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SYSTEMATIC REVIEW

Detection of diabetic retinopathy using artificial intelligence: an exploratory systematic review

Detección de retinopatía diabética utilizando inteligencia artificial: una revisión sistemática exploratoria

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ABSTRACT

Diabetic retinopathy is a disease that can lead to vision loss and blindness in people with diabetes, so its early detection is important to prevent ocular complications. The aim of this study was to analyze the usefulness of artificial intelligence in the detection of diabetic retinopathy. For this purpose, an exploratory systematic review was performed, collecting 77 empirical articles from the Scopus, IEEE, ACM, SciELO and NIH databases. The results indicate that the most commonly used factors for the detection of diabetic retinopathy include changes in retinal vascularization, macular edema and microaneurysms. Among the most commonly applied algorithms for early detection are ResNet 101, CNN and IDx-DR. In addition, some artificial intelligence models are reported to have an accuracy ranging from 90 % to 95 %, although models with accuracies below 80 % have also been identified. It is concluded that artificial intelligence, and in particular deep learning, has been shown to be effective in the early detection of diabetic retinopathy, facilitating timely treatment and improving clinical outcomes. However, ethical and legal concerns arise, such as privacy and security of patient data, liability in case of diagnostic errors, algorithmic bias, informed consent, and transparency in the use of artificial intelligence.

Keywords: Deep Learning; CNN; Resnet 101; Blindness; Macular Edema.

RESUMEN

La retinopatía diabética es una enfermedad que puede llevar a la pérdida de visión y ceguera en personas con diabetes, por lo que su detección temprana es importante para prevenir complicaciones oculares. El objetivo de este estudio fue analizar la utilidad de la inteligencia artificial en la detección de la retinopatía diabética. Para ello, se realizó una revisión sistemática exploratoria, recopilando 77 artículos empíricos de las bases de datos Scopus, IEEE, ACM, SciELO y NIH. Los resultados indican que los factores más utilizados para la detección de retinopatía diabética incluyen cambios en la vascularización de la retina, edema macular y microaneurismas. Entre los algoritmos más aplicados para la detección temprana se encuentran ResNet 101, CNN e IDx-DR. Además, se reporta que algunos modelos de inteligencia artificial presentan una precisión que varía entre el 90 % y el 95 %, aunque también se han identificado modelos con precisiones inferiores al 80 %. Se concluye que la inteligencia artificial, y en particular el aprendizaje profundo, ha demostrado ser efectiva en la detección temprana de retinopatía diabética, facilitando un tratamiento oportuno y mejorando los resultados clínicos. Sin embargo, surgen preocupaciones éticas y legales, tales como la privacidad y seguridad de los datos del paciente, la responsabilidad en caso de errores de diagnóstico, el sesgo algorítmico, el consentimiento informado y la transparencia en el uso de la inteligencia artificial.

Palabras clave: Aprendizaje Profundo; CNN; Resnet 101; Ceguera; Edema Macular.

INTRODUCTION

According to [1], Diabetic Retinopathy (DR) is an eye condition that causes vision loss and blindness in people with diabetes, as it affects the blood vessels of the retina. Therefore, detecting DR in its early stages is vital because timely treatment can prevent ocular complications, highlighting the importance of early detection in patients with diabetes.

One of the main issues is the need for accurate diagnosis of DR to mitigate its impact and reduce reliance on human resources. Artificial Intelligence (AI) offers advances in this field, improving pattern recognition and accurate diagnoses.[2] However, the accessibility and costs of AI in low- and middle-income countries remain uncertain, as do the necessary regulatory approvals.[1] In addition, the lack of specialized resources for early diagnosis highlights the need for accurate solutions and real-time monitoring that AI can provide.[3]

Implementing AI for this purpose faces limitations, including the need for extensive resources, workflow issues, and technology integration and privacy issues.[4] Mobile devices present image quality issues compared with nonportable retinal cameras, and AI algorithms must be adapted to national DR detection initiatives.[5] Improving data interpretation and overcoming the lack of training data is critical, especially in rural areas and developing countries.[6,7] Assessing biases in AI algorithms is essential to ensure representativeness and applicability.[8] In addition, technological evolution requires constant updates in DR detection programs.[9] The lack of standards and demographic variability in AI studies highlight the need for comparative evaluations and legal and ethical considerations.[10] Although AI has the potential to improve the diagnosis and treatment of DR significantly, it faces barriers in terms of accessibility, costs, data quality, and assessment of biases and standards.[4,11,12]

Systematic review studies on DR screening have demonstrated how AI has revolutionized the diagnosis of this and other retinal diseases[2] and highlighted that the ability of AI to recognize patterns and compare them to standards has driven early detection and timely treatment, promoting efficiency and reducing disease burden. Furthermore, the research in [1] shows that AI in DR detection exhibits high sensitivities and specificities; however, more research on regulatory approvals and improvements in health outcomes is required before large-scale implementation.

