Finally, the discussion section presents a comprehensive analysis of the findings, encompassing an examination of pertinent contemporary issues, a projection of potential future trajectories and obstacles in the field, and a transparent elucidation of the study's inherent limitations.

The study is structured to guide you through this journey of discovery, where: Section II lays out the methodology, detailing the data sources, search strategies, and the bibliometric tools employed. Section III forms the core of this study, presenting the findings across the four key aspects mentioned above. Furthermore, discussing the analysis from each of the components and the implications for current issues in the field. Section IV presents limitations and biases. Section V details the future trends. Finally, Section VI summarizes the key findings, future directions, potential hurdles and significance for the research community.

## II. METHODOLOGY

### A. Article Selection Method

The literature search for this study was carried out on January 15, 2026, using the Scopus database. The Scopus database was searched for articles that included the keywords "Artificial Intelligence", "Detection", "Segmentation", "Mobile", and "Smartphone". Each of these terms was paired with five specific keywords related to various ocular diseases: "cataract", "keratoconus", "glaucoma", "diabetic retinopathy", and "age-related macular degeneration", the first phase of the paper selection process, as illustrated in Fig. 2. The criteria in Fig. 2 yielded 6390 publications across all five keyword pairs, with the following distribution: 507 for cataract, 110 for keratoconus, 511 for AMD, 3571 for diabetic retinopathy, and 1691 for glaucoma. Subsequently, publications were filtered based on specific exclusion criteria:

- Publications unrelated to the research objective,
- Duplicate publications,
- Publications not related to any of the five ocular diseases.

Furthermore, the flowchart in Fig. 2 outlines the processes used for the bibliometric analysis in this study. Fig. 2 shows that 4280 publications were selected for further analysis, with the following distribution: 243 for cataract, 104 for keratoconus, 440 for AMD, 2332 for diabetic retinopathy, and 1161 for glaucoma. These were included in the bibliometric study.

### B. Analytical Tool

The bibliometric analysis for this study was conducted using Biblioshiny ver. 4.3.0, a tool integrated within the open-source R package, which is developed by RStudio [20]. Biblioshiny 4.0 stands out from other bibliometric tools due to its extensive range of statistical techniques and visualizations, which facilitate both performance analysis and conceptual mapping of research topics. As an R package with a web-based graphical interface, Biblioshiny offers a user-friendly and well-organized interface. The menu is designed to include statistics and graphs across four levels of metrics—source, author, document, and clustering by coupling—as well as the knowledge structure. The analysis encompasses three distinct epistemological

frameworks: the Conceptual Structure, which delineates the domain's theoretical underpinnings; the Intellectual Structure, which elucidates the interrelationships among key ideas and paradigms; and the Social Structure, which explicates the network of scholarly collaborations and influences within the field. The program's analysis capabilities are diverse, organized into eight main categories [20]: 1) Overview, 2) Sources, 3) Authors, 4) Documents, 5) Clustering, 6) Conceptual Structures, 7) Intellectual Structure, and 8) Social Structure.

