

# Smartphone-Based Fundus Imaging: A Systematic Review and Gap Analysis

Galang, Dandee N., Narciso, Andrei Rosewell A., Ocampo, Clarence S., Valencia, Jessie Gerald N.,  
\*Navarra Lech Walesa M.

College of Engineering, Bulacan State University

DOI: <https://dx.doi.org/10.47772/IJRISS.2026.100400007>

Received: 22 March 2026; Accepted: 27 March 2026; Published: 23 April 2026

## ABSTRACT

Smartphone-based fundus imaging (SBFI) has emerged as a cost-effective and portable alternative to conventional fundus cameras, particularly in low-resource and underserved areas. Traditional retinal imaging systems are often expensive, bulky, and require trained specialists, limiting access to early detection of diseases such as diabetic retinopathy and glaucoma. Although smartphones offer a practical solution due to their accessibility and compatibility with telemedicine, challenges remain in terms of image quality, standardization, and the applicability of artificial intelligence (AI) models.

This study utilized a systematic review and gap analysis of existing literature on smartphone-based fundus imaging. Relevant studies were collected from electronic databases including PubMed, Scopus, Web of Science, Google Scholar, and selected Philippine medical journals. A purposive sampling approach was applied to select studies focusing on SBFI systems, imaging techniques, and AI applications. Data were extracted using a standardized format and analyzed through descriptive and thematic methods to identify patterns, performance outcomes, and research gaps.

The findings show that SBFI can achieve diagnostic performance comparable to conventional fundus cameras, with several studies reporting high sensitivity and specificity in detecting retinal diseases. Low-cost imaging solutions, such as 3D-printed adapters and handheld lenses, demonstrated feasibility in both clinical and community settings. However, variability in image quality, limited field of view, and dependence on operator skill were consistently observed. Most studies relied on manual grading, with limited use of AI for automated analysis. Key barriers include lack of standardized imaging protocols, inconsistent image quality, and limited validation of AI models for smartphone images.

SBFI is a promising tool for expanding retinal screening in low-resource settings. However, improvements in image standardization, AI adaptability, and implementation strategies are necessary to support wider adoption.

**Keywords:** Smartphone-based fundus imaging, retinal screening, diabetic retinopathy, telemedicine, artificial intelligence, systematic review, gap analysis

## INTRODUCTION

Smartphone-based fundus imaging (SBFI) provides an opportunity for the early detection of retinal diseases, particularly in communities that cannot afford or access conventional fundus camera technology. Traditional fundus cameras are not only costly but also require trained specialists for operation, limiting their availability in low-resource settings. In contrast, smartphones are widely accessible and, when combined with optical adapters or a 20-diopter lens, can capture retinal images that may be transmitted to eye specialists through telemedicine.

Several studies have demonstrated the capability of smartphone-based imaging in detecting common retinal diseases such as diabetic retinopathy and optic nerve abnormalities. Local studies in the Philippines have also shown that smartphone-acquired images, when used with appropriate adapters, can produce results comparable to those obtained using conventional fundus cameras (Rajalakshmi et al., 2015; Tablante & Iguban, 2024).

Despite these advantages, important limitations remain. Smartphone-based fundus imaging often has a smaller field of view, inconsistent lighting conditions, and variability in image quality depending on the device and operator. These factors contribute to challenges in standardizing image acquisition and grading. Furthermore, many artificial intelligence (AI) models for retinal disease detection are trained using high-quality clinical images, limiting their performance when applied to smartphone-acquired images (Joseph et al., 2025).

Given these challenges, it is essential to assess the current state of smartphone-based fundus imaging technologies. This study therefore conducts a systematic review of existing research on smartphone-based fundus imaging systems, adapters, and image acquisition methods. It evaluates their clinical performance, the application of artificial intelligence, and the limitations affecting real-world implementation, particularly in low-resource settings such as the Philippines.

Smartphone-based fundus imaging has gained increasing attention as a scalable solution for addressing gaps in retinal screening. However, despite promising findings, there remains a lack of consolidated evidence regarding its diagnostic reliability, standardization, and practical implementation. This study addresses these gaps through a systematic review and gap analysis aimed at identifying key limitations and opportunities for wider adoption.