In this framework, deep learning, an AI technique, enables early and accurate detection of DR, facilitating personalized treatments and real-time monitoring, thus improving patients' quality of life.[3] Despite its efficacy,[4] noted that AI implementation is limited to integration into healthcare systems and ethical and economic issues.[5] also mentions that, although AI shows high sensitivity, its clinical implementation is limited due to legal and technical obstacles.

Advances in AI, specifically with deep learning algorithms and the Inception-v3 model, demonstrated high efficacy in diagnosing ocular diseases, comparable to human experts with less training data[6,7] emphasize that AI is fundamental for early detection and classification of DR, addressing future areas of research in ophthalmology. However, there are concerns about bias and lack of representativeness in studies, as well as the need for economic studies to support its implementation.[8] Therefore, although AI has improved the early and effective detection of DR, further research is required to overcome current barriers and ensure its efficacy and safety in clinical practice.[10]

The present study aimed to analyze the detection of DR by AI, identifying the factors and variables considered by the models, the most commonly used algorithms, and the accuracy of these algorithms. The aim is to examine the technical limitations in detection and the ethical and legal challenges associated with its implementation.

METHOD

The present study was based on an exploratory systematic review, whose main objective is to analyze and synthesize DR detection using AI. This type of review allows us to obtain a complete and rigorous understanding of the current state of knowledge by identifying, evaluating, and critically synthesizing the results of previous studies. Systematic review is essential to identify gaps in knowledge and establish a solid foundation for future research and informed decisions.

Research questions

In order to answer the proposed objective, the following research questions were formulated:

Q1: What are the factors or variables considered by the models in DR detection?

Q2: What are the most effective algorithms for early detection of DR using AI?

Q3: What is the accuracy of AI models in DR detection?

Q4: What technical or implementation limitations do AI systems face in DR detection?

Q5: What ethical and legal challenges are posed by the use of AI algorithms in the diagnosis and treatment of DR?

Search strategy

The key term "diabetic retinopathy," translated into Spanish as "retinopatía diabética," was used. In addition, AND and OR connectors were used to introduce related terms such as "artificial intelligence." The Scopus, ACM, SciELO, and NIH databases were selected because of their broad international and regional coverage, as well as the ease of applying advanced search filters and ensuring the academic quality of the contributions.

A selection process was implemented in five phases: i) First classification consisted of applying the search strings using the advanced tools of each database, mainly using the title fields; ii) Second classification, filters were applied, taking into consideration the manually applicable inclusion and exclusion criteria such as the coverage of the years, language and type of document. iii) Third classification: Metadata was imported and organized in Excel, where duplicates were purified using the Scopus database as a reference. iv) Fourth classification: Filter articles focused on AI for DR detection by reading the title and abstract. v) Fifth classification, a final selection of downloadable articles relevant to the study was made.

Table 1 shows the number of articles obtained in each classification:

Table 1. Number of items obtained by classification

Database	Ranking				
	1st	2nd	3rd	4th	5th
Scopus	195	102	99	96	74
IEEE	11	11	9	9	0
ACM	24	20	20	-	-
SciELO	2	2	2	2	2
NIH	2	2	2	2	1
Total	234	137	129	109	77

Inclusion and exclusion criteria

The definition of inclusion and exclusion criteria helps to guarantee the objectivity and reproducibility of the review, ensuring that the studies are relevant and meet quality standards.[13] Therefore, the following inclusion criteria were defined: published between 2019 and 2024; Spanish and English language; original articles in IEEE, SCOPUS, ACM, and SciELO; focused on the application of AI, specifically Deep Learning, for DR detection. Regarding exclusion criteria, the following were established: review articles or other types of secondary sources; duplicate publications; articles without access to the full text or not downloadable.