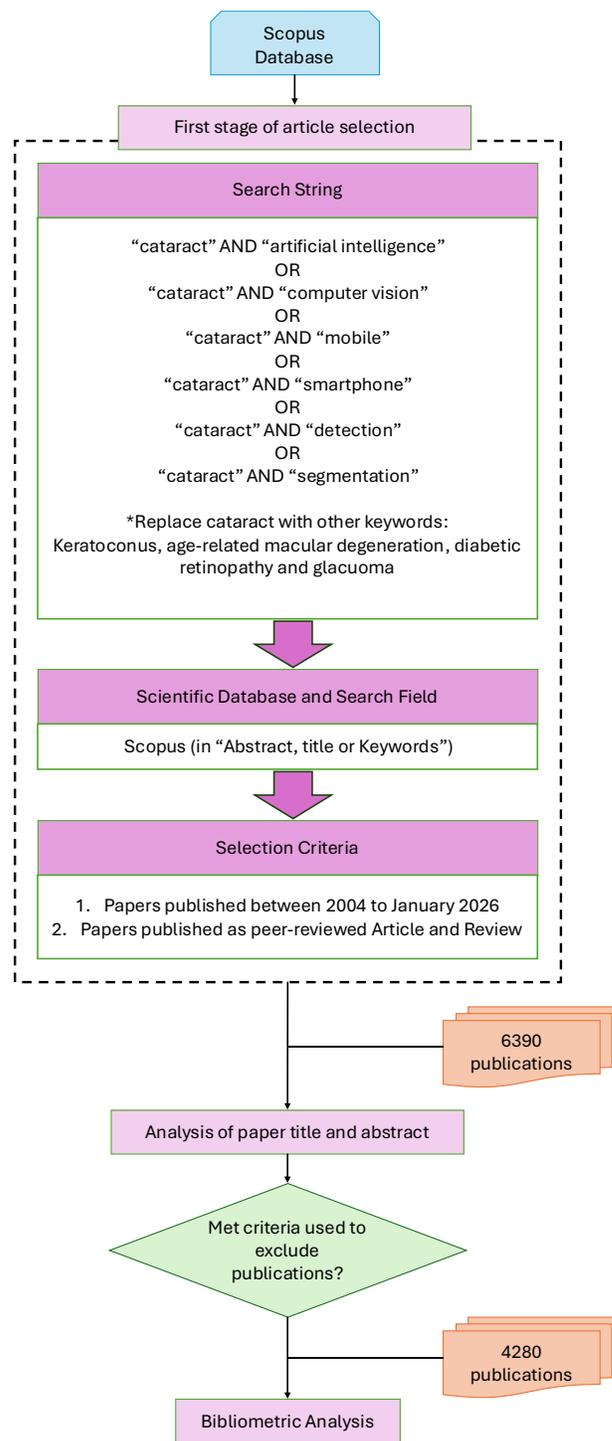


Fig. 2. Process of selecting publications for the bibliometric analysis.

The present study employs a comprehensive bibliometric analysis, encompassing both performance analysis and scientific mapping, to elucidate the evolutionary trajectory of AI-based ocular detection research. The performance analysis component evaluates the productivity and impact of diverse scientific entities, including nations, academic institutions, and individual researchers [21]. This quantitative assessment provides insights into the relative contributions and influence of various stakeholders within the field. Conversely, the scientific mapping analysis aims to delineate the underlying knowledge structure and its dynamic organization within this specific research domain [22]. The data extracted from Biblioshiny for performance analysis include annual scientific production, corresponding authors' countries, most relevant affiliations, sources' production over time, sources' local impact by citation counts, and the most globally cited documents. Furthermore, this analysis covers aspects such as the collaboration world map, co-citation network, most relevant words, word cloud, co-occurrence word network, words' frequency over time, and the three-fields plot (Sankey diagram). This approach facilitates the visualization of conceptual relationships, intellectual trends, and the evolving landscape of ideas that characterize the field.

### III. RESULTS AND DISCUSSION

Based on the retrieved data from the Scopus database and Biblioshiny tools, the bibliometric analysis can be performed and discussed meticulously to extract the trend and pattern of publication in AI for NCEDs application wise.

#### A. Overall Publication Trend

The volume of academic publications on a particular topic serves as a reliable indicator of research trends within that field, providing valuable insights into the research process of the discipline, as depicted in Fig. 3. A total of 137 duplicate documents were identified by Biblioshiny and subsequently excluded from the analysis. The data demonstrate a strong and

sustained upward trend in AI-based research on ocular disease detection from 2004 to 2025. Scholarly output remained relatively low between 2004 and 2011, with fewer than 40 publications annually, indicating limited early adoption of AI techniques in this domain. A gradual increase became evident after 2012, followed by a marked acceleration from 2018 onward. Research activity rose sharply from 167 publications in 2018 to 301 in 2019 and continued to grow steadily through 2020 (368 publications) and 2021 (411 publications). The upward momentum persisted in 2022 and 2023, reaching 476 and 516 publications, respectively. Although a slight dip was observed in 2024, with 417 publications recorded, a significant rebound occurred in 2025, where scientific production peaked at 695 publications the highest level observed across the entire study period. Overall, the findings highlight an exponential growth pattern in AI-driven ocular disease detection research, particularly over the past decade, reflecting increasing research maturity, clinical relevance, and sustained academic interest in this field.

This can be linked to the adoption of CNNs and can be traced to the 2012 ImageNet challenge, where AlexNet [12], a CNN architecture, achieved unprecedented success, significantly outperforming traditional methods. This watershed event catalyzed a proliferation of AI-related research and publications across diverse sectors. Subsequently, there has been a gradual shift away from systems that rely on handcrafted features, such as conventional image processing methods, as CNNs gained prominence not only in medical imaging but across various domains. The widespread adoption of CNNs can be attributed, in part, to the challenges associated with handcrafted feature techniques, which often require problem-specific implementations and lack generalizability. In the field of computer vision, deep convolutional networks have emerged as the preeminent methodology, supplanting traditional approaches due to their superior performance and adaptability [23].