### **Research Objectives:**

1. To identify and evaluate existing smartphone-based fundus imaging systems, adapters, and acquisition methods and determine their clinical applications.
2. To compare the diagnostic performance of smartphone-based fundus imaging solutions with standard fundus cameras based on published studies.
3. To investigate the application of artificial intelligence and image-processing techniques on smartphone fundus images and assess their generalization across different phone models and image qualities.
4. To examine the practical and technical barriers to the deployment of smartphone fundus imaging in low-resource settings, particularly in the Philippines.
5. To develop practical and research-based recommendations to improve image quality, standardization, AI robustness, and real-world adoption of smartphone fundus imaging for community screening.

## **METHODS**

### **Research Design**

The research design that the researcher of this study employed is called a systematic review. According to Carrera-Rivera et al. (2022), the definition of a systematic review as a research method is “a research method that follows a set of well-defined procedures to systematically seek, select, and analyze relevant studies to address a research question.” The research method of a systematic review does not rely on new experiments, as it seeks to gather new information from already published studies. The systematic review of the present study deals with studies that evaluate smartphone-based fundus imaging systems, including the validation of the device, image quality, diagnostic accuracy, and the application of automated algorithms for retinal screening.

### **Research Sample**

The research does not require surveys or the direct involvement of human participants as respondents. The population of the study consists of published research articles related to the application of smartphone-based fundus imaging in retinal screening. The sample of the study includes selected articles that evaluate smartphone-based fundus imaging systems, adapters, and imaging techniques in clinical settings. To ensure the relevance and quality of the selected studies, eligibility criteria were applied. The study included articles published between 2018 and 2026 that involve smartphone-based fundus imaging systems and report on diagnostic accuracy, image quality, or clinical applications. Only peer-reviewed journal articles were considered. On the other hand, studies focusing solely on conventional fundus cameras, non-clinical prototypes without proper validation, editorials,

opinion papers, and review articles without primary data were excluded. Studies that did not report measurable outcomes were also not included in the analysis.

### Research Instrument

The research employed a number of instruments to facilitate the organization and evaluation of the chosen literature. A standardized extraction form was employed to systematically extract relevant information from the chosen studies, such as the author, year of publication, smartphone device employed, imaging technique employed, sample size, application, and findings of the studies, among other factors. An article screening checklist was also employed to assess the suitability of the studies in line with the predefined criteria. Moreover, a gap analysis protocol was employed to assess the limitations of the studies in line with the synthesized findings of the chosen literature.