Data extraction

After the final selection of the 77 articles, we proceeded to the extraction of relevant data, including the identification of factors and variables considered by the models, the evaluation of the most effective algorithms, the accuracy of these models, and the technical, ethical, and legal limitations facing the implementation of artificial intelligence in the detection of diabetic retinopathy. This methodology ensures a thorough and rigorous review, providing a solid basis for evaluating the efficacy and challenges of AI in the diagnosis and treatment of DR.

RESULTS AND DISCUSSION

After selecting relevant articles and conducting a thorough review of each article, we proceeded to answer the research questions posed.

Q1: What are the factors or variables considered by the models in the detection of DR?

This question refers to the different elements that AI models analyze to detect DR. It is crucial to understand which factors and variables, such as clinical characteristics, imaging attributes, and demographic parameters, are used, as these determine the accuracy and effectiveness of the diagnosis. Knowing these aspects helps to improve the models and their application in various clinical settings.

Table 2. Factors or variables considered by the models in the detection of diabetic retinopathy

Factor/Variable	Articles
Neovascularization	(14); (15); (16); (17); (18); (19); (20); (8); (21); (22); (23); (24); (25); (26); (27); (28); (29); (30); (31); (32); (33); (34); (35); (36); (37); (38); (39)
Macular edema	(40); (41); (42); (43); (44); (45); (46); (47); (15); (48); (16); (17); (49); (18); (50); (20); (8); (51); (52); (24); (26); (28); (53); (54); (55); (56); (57); (35); (58); (59); (60); (61); (62); (38); (39)
Changes in retinal vascularization	(40); (4); (41); (63); (64); (65); (66); (42); (43); (14); (44); (45); (67); (46); (47); (15); (3); (68); (69); (17); (49); (18); (1); (70); (19); (20); (71); (8); (51); (72); (22); (73); (25); (28); (53); (31); (32); (54); (33); (74); (35); (58); (60); (75); (61); (76); (62); (37); (38); (77)
Optic disc size	(78); (4); (41); (63); (64); (65); (42); (67); (15); (79); (48); (69); (17); (49); (20); (8); (80); (23); (24); (26); (28); (29); (54); (34); (75); (61); (36); (37)

Microaneurysms	(78); (4); (41); (81); (63); (64); (65); (66); (42); (43); (14); (82); (44); (67); (46); (15); (79); (48); (16); (3); (68); (69); (17); (49); (18); (1); (70); (50); (83); (19); (20); (84); (71); (8); (51); (52); (21); (80); (22); (23); (24); (73); (25); (26); (28); (53); (29); (30); (32); (54); (85); (56); (33); (34); (74); (57); (35); (58); (59); (60); (75); (86); (61); (36); (76); (62); (37); (38); (77); (39)
Exudates	(78); (4); (41); (63); (64); (65); (66); (42); (14); (44); (67); (46); (15); (79); (48); (16); (68); (69); (17); (49); (18); (1); (70); (50); (83); (19); (20); (84); (71); (8); (51); (21); (80); (22); (23); (24); (73); (25); (26); (28); (53); (29); (30); (32); (54); (85); (56); (33); (34); (74); (57); (35); (59); (60); (75); (86); (61); (36); (76); (62); (37); (38); (77)

Table 2 provides a detailed overview of the different factors or variables considered by the models in the detection of DR. The results indicate that microaneurysms are the most recurrently addressed factor, with a presence in 71 of the 77 articles collected. This suggests that microaneurysms are a prominent and relevant feature in the detection and diagnosis of DR, according to the literature reviewed. The high incidence of microaneurysms in the models may indicate their importance as an early marker of DR. These small dilations of capillaries are indicative of retinal vascular damage, some associated with diabetes mellitus. However, other factors are also highlighted in the literature, such as macular edema and changes in retinal vascularization, which are present in 35 and 53 articles, respectively. These findings suggest that models also pay attention to the presence of macular edema and vascular changes as key indicators of disease progression. The inclusion of different factors in the models reflects the diversity of DR manifestations and the importance of a comprehensive approach to its detection and clinical management. The focus on exudates and changes in vascularization reflects the need for AI models to address both early signs and those indicative of advanced disease.

Q2: What are the most effective algorithms for early detection of DR using AI?

This question seeks to identify the specific algorithms that have been shown to be most effective in the early detection of DR. It is important to know these algorithms to understand which ones provide the best results in terms of sensitivity, specificity, and diagnostic accuracy, which is crucial to optimize the use of AI in eye care.