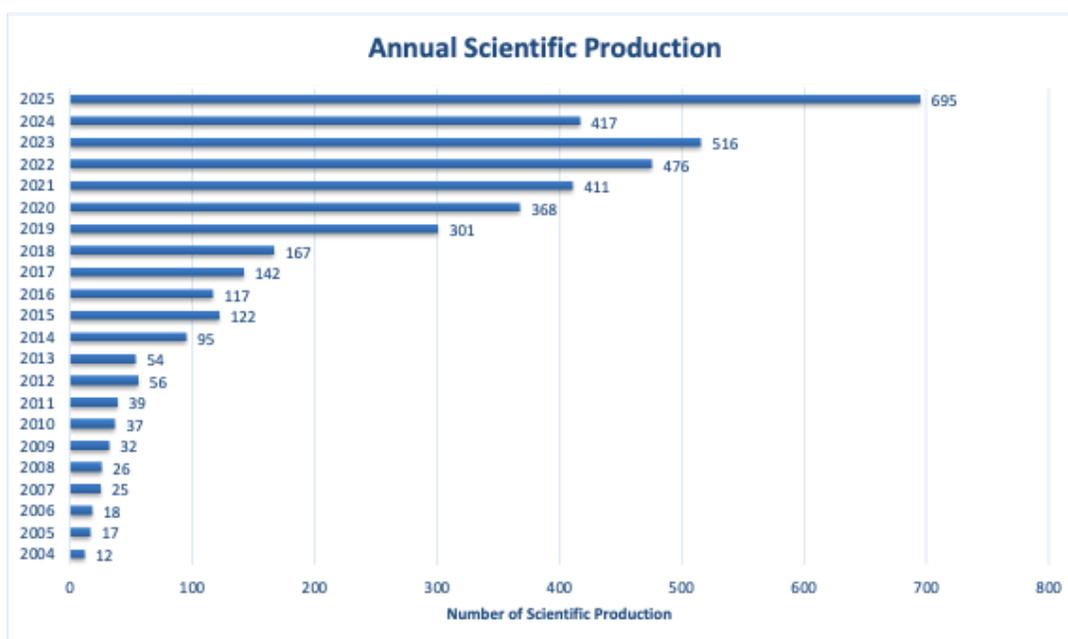


Fig. 3. Bibliometric analysis on 4,280 publications focused on ocular disease detection, categorized by their publication year from 2004 to 2026.

*B. Analysis of the Countries and Research Institutes*

Research conducted through Biblioshiny reveals that studies on AI-based ocular disease detection have been published by researchers from 76 different countries. Table I presents the top 10 most productive countries, which collectively account for 62.2% of all publications. India emerges as the most prolific contributor in terms of publication volume (26.5%), followed by China (15.7%) and the United States (7.1%). In contrast, China leads in citation impact (17.5%), slightly ahead of India (15.5%), while the USA demonstrates a strong citation-to-publication ratio (10.5% citations). Other countries, including Singapore and the Netherlands, show comparatively smaller publication shares but notable citation influence, highlighting the quality and impact of their contributions. Overall, the findings confirm the dominant roles of India and China in research output, alongside the strong scholarly influence of the USA and selected European and Asian countries.

TABLE I. TEN MOST CONTRIBUTING COUNTRIES IN AI-BASED OCULAR DISEASE DETECTION

Country	Articles %	Citations %
CHINA	15.7	17.5
INDIA	26.5	15.5
USA	7.1	10.5
SINGAPORE	1.4	6.3
NETHERLANDS	0.5	5.7
SPAIN	2.2	4.8
UNITED KINGDOM	2.1	4.3
PAKISTAN	1.9	2.7
FRANCE	0.9	2.5
CANADA	1.1	2.2

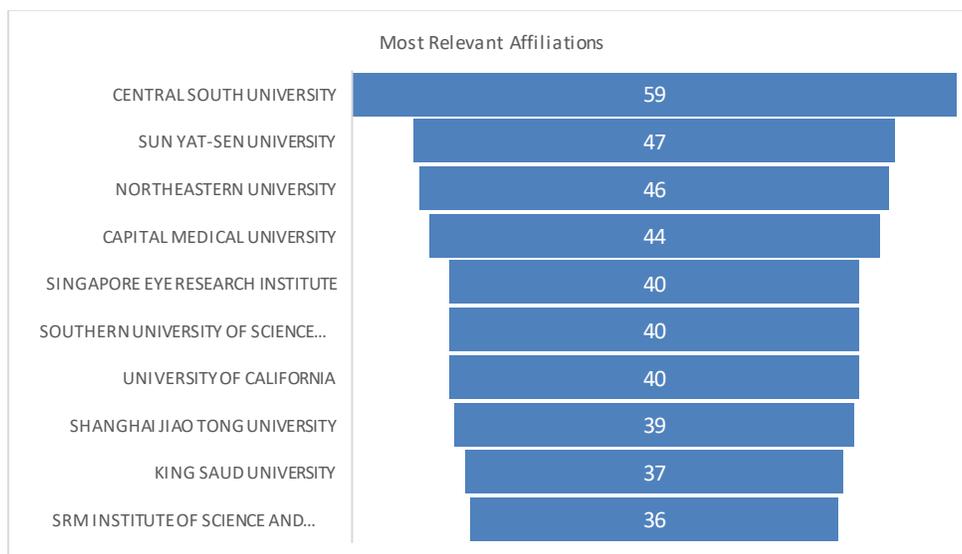


Fig. 4. Top 10 most relevant affiliations based on research output.