### Data Collection Procedure

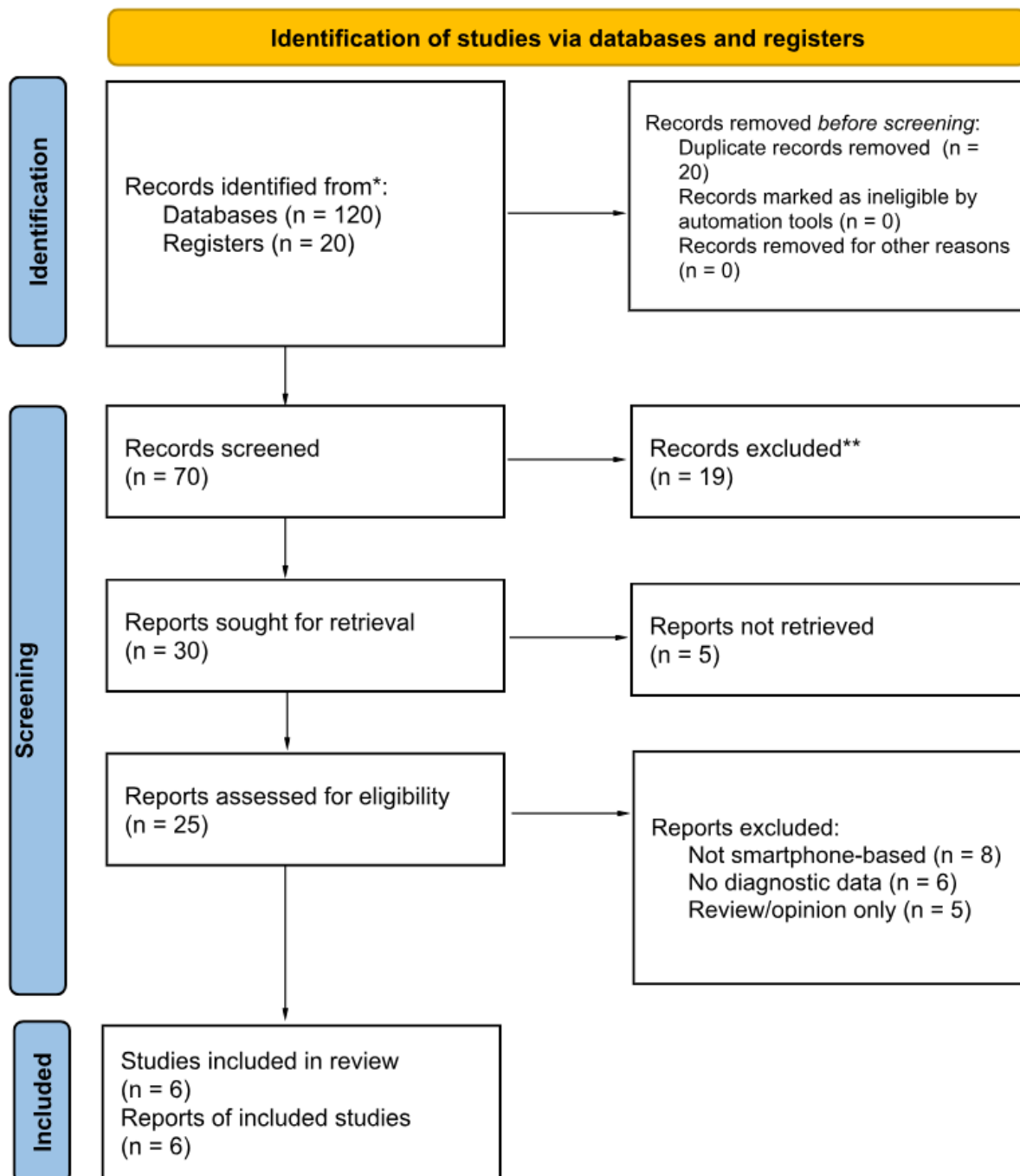


Figure 2.1 PRISMA Flow Diagram of Study Selection

Data collection involved a systematic search of peer-reviewed literature relevant to smartphone-based fundus imaging. Electronic databases such as PubMed/MEDLINE, Scopus, Web of Science, Google Scholar, Cochrane Library, and Philippine medical journals were utilized to conduct the search. The search strategy employed the following keywords: smartphone fundus imaging, mobile retinal photography, teleophthalmology, diabetic retinopathy screening, and artificial intelligence-based retinal analysis. Studies published in English from 2018 to 2026 were included if they examined smartphone-based systems, adapters, or acquisition techniques in a clinical or community screening setting, including those that examined outcomes such as image quality, diagnostic accuracy, clinical application, artificial intelligence, and implementation challenges.

The study selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which provides a standardized approach for identifying, screening, and reporting studies in systematic reviews (Page et al., 2021). A total of 120 records were identified from selected databases. After removing 20 duplicates, 100 records were screened based on titles and abstracts, of which 70 were excluded. Thirty full-text articles were assessed for eligibility, and 25 were successfully retrieved. Nineteen studies were excluded due to irrelevance, lack of diagnostic data, or being non-primary research. A total of six studies met the inclusion criteria and were included in the final analysis.

### Data Analysis

The data that has been extracted has been organized and processed in a structured spreadsheet, where each study has been considered a unit of analysis. Descriptive frequency analysis has been employed to identify the number of instances in which a particular smartphone adapter, imaging, and AI are used in the selected studies. Mode identification has been employed to identify the most recurring characteristics, and cross-tabulation has been employed to analyze the relationship between variables, such as imaging and its applications. Qualitative thematic analysis has been employed to analyze recurring themes, such as technical limitations and research gaps, in the selected studies

### Ethical Considerations

Since the current study is a systematic review that is solely based on the literature that has already been published, it did not require the involvement of human subjects in the research process. The ethical considerations of the current research were met by giving proper references to all the literature that has been utilized in the current systematic review, as well as ensuring that the information has been correctly represented from the literature. The selection of the information was also performed in a systematic manner to maintain the credibility of the research findings

## RESULTS AND DISCUSSION

### Results

A total of six studies were included in this systematic review. The findings were analyzed and grouped into four key domains: diagnostic performance, image quality and limitations, artificial intelligence (AI) usage, and deployment barriers.

