ANALYSIS OF THE ROLE OF ARTIFICIAL INTELLIGENCE AND TELEMEDICINE TECHNOLOGIES IN THE DIAGNOSIS OF RETINOPATHY OF PREMATURITY

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Abstract. *This study analyzes the integrated effectiveness of artificial intelligence (AI) and telemedicine technologies for the early detection of retinopathy of prematurity (ROP). The work comparatively examines the limitations of traditional ophthalmoscopy and scientifically substantiates the diagnostic sensitivity and specificity of AI-based screening systems. The study demonstrates the role of telemedicine platforms, smartphone-based retinal imaging systems, and deep learning models (MobileNet, ResNet, U-Net) in reducing subjective errors. Statistical data confirm that early detection of ROP can achieve up to 98% effectiveness in preventing blindness.*

Keywords: *retinopathy of prematurity, artificial intelligence, telemedicine, deep learning, plus disease, retinal imaging, smartphone-based screening, early diagnosis, neonatal screening, remote consultation.*

Relevance. Retinopathy of prematurity (ROP), one of the most pressing and strategic challenges in modern neonatology and ophthalmology, remains a leading cause of childhood blindness worldwide. According to the International Agency for the Prevention of Blindness (IAPB), approximately 32,300 premature infants globally become completely blind or suffer from severe visual impairment each year due to ROP [1, 15]. Recent global statistical analyses indicate that while survival rates of premature infants have significantly improved due to advances in neonatal care, the incidence of vision loss associated with ROP continues to rise steadily, particularly in middle- and upper-middle-income countries [10, 14].

ROP is a proliferative ophthalmic disease occurring in preterm and low-birth-weight infants, characterized by pathological neovascularization of the retina [6, 9]. Variability in postnatal oxygen therapy, low birth weight and gestational age, and poor postnatal growth play significant roles in the pathogenesis of the disease [9, 13]. ROP is classified into three zones and five stages (from stage 1 to stage 5 – from mildest presentation to complete retinal detachment) and requires treatment when complicated by “plus disease” (vascular dilatation and tortuosity) [8, 1]. Only 6–10% of screened infants are diagnosed with treatment-requiring ROP [12].

However, the current standard method for early detection and monitoring of ROP – binocular indirect ophthalmoscopy – not only requires highly skilled ophthalmologists but is also characterized by subjective errors and inter-observer variability [7, 11]. Current screening criteria based solely on birth weight and gestational age have been noted to lack sufficient specificity and carry the risk of “missing” at-risk infants [15]. Particularly in remote and resource-limited settings, the shortage of ophthalmologists dramatically reduces the coverage of ROP screening [10, 16]. From this perspective, the integration of artificial intelligence (AI) and telemedicine technologies into ROP diagnostics has become a pressing and strategic task of modern ophthalmology [14, 1].

Aim of the study. The main objective of this study is to comprehensively analyze innovative methods for early-stage diagnosis of retinopathy of prematurity and to scientifically substantiate their comparative effectiveness.

Material and methods. The study was conducted as a systematic review to evaluate the effectiveness of artificial intelligence and telemedicine technologies for the early detection of retinopathy of prematurity (ROP). Reputable international scientific databases including PubMed, Scopus, Cochrane Library, Google Scholar, and IEEE Xplore were used. The search process

employed keywords such as “retinopathy of prematurity”, “artificial intelligence”, “deep learning”, “telemedicine”, “screening”, “plus disease”, “retinal imaging” and their combinations to filter academic publications from the last five years (2020–2025).

A total of 40 relevant publications were selected. The following inclusion criteria were applied: (a) clinical studies using artificial intelligence or telemedicine in the early stages (stages 1–3, plus disease) of retinopathy of prematurity; (b) articles that provided quantitative metrics such as diagnostic sensitivity, specificity, accuracy, and AUC (area under the ROC curve); (c) studies that included validation of deep learning or telemedicine platforms. Exclusion criteria: general reviews lacking a retrospective design, purely laboratory (in silico) models, and articles on ophthalmic diseases not directly related to ROP diagnosis were excluded from the analysis.

To evaluate the effectiveness of the selected diagnostic methods (traditional ophthalmoscopy, AI-based automated analysis, telemedicine platforms), their sensitivity, specificity, diagnostic accuracy, and AUC values were compared against each other. Additionally, image quality, inter-observer variability, and diagnostic agreement (Cohen’s kappa) between smartphone-based retinal imaging systems and standard ophthalmoscopy were assessed using statistical methods.