Fig. 4 presents the top 10 most relevant institutions based on research output. Central South University leads with 59 publications, followed by Sun Yat-sen University (47) and Northeastern University (46). Capital Medical University ranks fourth (44 publications), while Singapore Eye Research Institute, Southern University of Science and Technology, and the University of California each contribute 40 publications. Shanghai Jiao Tong University (39), King Saud University (37), and SRM Institute of Science and Technology (36) complete the top ten. Notably, five of the top ten institutions are based in China, reinforcing the country’s strong institutional presence in this domain. The inclusion of leading institutions from the USA, Singapore, Saudi Arabia, and India further reflects the global and collaborative nature of AI-driven research in ocular disease detection.

*C. Analysis of Co-Citation and Co-Authorship*

A network map illustrating co-authorship among 95 countries, highlighting eight countries—China, India, the USA,

Pakistan, Singapore, the United Kingdom, Saudi Arabia, and Malaysia—that have collaborated on at least 10 publications each, is shown in Fig. 5. India and China emerge as prominent nodes, signifying their central roles in AI-based ocular disease detection research. Notably, there are robust research partnerships between India and the USA, as well as between China and the USA. Additionally, the European nations demonstrate strong intra-continental collaboration, indicating a high level of cooperation both within Europe and with other regions. Within Asia, a concentrated collaborative effort is evident, particularly between India and China. Interestingly, despite the complex political and economic relationship between China and the USA, there is substantial research collaboration between these two nations in this field. This pattern of international cooperation suggests that scientific collaboration in AI and ophthalmology transcends geopolitical tensions, fostering a global approach to advancing medical imaging technology.

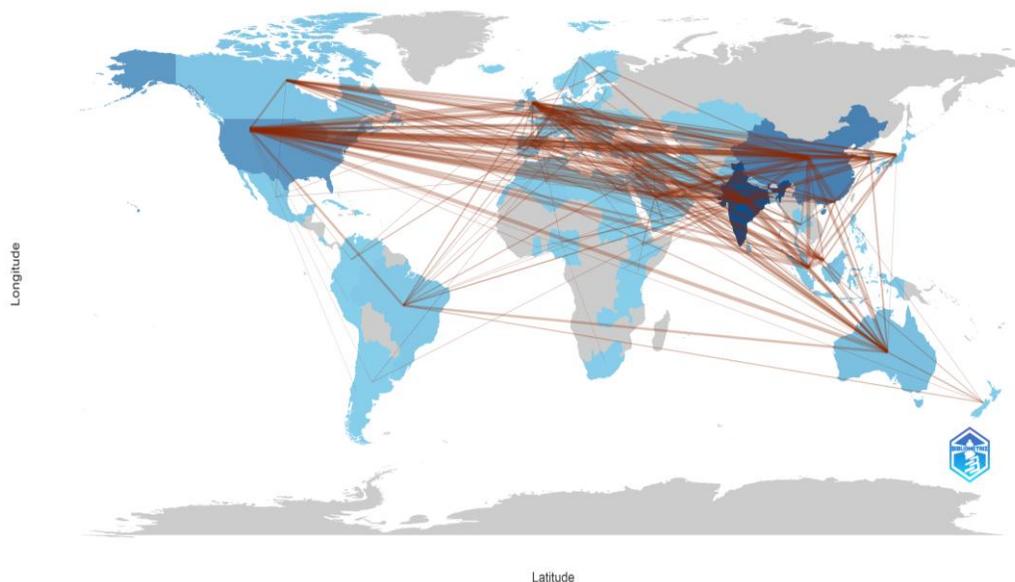


Fig. 5. The map visually represents global research partnerships, with each country's node colored according to its contribution level. Darker blue nodes represent countries with a higher number of publications, underscoring their significance in the research domain. The red lines connecting the nodes indicate collaborative research activities between countries, with the thickness and density of these lines reflecting the strength and frequency of these collaborations.

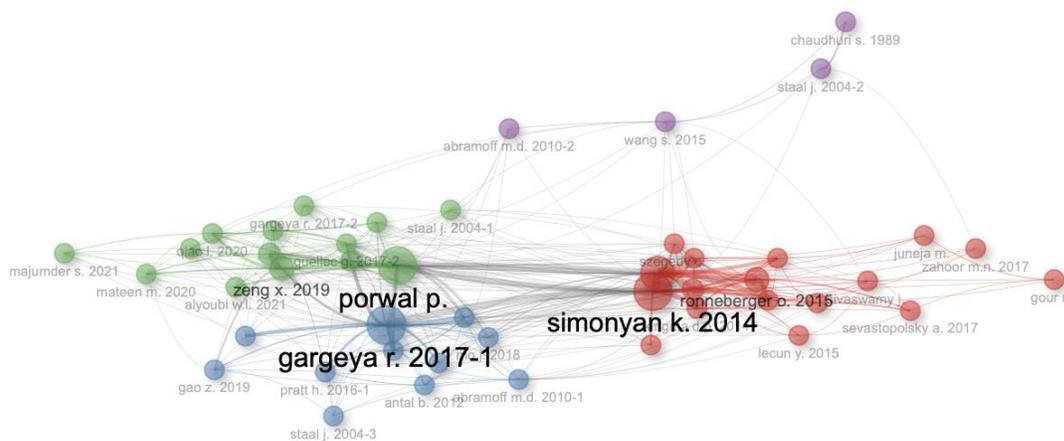


Fig. 6. Visualization diagram of a co-citation analysis on a network, limiting the minimum degree of co-citation to two and defining a threshold of 29 network nodes. Each node in this network is identified with the initial author and the year of publication of the relevant paper, while the edges represent co-citation links between publications. The node size corresponds to the number of local citations obtained by the papers, while the edge thickness represents the intensity of the co-citation links. The node color indicates the cluster to which the paper belongs.