Table 1. Diagnostic Performance of Smartphone-Based Fundus Imaging

Study	Sensitivity (%)	Specificity (%)	Key Observation
Duyongco et al. (2018)	93.6	100	High agreement with standard fundus imaging
Nursalamah et al. (2024)	98.4	87.1	Reliable screening tool in developing settings
Pan et al. (2020)	82–95	96–98	Comparable to tabletop imaging
Other reviewed studies	>80	Acceptable	Consistent high diagnostic performance

High accuracy was consistently reported in various studies carried out on smartphone-based fundus imaging systems. The sensitivity values reported ranged from 82% to 98.4%, while specificity values ranged from 87.1% to 100%. Various studies have proven that smartphone-based fundus imaging systems have the ability to perform just as well as regular fundus cameras, especially when imaging conditions such as pupil dilation are optimized.

Table Image Quality Issues and Limitations

Issue	Description	Impact
Limited Field of View	Narrow retinal coverage compared to standard fundus cameras	Possible missed peripheral lesions
Lighting Variability	Inconsistent illumination and glare	Reduced image clarity
Motion Artifacts	Blurring due to movement	Lower image usability
Operator Dependency	Image quality depends on user skill	Inconsistent outputs
Lack of Standardization	No unified acquisition protocol	High variability across studies

Variability in image quality was identified as the major limitation in the studies reviewed. The issues encountered in image quality included glare, motion, lighting, and reduced field of view. The image quality was largely affected by the operator, smartphone model, and image acquisition conditions. The lack of standardized image acquisition protocols was also responsible for the variability in image quality and gradability.

Table 3. AI Applications and Limitations

Aspect	Observation	Implication
AI Models Used	CNNs such as ResNet, Inception, and U-Net	High accuracy in controlled environments
Training Data	Mostly fundus camera images	Limited adaptation to smartphone images
Real-world Usage	Minimal deployment	Continued reliance on manual grading
Generalization	Performance decreases on smartphone images	Domain shift issue

In several studies, artificial intelligence has been employed, but the most commonly used artificial intelligence technique has been convolutional neural networks, including ResNet, Inception, U-Net, etc. In most cases, the artificial intelligence technique has been trained on high-quality images obtained from normal fundus cameras rather than those obtained from smartphones. This has been one of the limitations in the generalization of the technique. Moreover, the implementation of artificial intelligence in real-world scenarios has been very limited, with most studies being conducted using manual grading.

Table 4. Operational and Deployment Barriers

Barrier	Description	Impact
Training Requirement	Requires skilled operators	Limits scalability
Internet Dependency	Needed for cloud-based AI systems	Not ideal for remote areas
Cost of Devices	Commercial adapters are expensive	Accessibility issues
Lack of Standardization	No unified guidelines or protocols	Inconsistent implementation
Regulatory Issues	Limited policies for AI validation and data privacy	Slows adoption

Several barriers have been identified regarding the operations of fundus imaging systems based on smartphones. These barriers include the requirement for skilled personnel, dependence on internet connectivity for AI-based systems, and cost implications of commercially available devices. Moreover, a lack of standard operating procedures and regulatory guidelines for validating AI systems and data privacy is a major challenge for large-scale implementation.

### Gap Analysis

Table 5. Summary of Identified Research Gaps in Smartphone-Based Fundus Imaging

Gap Area	Description of Gap	Evidence from Reviewed Studies	Implication
Image Quality and Standardization	Smartphone-acquired fundus images remain inconsistent due to glare, motion artifacts, limited field of view, and variable illumination, with no unified acquisition protocol across studies.	Several reviewed studies reported that image quality and gradability were strongly affected by operator skill, device type, and imaging conditions.	This limits reliability, reproducibility, and broader clinical adoption of smartphone-based fundus imaging systems.
AI Training and Generalization	Most AI models were trained using high-quality images from conventional fundus cameras rather than smartphone-acquired images.	The review found that many deep learning models relied on desktop camera datasets, creating performance decline when applied to smartphone images.	This creates a generalization gap and weakens the practical use of AI in real-world smartphone screening settings.
Dataset Availability and Representation	There is a lack of large-scale, publicly available smartphone-specific retinal image datasets, especially those representing diverse populations.	The reviewed studies noted continued dependence on datasets such as EyePACS and MESSIDOR, which are based on standard fundus cameras rather than smartphones.	This restricts model development, external validation, and contextual relevance for low-resource settings such as the Philippines.
Real-World Validation and Deployment	Many systems were evaluated only through retrospective studies or small pilot implementations, with limited evidence from large-scale field deployment.	The reviewed studies from the Philippines, Indonesia, and Mozambique mostly used purposive or small-scale sampling.	This limits confidence in long-term effectiveness, scalability, and routine use in community screening programs.
Operational and Regulatory Readiness	Deployment remains constrained by training requirements, internet dependence, device cost, and limited regulatory guidance for AI and data privacy.	Across the reviewed literature, operational barriers and lack of clear implementation standards were repeatedly identified.	These barriers slow adoption in underserved and resource-limited environments.