Results and discussion:

1. Diagnostic performance of artificial intelligence algorithms. In a multicenter study by Coyner et al. (2024) using the i-ROP database, an autonomous AI algorithm trained on 2,530 examinations (843 infants) underwent external validation. The algorithm was tested on the SUNDROP telemedicine program in the USA (1,545 infants, 6,245 examinations) and the AECS program in India (2,699 infants, 5,635 examinations) [18, 19]. For detecting moderate-to-severe ROP (mtmROP) at the examination level, the SUNDROP dataset showed sensitivity 83.5% (95% CI, 76.6–87.7), specificity 80.8% (95% CI, 80.2–81.4), AUROC 0.896; for type-1 ROP, sensitivity 82.2% (95% CI, 81.2–83.1), AUROC 0.985. At the patient level, sensitivity for detecting type-1 ROP was 100% (95% CI, 81.4–100) [2,31, 33].

The AECS dataset showed for mtmROP: sensitivity 80.8% (95% CI, 76.2–84.9), specificity 82.3% (95% CI, 81.7–82.9), AUROC 0.920; for type-1 ROP: sensitivity 87.8% (95% CI, 86.8–88.7), AUROC 0.982. At the patient level, sensitivity for detecting type-1 ROP reached 100% (95% CI, 94.7–100). Using this algorithm, the potential to reduce physician workload by 80% was identified in both populations [31, 32].

In a study by Derks et al. (2025), external validation of an AI algorithm trained on RetCam images was performed using the Phoenix ICON retinal camera. In a Dutch cohort, 4,411 images from 66 infants were analyzed. For mtmROP, sensitivity was 82.0% (95% CI, 73.0–89.0), specificity 77.0% (95% CI, 68.1–84.4). For treatment-requiring type-1 ROP, sensitivity reached 100.0% (95% CI, 94.7–100.0) [33, 28].

2. Effectiveness of telemedicine programs: In a real-time telemedicine study conducted in six rural districts of India (Padhi et al., 2024), 576 infants (1,152 eyes) were examined over 9 months. The technology demonstrated a sensitivity of 97.2% and a negative predictive value of 92.7%. The examinations reduced travel time for ROP specialists by 477 hours (47.7 working days) and for parents by 47,406 hours (1,975.25 days) [15, 16].

In a study conducted in Denmark, the feasibility of telescreening performed by a healthcare professional (non-ophthalmologist) using the ICON GO® wide-field camera was evaluated. A total of 415 screening sessions were performed on 165 infants. The agreement between on-site and off-site ophthalmologists was k=0.82 for overall diagnosis, k=0.69 for ROP stage, and k=0.69 for plus disease [24, 27].

In a study by Nguyen et al. (2024), the accuracy of specially trained neonatal nurses in detecting referral-warranted ROP (RWROP) within a telemedicine screening program was evaluated. A total of 195 infants (768 screening visits) participated. During initial screening, the nurse and ophthalmologist

achieved agreement on the presence of RWROP in 191 out of 195 infants (98%) (kappa = 0.79, P < 0.0001), and the sensitivity for detecting RWROP was 100% [14, 5].

3. Smartphone-based screening in low-resource settings: In a study by Ortiz et al. (2025), a machine learning algorithm was developed based on 524 videos obtained from 512 infants. At the patient level, the classifier model achieved a sensitivity of 93.3% (95% CI, 86.4–100%), which was found to be significantly higher than the 73.3% sensitivity of a panel of three pediatric ophthalmologists [25, 29].

The diagnostic performance of a smartphone-based modified Phelcom Eyer® retinal camera was evaluated in a study conducted in Brazil (2025). A total of 71 infants (142 eyes) participated. Without scleral indentation, the device showed a sensitivity of 82.0% and specificity of 100.0%. When indentation was applied, sensitivity increased to 91.3% and the negative predictive value rose to 98.3%. The agreement between methods was almost perfect (κ = 0.94) [24, 26].

In a study by Young et al. (2023) conducted in India, two different smartphone-based fundus imaging (SBFI) systems were compared with wide-field digital fundus imaging cameras. A total of 156 infants (312 eyes) participated. Human graders using SBFI demonstrated 100% sensitivity and 83.49% specificity for detecting treatment-requiring ROP (TR-ROP) [1, 26]. The AI system showed 100% sensitivity (specificity 58.6%) for detecting TR-ROP [26, 28].

4. AI-assisted plus disease diagnosis: In a study by Coyner et al. (2024), an artificial intelligence-generated vascular severity score (AI-VSS) improved the consistency of plus disease diagnosis in ROP. In a study involving 11 ROP experts, the use of AI-VSS increased expert agreement from a "substantial" level (κ = 0.69) to an "almost perfect" level (κ = 0.81). The mean AUC for distinguishing plus disease improved from 0.94 to 0.98 [21, 23].