The global map highlights India, China, and the USA as central hubs in the research network, with Asia and the USA leading in the frequency of collaborations. However, the map also shows thinner connections in regions like Africa and South America, suggesting lower involvement in this research area and potential opportunities for increased collaboration.

Fig. 6 illustrates the co-citation network, revealing the intellectual structure of AI-based research on ocular disease detection. The network demonstrates a multi-component configuration, consisting of a dominant interconnected core and a smaller isolated cluster, reflecting both established theoretical foundations and emerging research directions. The most central community (red cluster) represents the methodological backbone of the field, anchored by seminal deep learning works such as Simonyan and Zisserman [24], He et al. [25], and

Ronneberger et al. [26]. These foundational studies introduced influential convolutional neural network architectures, including VGGNet and U-Net, and established deep learning principles that underpin contemporary medical image analysis.

Closely connected to this methodological core is the blue cluster, which focuses on applied deep learning in ocular disease detection, particularly diabetic retinopathy. Highly co-cited works within this cluster include Gargeya et al. [27] and Porwal et al. [28], reflecting significant contributions to automated retinal image classification and benchmark dataset development. The purple cluster highlights earlier clinical and computational foundations, notably Abramoff et al. [29], representing traditional automated retinal analysis approaches prior to the widespread adoption of deep learning. The green cluster captures more recent refinements and methodological

advancements, indicating continued innovation in model optimization and application. Additionally, a smaller and relatively isolated orange cluster centers on Gulshan et al. [16], a landmark study on the development and clinical validation of a deep learning algorithm for diabetic retinopathy detection, suggesting a specialized research stream focused on real-world clinical implementation.

D. Analysis of Highly Cited Source

The 4280 documents analyzed were published across 571 different sources, with an average of 6 publications per journal. Among these sources, the Translational Vision Science and Technology journal (30.1%) led the way with 217 papers, followed by Multimedia Tools and Applications (22.4%) with

162 papers, IEEE Access (18.6%) with 134 articles, and Biomedical Signal Processing and Control (16.1%) with 116 articles. Fig. 7 illustrates the publication trends over time in the top five journals in AI-based ocular disease detection research. This trend shows a steady increase in publications across all sources, beginning around 2014. The pace of growth accelerates after 2018, with each source showing a significant rise in cumulative occurrences. By 2025, the data indicate substantial growth across all sources, with Translational Vision Science and Technology demonstrating the highest cumulative occurrences, followed by Multimedia Tools and Applications and IEEE Access. Other journals, such as Computers in Biology and Medicine and Biomedical Signal Processing and Control, also show consistent growth over time.

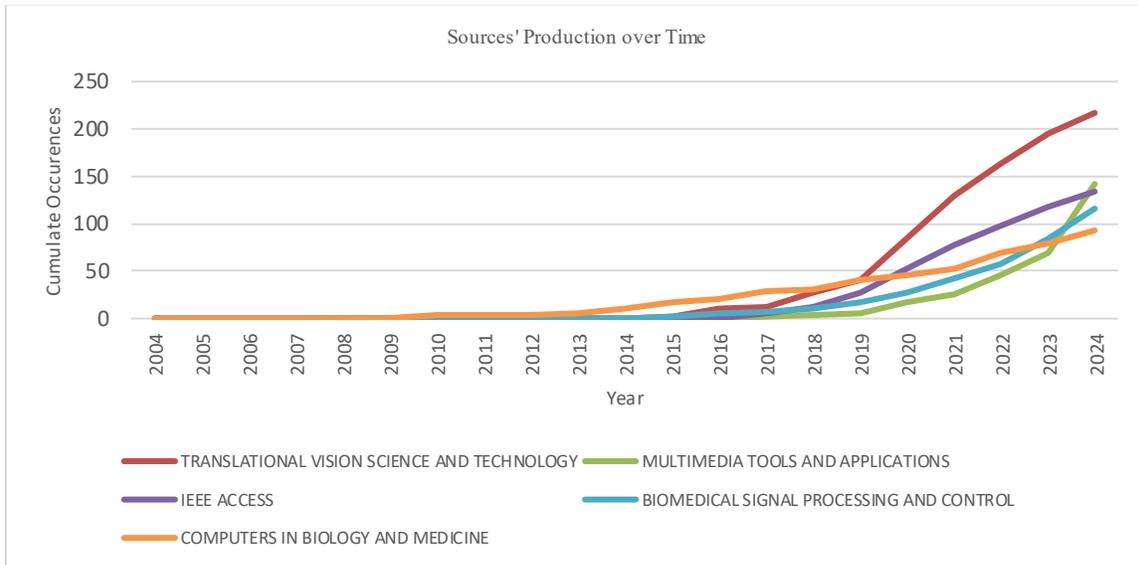


Fig. 7. Publication trends over time in the top five journals within the field of AI-based ocular disease detection research.