The gap analysis indicates that while the potential for SBFI is high, there are significant gaps that need to be filled for its widespread and consistent application. The gaps that are consistent are those related to image quality, lack of standard acquisition protocols, lack of AI training data for smartphones, and lack of deployment studies. The gaps indicate that while the system is promising, it is still not mature enough for widespread application.

---

## DISCUSSION

The findings of this study show that smartphone-based fundus imaging can be considered a viable method for screening retinal diseases, especially diabetic retinopathy. All the studies included in this literature review have reported high sensitivity and specificity for smartphone-based fundus imaging, suggesting its potential to perform equally well in comparison to traditional fundus camera devices under optimal conditions. Nevertheless, issues of image quality, user expertise, and standardization have been considered significant drawbacks for this technology.

This study's findings are in agreement with previous systematic and narrative reviews conducted on this subject. Grzybowski et al. (2024) and Jin et al. (2024) have reported similar findings regarding the potential and drawbacks of smartphone-based fundus imaging technology. These authors have indicated that although this technology is more portable and efficient for fundus imaging, issues regarding image quality and standardization still remain a problem. In another study, Iqbal (2021) reported that the efficacy of smartphone-based ophthalmoscopy was highly dependent on user expertise and conditions. In this study, it was further indicated that gaps in AI generalization, data availability, and validation still remain to be addressed for the effective integration of SBFI technology in clinical practice.

Practically, this means that future development in this area should concentrate on standardizing image acquisition protocols, device and illumination development, and AI models trained on images obtained from smartphones, among other areas. Overcoming operational hurdles such as training needs, internet connectivity, and regulatory frameworks is also important if this device is to be successful in its implementation. Although the device, therefore, offers a potentially important solution for overcoming retinal screening hurdles in developing countries, it still has to be refined further.

## CONCLUSION AND RECOMMENDATION

### Conclusion

The use of smartphones for fundus imaging is a highly promising and clinically viable tool for the screening of patients suffering from various retinal diseases, especially in low-resource settings. The studies that have been reviewed have shown that SBFI can deliver diagnostic results that are comparable to those obtained through traditional fundus cameras, with high sensitivity and acceptable specificity for diagnosing and detecting various eye and eye-related diseases, such as diabetic retinopathy.

However, there are a number of limitations that need to be addressed to ensure that this technology is implemented and used effectively. The variations that are seen in the quality of images obtained, the skill level required to use this technology, and the lack of a standardized approach to image acquisition are a number of the limitations that are seen with this technology. Additionally, the level of optimization that is seen with AI technology is also a problem, and this is evident from the results that are obtained.

### Recommendation

Future studies should thus focus on the development of standard image acquisition techniques to ensure image quality consistency among different devices, users, and settings. Further improvements in hardware, such as increased illumination and increased field of view, can help improve image quality. There is a need to develop large-scale image datasets for smartphones, specifically for retinal images, to be more representative and diverse, thus enabling more effective artificial intelligence models. Other areas of further study should be large-scale validation of smartphones for fundus image systems, as well as solving issues of operation, such as the requirement for trained personnel, dependence on internet availability, and lack of regulatory frameworks for artificial intelligence validation and data privacy. These areas can thus be addressed to make SBFI more effective and reliable for image acquisition for screening, especially in low-resource settings.