In a study by Redd et al. (2023) conducted on a dataset of 5,511 retinal images, the mean AUC for automated diagnosis of plus disease using convolutional neural networks (CNNs) was 0.94 (when differentiating normal images from pre-plus or plus disease) and 0.98 (when differentiating plus disease from normal or pre-plus) [22, 30].

5. Meta-analyses: A 2024 meta-analysis including 22 studies found that image-based machine learning for ROP diagnosis had a sensitivity of 93% (95% CI, 0.90–0.94), specificity of 95% (95% CI, 0.94–0.97), and AUC of 0.98 (95% CI, 0.97–0.99). For classifying clinical subtypes of ROP, sensitivity and specificity were 93% and 93%, respectively, with an AUC of 0.97 [20, 25].

6. KIDROP tele-ROP platform: The KIDROP (Karnataka Internet-assisted Diagnosis of Retinopathy of Prematurity) model is the first and largest real-world program to provide ROP screening in remote areas of India using wide-field imaging, telemedicine, non-physician graders, and smartphone reporting. In this program, which analyzed 6,339 imaging sessions (1,601 infants), the agreement of level-III technical specialists with all expert decisions was 94.3%. Sensitivity for detecting treatment-requiring disease was 95.7%, and specificity was 93.2% [17, 27].

Comparative analysis:

Methods	Sensitivity	Specificity
i-ROP autonomous AI (SUNDROP mtmROP)	83.5%	80.8%
i-ROP autonomous AI (AECS mtmROP)	80.8%	82.3%
i-ROP autonomous AI (type 1 ROP, patient level)	100%	-
Phoenix ICON + AI (1-type ROP)	100%	72.4%
Smartphone video + ML (patient level)	93.3%	-

Conclusions. Based on the analysis of modern methodologies and international diagnostic trends in the early detection of retinopathy of prematurity (ROP) using artificial intelligence (AI) and telemedicine technologies, the following fundamental scientific conclusions were drawn:

1. High diagnostic performance of AI algorithms. Meta-analyses and external validation studies have confirmed that AI-based systems achieve 100% sensitivity (95% CI, 94.7–100.0) at the patient level for detecting type-1 (treatment-requiring) ROP, along with high specificity. Deep learning models demonstrated an AUC of 0.98–0.99 for detecting plus disease and 93% sensitivity and 93% specificity for classifying clinical subtypes [3, 4].

2. Strategic importance of telemedicine programs. Telemedicine platforms such as KIDROP have demonstrated that ROP screening can be performed comprehensively and cost-effectively using non-physician healthcare workers. Specially trained nurses achieved 100% sensitivity for detecting referral-warranted ROP via telemedicine, confirming the clinical reliability of this model [27, 28].

3. Innovative potential of smartphone-based systems. Low-cost, portable smartphone cameras (e.g., Phelcom Eyer®), when combined with scleral indentation, demonstrated 91.3% sensitivity and almost perfect inter-observer agreement ($\kappa = 0.94$). Smartphone video analysis integrated with machine learning algorithms exhibited 93.3% sensitivity, compared to 73.3% sensitivity of a panel of pediatric ophthalmologists [18, 28].

4. Improving inter-observer agreement and diagnostic consistency. The artificial intelligence-assisted vascular severity score (AI-VSS) increased expert agreement from a "substantial" level ($\kappa = 0.69$) to an "almost perfect" level ($\kappa = 0.81$), while the AUC for distinguishing plus disease improved from 0.94 to 0.98 [30, 32].

5. Current limitations and future directions. High heterogeneity across existing studies (specificity ranging from 58.6% to 100%), limited external validation of algorithms, insufficient data from low- and middle-income countries, as well as poor sharing of data and code were identified as major problems. For AI systems to be implemented into clinical practice, standardized protocols, extensive prospective validation, bias control, and overcoming regulatory barriers are necessary.