E. Keyword Analysis

1) Analysis of most relevant keywords: The authors' keyword terms reflect the article's limitations and its impact on the scientific community. Keyword analysis involves collecting keywords from relevant works within a specific area of study. This tool identifies keywords, analyzes patterns, and highlights research trends. Table II presents the top 15 keywords. To ensure consistency, we merged semantically equivalent or similar terms, such as "DR" and "diabetic retinopathy", as well as "CNN" and "convolutional neural network". From the table, it is evident that diabetic retinopathy, glaucoma, and AMD are the most commonly researched topics in AI-based NCEDs detection. Additionally, techniques like deep learning, image segmentation, and machine learning are frequently utilized in this field. A word cloud visualization was used in this study to represent the most popular author keywords, as shown in Fig. 8. These keywords represent key areas of AI-based ocular disease detection research. The figure suggests that deep learning and machine learning are among the most recommended methodologies and are predominantly used by researchers in AI-based NCEDs detection. In the next section, we will examine the correlation of these words over the past 21 years.

TABLE II. TOP 15 KEYWORDS

Words	Occurrences
diabetic retinopathy	1256
deep learning	809
glaucoma	527
machine learning	262
segmentation	245
fundus image	220
fundus images	217
classification	197
artificial intelligence	187
optical coherence tomography	177
convolutional neural network	165
optic disc	155
transfer learning	148
image processing	145



Fig. 8. The word cloud represents the author's keywords.

2) *Analysis of co-occurrence keywords:* Co-occurrence analysis examines the relationships among author keywords that frequently appear together, thereby revealing research hotspots and thematic structures within a field. In bibliometric studies, author keywords are commonly used to identify dominant research themes and emerging trends. As shown in Fig. 9, the co-occurrence network identifies three major clusters, each representing a distinct yet interconnected research focus in AI-based ocular disease detection.

The largest cluster (red) is centered on the keywords “diabetic retinopathy” and “deep learning”, indicating that diabetic retinopathy remains the most intensively studied ocular disease within this domain. This cluster is strongly associated with methodological terms such as “convolutional neural networks,” “image classification,” “transfer learning,” “medical image analysis,” and “fundus images”, highlighting the widespread adoption of deep learning architectures for retinal image analysis. The prominence and central positioning of “deep learning” within this cluster underscore its dominant role as the core analytical approach for AI-driven detection of NCEDs.

The second cluster (blue) focuses primarily on “glaucoma” and is closely linked to keywords such as “segmentation”, “classification”, “retinal images”, “optic disc”, “optic cup”, and

“blood vessel segmentation”. This indicates a strong emphasis on structural analysis of retinal components, particularly optic disc and cup segmentation, which are critical for glaucoma screening and diagnosis. Traditional machine learning techniques, including “support vector machine” and “feature extraction”, also appear within this cluster, suggesting a coexistence of classical and deep learning-based approaches in glaucoma research.

The third cluster (green) represents other ocular diseases and imaging modalities, including “cataract”, “age-related macular degeneration”, “retina”, “fundus”, and “optical coherence tomography (OCT)”. This cluster reflects broader ophthalmic applications of AI beyond diabetic retinopathy and glaucoma, with a particular focus on multimodal retinal imaging and screening. The presence of OCT-related keywords indicates the growing integration of advanced imaging technologies with AI-based analysis.

Overall, Fig. 9 clearly demonstrates that deep learning acts as a central bridging keyword, connecting all three clusters and facilitating methodological integration across different ocular diseases. The dense interconnections between clusters suggest that contemporary research increasingly applies shared AI methodologies, particularly deep learning to multiple ophthalmic conditions rather than addressing diseases in isolation.