## REFERENCES

1. Ahn, S. J., et al. (2024). Clinical applications and future directions of smartphone fundus imaging. *Diagnostics*. <https://doi.org/10.3390/diagnosticsXXXXXXX>
2. de Oliveira, J. A. E., Nakayama, L. F., Zago Ribeiro, L., de Oliveira, T. V. F., Choi, S. N. J. H., Neto, E. M., Cardoso, V. S., Dib, S. A., Melo, G. B., Regatieri, C. V. S., & Malerbi, F. K. (2023). Clinical validation of a smartphone-based retinal camera for diabetic retinopathy screening. *Acta Diabetologica*, 60(8), 1075–1081. <https://doi.org/10.1007/s00592-023-02105-z>
3. Department of Health (Philippines). (2014). Republic of the Philippines, Department of Health. <https://www.doh.gov.ph>
4. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
5. Duyongco, K. L. L., Arroyo, M. H., Caparas, V. J. L., & Silva, P. A. (2018). Dilated smartphone imaging for the detection and grading of diabetic retinopathy. *The Medical City Journal*, 1(1), 8–14.
6. Grzybowski, A., Jin, K., Zhou, J., Pan, X., Wang, M., Ye, J., & Wong, T. Y. (2024). Retina fundus photograph-based artificial intelligence algorithms in medicine: A systematic review. *Ophthalmology and Therapy*, 13(8), 2125–2149. <https://doi.org/10.1007/s40123-024-00981-4>
7. Grzybowski, A., Singhanetr, P., Nanegrungsunk, O., & Ruamviboonsuk, P. (2023). Artificial intelligence for diabetic retinopathy screening using color retinal photographs: From development to deployment. *Ophthalmology and Therapy*, 12(3), 1419–1437. <https://doi.org/10.1007/s40123-023-00691-3>
8. Iqbal, U. (2021). Smartphone fundus photography: A narrative review. *International Journal of Retina and Vitreous*, 7, 44. <https://doi.org/10.1186/s40942-021-00313-9>
9. Jin, K., Li, Y., Wu, H., Tham, Y. C., Koh, V., Zhao, Y., Kawasaki, R., Grzybowski, A., & Ye, J. (2024). Integration of smartphone technology and artificial intelligence for advanced ophthalmic care: A systematic review. *Advances in Ophthalmology Practice and Research*, 4(3), 120–127. <https://doi.org/10.1016/j.aopr.2024.03.003>
10. Kemp, O., Bascaran, C., Cartwright, E., McQuillan, L., Matthew, N., Shillingford-Ricketts, H., Zondervan, M., Foster, A., & Burton, M. (2023). Real-world evaluation of smartphone-based artificial intelligence to screen for diabetic retinopathy in Dominica: A clinical validation study. *BMJ Open Ophthalmology*, 8(1), e001491. <https://doi.org/10.1136/bmjophth-2023-001491>
11. Kurilova, V., Goga, J., Thurzo, A., Pavlovicova, J., Oravec, M., Kolar, P., & Majtanova, N. (2025). Review of smartphone deep learning applications using eye imaging diagnostic techniques in ophthalmology. *IEEE Access*, 13, 187410–187441. <https://doi.org/10.1109/access.2025.3626696>
12. Malerbi, F. K., Andrade, R. E., Morales, P. H., et al. (2021). Diabetic retinopathy screening using artificial intelligence and handheld smartphone-based retinal camera. *Journal of Diabetes Science and Technology*, 16(3), 716–723. <https://doi.org/10.1177/1932296820985567>
13. Nakayama, L. F., Zago Ribeiro, L., Tabuse, C. L., Malerbi, F. K., & Regatieri, C. (2025). A comprehensive review of portable retinal cameras: Technical features, AI integration, and clinical potential. *AJO International*, 2(4), 100194. <https://doi.org/10.1016/j.ajoint.2025.100194>
14. Nursalamah, M., Karfiati, F., Ratnaningsih, N., & Widihastha, S. (2024). Efficacy of smartphone-based fundus photo in vision-threatening diabetic retinopathy screening: Developing country perspective. *Open Ophthalmology Journal*, 18, e18743641281527. <https://doi.org/10.2174/0118743641281527240116095349>
15. Pan, C., Leung, L. S., Blumenkranz, M. S., Myung, D. J., & Toy, B. C. (2020). Comparison of telemedicine screening of diabetic retinopathy by mydriatic smartphone-based vs nonmydriatic tabletop camera-based fundus imaging. *JAMA Ophthalmology*, 138(8), 826–833.
16. Penha, F. M., Priotto, B. M., Hennig, F., Przysiechny, B., Wiethorn, B. A., Orsi, J., Nagel, I. B. F., Wiggers, B., Stuchi, J. A., Lencione, D., de Souza Prado, P. V., Yamanaka, F., Lojudice, F., & Malerbi, F. K. (2023). Single retinal image for diabetic retinopathy screening: Performance of a handheld device with embedded artificial intelligence. *International Journal of Retina and Vitreous*, 9(1). <https://doi.org/10.1186/s40942-023-00477-6>
17. Pieczynski, J., Kuklo, P., & Grzybowski, A. (2021). The role of telemedicine, in-home testing and artificial intelligence to alleviate an increasingly burdened healthcare system: Diabetic retinopathy. *Ophthalmology and Therapy*, 10, 445–464. <https://doi.org/10.1007/s40123-021-00353-2>