Table 3. Algorithms for early detection of DR with AI

Algorithms	Article(s)
ResNet 101	(40), (16), (30), (24), (59)
CNN	(78), (68), (21), (62)
IDx-DR	(4), (45), (8), (25), (60)
Retinalyze	(4)
VeriSee DR	(65)
Deep Learning (DL)	(66), (79), (39)
EyeWisdom	(14)
DART (TeleDx)	(82), (77)
AI general	(44), (47), (73), (85)
Ensemble AI	(46)
SqueezeNet	(50)
AlexNet	(19)
Modified GoogLeNet	(20)
Grey Level Co-occurrence Matrix	(84)
VGG-16	(71)
EyeArt™	(51), (31)
EyeCheckup AI	(52)
Deep Convolutional Neural Network	(69)
Support Vector Machine (SVM)	(69), (68)
PNN	(68)
ExplAIn	(17)
Selena + Aurora	(53)
THEIA™	(55)
EBM y XGBoost	(32)
Medios AI	(57), (75)
PhelcomNet	(86)
Phoebus Algorithm	(61)
RetCAD AI	(33)
DeepDR	(74)
ResNet-50	(38)
DLA	(76)

Table 3 shows a variety of algorithms used in the early detection of DR using AI. The algorithms included in the list are representative of the different approaches and approaches used in the detection of this disease. Among the most commonly used algorithms are those based on convolutional neural networks (CNN) and those based on deep learning (DL). These algorithms have proven to be effective in DR detection due to their ability to learn patterns in images and detect changes in the retina. Another group of algorithms includes those based on supervised learning machines, such as SVM and PNN. These algorithms have also been shown to be effective in DR detection, as they can learn to recognize patterns in images and classify them according to their correspondence with the disease. The inclusion of algorithms such as EyeArt™, EyeCheckup AI, and Medios AI in the list suggests that early detection of DR can also be performed using machine learning tools and computer vision systems.

Q3: How accurate are AI models in DR detection?

This question examines how accurate AI models are in detecting DR. It is essential to assess the accuracy of these models, as this determines their feasibility and usefulness in clinical practice. Knowing the accuracy allows healthcare professionals to rely on these systems for diagnosis and management of the disease.

Table 4. Accuracy of AI models in DR detection

Accuracy in % of algorithm	**Items (Algorithms, Percentage)**
< 80 %	[59] (ResNet 101, 79 %), [41] (CNN, 76 %), [86] (Medios AI, 78 %)
80 - 85 %	[16] (ResNet 101, 83 %), [78] (CNN, 84 %), [69] (DL, 82 %), [68] (SVM, 84 %), [69] (SVM, 83 %), [14] (EyeWisdom, 82 %), [50] (SqueezeNet, 84 %)
85 - 90 %	[30] (ResNet 101, 89 %), [68] (CNN, 87 %), [53] (Selena + Aurora, 86 %), [8] (IDx-DR, 88 %), [82] (DART, 88 %), [73] (AI general, 87 %), [75] (Medios AI, 87 %), [19] (AlexNet, 88 %), [79] (DL, 85 %), [32] (EBM y XGBoost, 89 %)
90 - 95 %	[40] (ResNet 101, 98 %), [62] (CNN, 92 %), [4] (IDx-DR, 95 %), [45] (IDx-DR, 92 %), [25] (IDx-DR, 93 %), [60] (IDx-DR, 91 %), [51] (EyeArt™, 95 %), [31] (EyeArt™, 90 %), [52] (EyeCheckup AI, 92 %), [84] (Grey Level Co-occurrence Matrix, 85 %), [71] (VGG-16, 91 %), [20] (Modified GoogLeNet, 90 %), [74] (DeepDR, 89 %), [44] (AI general, 94 %), [46] (Ensemble AI, 92 %), A76 (DART, 90 %)
95 - 100 %	[65] (VeriSee DR, 96 %), [29] (AI general, 97 %), [41] (CNN, 76 %), [20] (Modified GoogLeNet, 90 %), [61] (Phoebus Algorithm, 95 %), [36] (ResNet-50, 90 %), [37] (DLA, 92 %), [80] (EyeCheckup AI, 93 %)

Table 4 shows the accuracy of different AI algorithms in DR detection. Examination of the data shows a varied distribution of accuracy among the different algorithms, with a wide range of percentages from less than 80 % to more than 95 %. Algorithms with an accuracy of less than 80 % could be considered less reliable for implementation in clinical practice, as there is a greater margin of error. However, it is important to recognize that some of these algorithms, such as ResNet 101 and CNN, approach the 80 % threshold, suggesting a potential for improvement with additional adjustments or training.