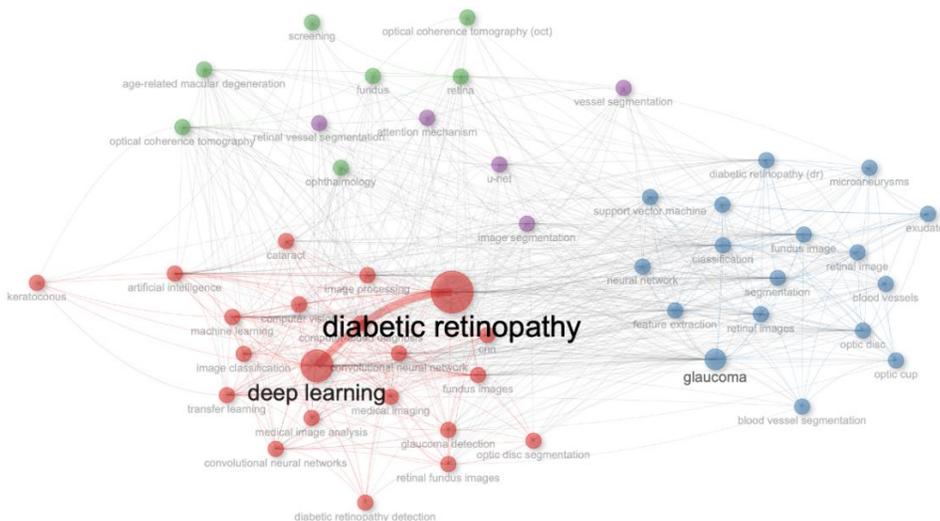


Fig. 9. The co-occurrence network of applied AI in NCEDs.

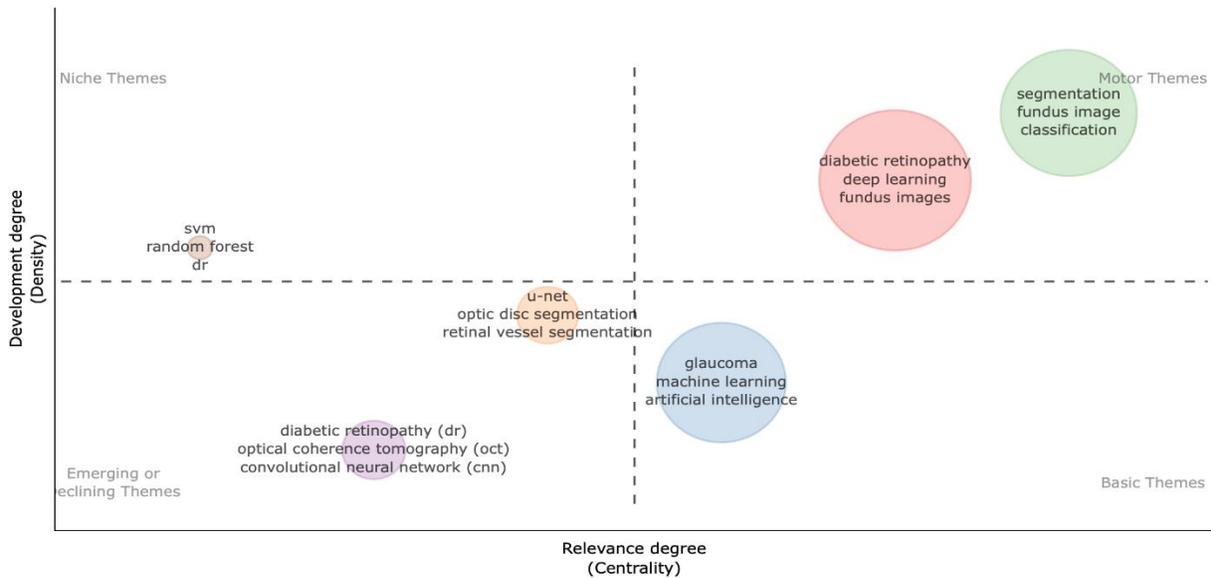


Fig. 10. Thematic diagram of niche themes, motor themes, basic themes and emerging or declining themes for NCEDs AI-based.

The keywords reveal a strong focus on diabetic retinopathy and deep learning, along with other crucial areas such as glaucoma, optical coherence tomography, and machine learning. This underscores the global emphasis on leveraging AI and advanced computational techniques for the detection and diagnosis of NCEDs. The dense network of connections between countries, sources, and keywords illustrates the highly collaborative and interdisciplinary nature of this research field. The visualization effectively captures the global research ecosystem in this domain, highlighting the key players, publication venues, and the most pressing research topics driving innovation in AI-assisted ophthalmology. This suggests a concerted effort to bridge the gap between theoretical advancements and practical clinical applications.

#### IV. LIMITATIONS AND BIASES

The study on NCEDs and AI highlights several potential limitations and biases that need to be addressed:

- **Need for Large, Diverse Datasets:** One of the primary limitations is the requirement for large and diverse datasets to train robust AI models. Without these, the models may not generalize well across different populations or imaging equipment, leading to biased outcomes in real-world applications.
- **Generalization Challenges:** Generalizing AI models across diverse demographics and imaging technologies is a significant challenge. This can result in disparities in the effectiveness of AI applications in different settings, which may not be adequately represented in the training data.
- **Clinical Validation:** There is an ongoing need to validate AI systems in real-world settings. Many AI models may perform well in controlled environments but fail to deliver the same results in clinical practice, undermining their reliability and acceptance.

- **Publication Bias:** The study's bibliometric analysis may also be subject to publication bias, where positive results are more likely to be published than negative or inconclusive findings. This can skew perceptions of AI's effectiveness in detecting and managing NCEDs.