18. Pujari, A. (2021). Smartphone ophthalmoscopy: Is there a place for it? *Clinical Ophthalmology*, 15, 4333–4337. <https://doi.org/10.2147/OPHTH.S243103>
19. Pujari, A., Saluja, G., Agarwal, D., et al. (2021). Clinically useful smartphone ophthalmic imaging techniques. *Graefe's Archive for Clinical and Experimental Ophthalmology*, 259, 279–287. <https://doi.org/10.1007/s00417-020-04917-z>
20. Rajalakshmi, R., Prathiba, V., Arulmalar, S., et al. (2021). Review of retinal cameras for global coverage of diabetic retinopathy screening. *Eye*, 35, 162–172. <https://doi.org/10.1038/s41433-020-01262-7>
21. Rajarajeshwari, G., & Selvi, G. C. (2024). Application of artificial intelligence for classification, segmentation, early detection, early diagnosis, and grading of diabetic retinopathy from fundus retinal images: A comprehensive review. *IEEE Access*, 12, 172499–172536. <https://doi.org/10.1109/access.2024.3494840>
22. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
23. Shortliffe, E. H., & Cimino, J. J. (2014). *Biomedical informatics: Computer applications in health care and biomedicine* (4th ed.). Springer. <https://doi.org/10.1007/978-1-4471-4474-8>
24. Szeliski, R. (2010). *Computer vision: Algorithms and applications*. Springer. <https://doi.org/10.1007/978-1-84882-935-0>
25. Tablante, C. V., & Iguban, E. B. (2024). Comparative efficacy of smartphone imaging with 3D-printed adaptor versus fundus camera for diabetic retinopathy screening. *Philippine Journal of Ophthalmology*, 49(2), 122–129.
26. Varo, R., Postigo, M., Bila, R., Díez, N., Vallés-López, R., Siteo, A., Vitorino, P., Mucasse, C., & Chiconela, H. (2023). Evaluation of the performance of a 3D-printed smartphone-based retinal imaging device as a screening tool for retinal pathology in Mozambique. *American Journal of Tropical Medicine and Hygiene*, 109(5), 1192–1198. <https://doi.org/10.4269/ajtmh.23-0378>
27. Vujosevic, S., Limoli, C., Luzi, L., et al. (2022). Digital innovations for retinal care in diabetic retinopathy. *Acta Diabetologica*, 59, 1521–1530. <https://doi.org/10.1007/s00592-022-01941-9>
28. Wang, T.-W., et al. (2025). Systematic review and meta-analysis of regulator-approved deep learning systems for fundus diabetic retinopathy detection. *npj Digital Medicine*. <https://doi.org/10.1038/s41746-025-02223-8>
29. Wintergerst, M. W. M., Keller, H., Scheler, R., et al. (2020). A novel device for smartphone-based fundus imaging and documentation in clinical practice: Comparative image analysis study. *JMIR mHealth and uHealth*, 8(7), e17480. <https://doi.org/10.2196/17480>
30. World Health Organization. (2016). Global diffusion of eHealth: Making universal health coverage achievable. World Health Organization. <https://apps.who.int/iris/handle/10665/252529>
31. Yusuf, A. M., et al. (2022). Validity of smartphone-based retinal photography (PEEK) compared with standard ophthalmic fundus camera. *PLOS ONE*, 17(7), e0273633. <https://doi.org/10.1371/journal.pone.0273633>
32. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>