On the other hand, algorithms with accuracy in the 90 % to 95 % range, such as IDx-DR and EyeArt™, show remarkably strong performance in DR detection. These results support the feasibility of using these algorithms in clinical practice, as they offer consistently high accuracy that inspires confidence in their diagnostic ability. Algorithms with 95-100 % accuracy, such as VeriSee DR and general AI, are especially promising, as they offer high accuracy in DR detection. These results suggest that these algorithms have the potential to be highly reliable and accurate tools for healthcare professionals in detecting and diagnosing the disease.

Q4: What technical or implementation limitations do AI systems face in DR detection?

This question addresses the technical and implementation barriers that hinder the effective use of AI systems in DR detection. Identifying these limitations is critical to developing solutions that improve the integration and performance of these systems in real clinical settings.

Table 5. Limitations in DR detection using AI systems

Technical or implementation limitations	**Artículos**
Dependence on image quality	(40), (4), (41), (81), (64), (65), (42), (43), (14), (44), (45), (46), (47), (79), (3), (68), (69), (17), (49), (18), (70), (50), (83), (19), (20), (71), (51), (72), (21), (22), (73), (28), (53), (31), (54), (55), (85), (33), (74), (58), (60), (61), (76), (62), (37), (38), (77)
Variability in interpretation of retinal features	(40), (78), (4), (41), (81), (63), (64), (65), (42), (43), (82), (45), (67), (47), (79), (3), (68), (69), (17), (49), (18), (1), (70), (50), (19), (20), (71), (8), (51), (72), (21), (22), (73), (25), (28), (53), (29), (31), (32), (54), (55), (85), (33), (74), (57), (35), (58), (60), (75), (61), (36), (62), (37), (38), (77)

Implementation and maintenance costs	(78), (41), (81), (63), (64), (65), (42), (43), (14), (44), (45), (46), (47), (15), (79), (3), (68), (69), (17), (49), (18), (1), (70), (50), (83), (19), (20), (8), (51), (72), (21), (80), (22), (73), (25), (28), (53), (31), (32), (55), (85), (33), (74), (57), (35), (58), (60), (75), (61), (36), (76), (62), (37), (38), (77)
Limited access to quality data	(40), (4), (81), (64), (66), (43), (14), (82), (44), (45), (46), (47), (15), (79), (3), (68), (69), (17), (49), (1), (70), (83), (19), (20), (8), (51), (72), (21), (80), (22), (24), (73), (25), (28), (53), (31), (32), (54), (55), (85), (33), (74), (57), (35), (58), (59), (60), (61), (76), (62), (37), (38), (77)
Lack of integration with electronic medical record systems	(40), (78), (4), (81), (63), (64), (65), (42), (43), (14), (82), (45), (46), (47), (15), (79), (3), (68), (69), (17), (49), (18), (1), (70), (50), (83), (19), (20), (71), (8), (51), (72), (21), (80), (22), (73), (25), (28), (53), (31), (32), (54), (55), (85), (33), (74), (57), (35), (58), (60), (61), (76), (62), (37), (38), (77)

According to table 5, major limitations include dependence on image quality, variability in the interpretation of retinal features, and implementation and maintenance costs. The quality of retinal images is crucial for diagnostic accuracy, and the lack of high-quality images may reduce the effectiveness of AI systems in DR detection. In addition, variability in the interpretation of retinal features can arise due to differences in algorithm training and human interpretation of image features, generating inconsistent and potentially erroneous results.

In addition, implementation and maintenance costs are an important factor to consider. The investment required to develop, implement, and maintain AI systems in clinical settings can be significant, limiting their adoption in areas with limited resources. Limited access to quality data and lack of integration with electronic medical record systems also emerge as challenges. Therefore, it is critical to develop solutions that address these limitations to improve the efficacy and adoption of artificial intelligence systems in diabetic retinopathy screening.

Q5: What ethical and legal challenges are posed by the use of AI algorithms in the diagnosis and treatment of DR?

This question explores the ethical and legal issues associated with the use of AI algorithms in the diagnosis and treatment of DR. It is important to consider these challenges to ensure that the implementation of AI is safe, fair, and compliant with legal regulations, thereby protecting patients and healthcare professionals.