#### V. FUTURE TRENDS OF NCEDS AI-BASED USING THEMATIC ANALYSIS

Based on the thematic analysis, the research landscape of AI-based NCEDs exhibits a clear structural evolution, demonstrating the progressive integration and maturation of artificial intelligence within ophthalmology. Fig. 10 presents a thematic map derived from 20 years of publications, illustrating the distribution of research themes by relevance (centrality) and level of development (density). The diagram reflects a balanced combination of well-established motor themes, foundational basic themes, emerging areas, and specialized niche topics, highlighting both the maturity of core research directions and ongoing innovation in the field.

The motor themes, positioned in the upper-right quadrant, represent highly developed and highly central research areas that drive the field forward. Prominent among these are diabetic retinopathy, deep learning, fundus images, segmentation, and classification. These themes form the backbone of AI-based ophthalmic research, underscoring diabetic retinopathy as a major focus due to its high global disease burden and suitability for image-based screening. Numerous studies have demonstrated the effectiveness of deep learning approaches for diabetic retinopathy detection and classification [30]–[33]. At the same time, machine learning approaches remain relevant for automated diabetic retinopathy analysis [34]–[38]. Hybrid strategies that combine machine learning and deep learning have also been explored to improve classification performance [34], [39]. Collectively, these findings reinforce diabetic retinopathy as a dominant motor theme in AI-based ophthalmic research.

Complementing these core themes, glaucoma, machine learning, and artificial intelligence appear within the basic themes quadrant (lower-right), indicating high relevance but comparatively lower internal development density. This positioning suggests that glaucoma-related AI research serves as a foundational pillar that continues to support and stimulate further methodological advancements. The reliance on machine learning and AI for glaucoma diagnosis highlights their fundamental role across ophthalmic applications, even as research increasingly shifts toward more advanced deep learning frameworks. In addition, multimodal glaucoma screening approaches that combine OCT and fundus imaging further demonstrate the expanding role of AI in structural ocular assessment [40].

The thematic map also identifies niche themes in the upper-left quadrant, including optic disc segmentation, retinal vessel segmentation, and U-Net. Although these topics demonstrate high developmental maturity, their lower centrality indicates a more specialized focus. Structural retinal analysis has long been supported by earlier vessel and optic-disc segmentation studies [41], [42], while more recent optic disc and cup segmentation work has further advanced this line of research [43]. Recent studies employing advanced deep learning architectures, such as two-stage U-Net models, have achieved high performance in optic disc and cup segmentation [44]. Additionally, generative adversarial networks (GANs) have been successfully applied to retinal vessel and optic disc segmentation, further enhancing segmentation robustness and accuracy [45]. These niche themes reflect concentrated innovation within specific diagnostic subtasks.

In contrast, the emerging or potentially declining themes, located in the lower-left quadrant, include keratoconus, OCT, CNNs, and early-stage diabetic retinopathy detection. Their lower density and centrality suggest either nascent research trajectories or areas that are transitioning toward consolidation. Earlier work on keratoconus detection employed fused handcrafted image features and conventional machine learning strategies [46], whereas more recent studies have adopted transfer learning and mobile-based deep learning approaches for keratoconus classification [47], indicating continued growth potential. OCT-related analysis also remains important, particularly in multimodal screening and structural assessment applications, including glaucoma-related imaging studies that combine OCT with fundus photographs [40]. In addition, CNN-based diabetic retinopathy detection studies continue to contribute to the broader development of retinal image classification pipelines [48].

Overall, the updated thematic map illustrates a dynamic and evolving research ecosystem in AI-based ophthalmic diagnostics. While motor themes such as diabetic retinopathy and deep learning continue to dominate, the emergence of advanced attention-based models and related deep learning architectures signals a shift toward increasingly sophisticated image interpretation strategies [49]–[53]. These developments suggest a trajectory toward more accurate, efficient, and scalable diagnostic systems. Future research should prioritize methodological refinement, cross-disease generalization, and standardization of AI-driven diagnostic tools to support broader clinical adoption and translational impact.

## VI. CONCLUSION

Research on artificial intelligence for NCED detection has grown substantially from 2004 to 2025, reflecting the increasing adoption of AI in ophthalmic diagnostics. Thematic analysis confirms that diabetic retinopathy, deep learning, fundus image analysis, segmentation, and classification are the dominant motor themes driving the field. Deep learning approaches, particularly convolutional neural networks, have become the prevailing methodology, consistently outperforming traditional image processing techniques in detecting major ocular diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. While glaucoma and general AI methodologies remain foundational to the field, more specialized tasks such as optic disc and retinal vessel segmentation represent mature niche areas. Emerging themes, including keratoconus and OCT-based analysis, indicate continued diversification of AI applications in ophthalmology. Despite strong global contributions led by China, India, and the United States, challenges related to data diversity, model generalizability, and clinical validation persist. Future research is expected to focus on multi-disease detection frameworks, explainable AI, and integration with telemedicine platforms. Overall, the continued evolution of AI-driven ophthalmic diagnostics holds significant potential to enhance early detection and reduce the global burden of preventable vision loss.

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