Table 6. Challenges of using AI algorithms in the diagnosis and treatment of DR

Challenge	Articles
Privacy and security of patient data	(40), (4), (41), (81), (64), (65), (42), (43), (14), (44), (45), (46), (47), (79), (3), (68), (69), (17), (49), (18), (70), (50), (83), (19), (20), (71), (51), (72), (21), (22), (73), (28), (53), (31), (54), (55), (85), (33), (74), (58), (60), (61), (76), (62), (37), (38), (77)
Liability for diagnostic errors	(40), (78), (4), (41), (81), (63), (64), (65), (42), (43), (82), (45), (67), (47), (79), (3), (68), (69), (17), (49), (18), (1), (70), (50), (19), (20), (71), (8), (51), (72), (21), (22), (73), (25), (28), (53), (29), (31), (32), (54), (55), (85), (33), (74), (57), (35), (58), (60), (75), (61), (36), (62), (37), (38), (77)
Algorithmic bias in medical care	(40), (78), (41), (81), (63), (64), (65), (42), (43), (14), (82), (45), (67), (47), (15), (79), (48), (3), (68), (17), (49), (18), (70), (50), (19), (20), (84), (71), (8), (51), (52), (21), (80), (23), (73), (25), (28), (29), (30), (31), (54), (85), (33), (74), (57), (59), (60), (75), (86), (36), (62), (37), (38), (77)
Informed consent and transparency in the use of AI	(78), (4), (41), (81), (64), (65), (42), (43), (14), (82), (45), (67), (46), (47), (15), (79), (48), (3), (68), (69), (17), (49), (18), (1), (70), (50), (83), (20), (84), (71), (8), (51), (72), (52), (21), (80), (23), (73), (25), (28), (29), (30), (31), (54), (85), (33), (74), (57), (35), (59), (75), (86), (36), (62), (38), (77)
Regulations on the use of medical data for research and development purposes.	(40), (78), (4), (41), (81), (63), (64), (65), (42), (43), (14), (82), (44), (45), (67), (46), (47), (15), (79), (48), (3), (68), (69), (17), (49), (18), (1), (70), (50), (83), (19), (20), (84), (71), (8), (51), (72), (52), (21), (80), (23), (73), (25), (28), (29), (30), (31), (54), (85), (33), (74), (57), (58), (59), (75), (86), (61), (36), (62), (38), (39)

According to table 6, the main concern revolves around the privacy and security of patient data, highlighting the need to protect sensitive information. In addition, liability in the case of diagnostic errors is a critical issue that requires a clear definition of the roles and responsibilities of healthcare professionals and algorithm developers. Algorithmic bias is also a significant concern, as a lack of diversity in training data can lead to erroneous medical decisions. Addressing this challenge is, therefore, essential to ensure equitable and fair medical care for all patients.

Transparency and informed consent are important elements in building a trusting relationship between patients and AI systems. Patients need to understand how their data is used and the implications of the use of AI algorithms in their medical care, highlighting the need for clear communication by healthcare professionals. Finally, regulations on the use of medical data for research and development purposes are necessary to ensure that the use of AI in healthcare is ethical and responsible. These regulations should establish clear standards to protect patient's rights and ensure integrity and ethics in medical research.

CONCLUSIONS

A systematic review has shown that AI, specifically deep learning, is an effective technological alternative for DR detection. Various algorithms, such as ResNet, CNN, IDx-DR, and EyeArt™, have reported high accuracy, with percentages above 90 % in identifying DR features. Also, AI models consider factors such as microaneurysms, macular edema, changes in retinal vascularity, and optic disc size. These algorithms have proven effective in the early detection of DR, which facilitates timely treatment and improves clinical outcomes.

However, there are technical and implementation limitations that need to be addressed. Dependence on image quality, variability in the interpretation of retinal features, implementation and maintenance costs, limited access to quality data, and lack of integration with electronic medical record systems are some of the challenges identified. In addition, ethical and legal concerns arise, such as privacy and security of patient data, liability in case of diagnostic errors, algorithmic bias, informed consent and transparency in the use of AI, and regulations on the use of medical data for research and development purposes.

Although the systematic review has provided relevant results, it is important to recognize some limitations. The search was restricted to specific databases and to a particular range of years, which could have excluded relevant studies. Future research should focus on broadening the data sources over several decades, using additional databases, and selecting specific AI techniques for more detailed analysis.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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