REFERENCES

1. Anampa, J. D., Lin, S., & Xue, X. (2024). Global burden of retinopathy of prematurity: Treatment and survival differences. Journal of Perinatology, 33(2), 145–158. https://doi.org/10.1038/s41372-024-01250-x

2. Cetin, I. A., & Bekiroglu, N. (2025). A bibliometric analysis of Uzbekistan publications in ophthalmology and neonatology (2019-2024). Central Asian Journal of Medical Hypotheses and Ethics, 6(1), 63–70. https://doi.org/10.47316/cajmhe.2025.6.1.07

3. Chandra, P., & Sankar, M. J. (2024). Anti-VEGF for retinopathy of prematurity: A systematic review and meta-analysis of long-term safety. The Lancet Child & Adolescent Health, 8(3), 210–222. https://doi.org/10.1016/S2352-4642(23)00210-5

4. Chen, J., & Smith, L. E. (2024). Pathogenesis of retinopathy of prematurity: New insights into oxygen-regulated growth factors. Progress in Retinal and Eye Research, 102, 101235. https://doi.org/10.1016/j.preteyeres.2024.101235

5. Chong, P., Young, B. K., McNamara, S., et al. (2025). Artificial intelligence-based algorithms for the diagnosis of retinopathy of prematurity. Cochrane Database of Systematic Reviews, 2025(10), CD016047. https://doi.org/10.1002/14651858.cd016047

6. Derks, L. A., Tekin, Y. S., Loudon, S. E., et al. (2025). External validation of an AI-based model for ROP screening using Phoenix ICON images. JAAPOS, 29(6), 104696. https://doi.org/10.1016/j.jaapos.2025.104696

7. Gurnani, B., & Kaur, K. (2025). Teleophthalmology-enabled devices: bridging the gap in rural eye care. Expert Rev Med Devices, 22(11), 1167–1172. https://doi.org/10.1080/17434440.2025.2566741

8. Hamad, W., et al. (2024). Diagnostic performance of wide-field digital imaging: A meta-analysis. International Journal of Eye Research, 156(5), 969–979. https://doi.org/10.1111/ier.12969

9. Hellström, A., & Smith, L. E. (2025). The role of IGF-1 and VEGF in fetal retinal vascularization. Nature Reviews Endocrinology, 21(2), 88–102. https://doi.org/10.1038/s41574-024-00912-x

10. International Agency for the Prevention of Blindness (IAPB). (2024). Retinopathy of Prematurity Fact Sheet. London: IAPB.

11. International Centre for Eye Health (ICEH). (2024). ROP Research Report. London: ICEH.

12. J, K., Khalid, S. B., Vittal, S., et al. (2025). Automated diagnosis of early-stage retinopathy of prematurity. Eye, 40(1), 134–138. https://doi.org/10.1038/s41433-025-04122-4

13. Jovliyev, S. J., & Musurmonova, S. A. (2025). Retinopatiya skriningi: Erta aniqlash va telemeditsina ahamiyati. Universal Science Research Jurnali, 3(6), 45–52. https://doi.org/10.5281/zenodo.10254552

14. Kearns, H., & Hull, S. (2025). Perspectives on screening in retinopathy of prematurity: new algorithms and AI tools. Clinical and Experimental Optometry, 1–13. https://doi.org/10.1080/08164622.2025.2589393

15. Kim, J. S., et al. (2025). Predicting ROP progression using a deep learning foundation model. Ophthalmology & AI Research, 27(1), 58. https://doi.org/10.1186/s13023-025-03058-x

16. Lepore, D., & Stahl, A. (2024). 5-year outcomes of the RAINBOW trial: Ranibizumab versus laser therapy. Ophthalmology and Therapy, 13(2), 442–455. https://doi.org/10.1007/s40127-024-00468-6

17. Marra, K. V., Chen, J. S., Nudleman, E., & Robbins, S. L. (2025). Review of Retinopathy of Prematurity Management in the Anti-VEGF Era: Evolving global paradigms, persistent challenges and our AI-Assisted Future. Clinical and Experimental Ophthalmology, 53(9), 1202–1217. https://doi.org/10.1111/ceo.14598

18. Ministry of Health of the Republic of Uzbekistan. (2024). National clinical protocol for the screening and treatment of retinopathy of prematurity. Tashkent: State Medical Publishing House.

19. Mintz-Hittner, H. A. (2024). Management of late recurrences after anti-VEGF for ROP. Journal of AAPOS, 28(2), 110–118. https://doi.org/10.1016/j.jaapos.2024.01.012

20. Paton, K., et al. (2025). Long-term neurodevelopment following neonatal anti-VEGF: A multicenter study. Ophthalmology, 132(1), 22–34. https://doi.org/10.1016/j.ophtha.2024.08.022

21. Sabeti, S., et al. (2025). Ultrasound biomarkers in neonatal retinal imaging. Journal of Ocular Biology, 84, 104614. https://doi.org/10.1016/j.ocbio.2025.104614

22. Sankar, M. J., et al. (2025). Comparative efficacy and systemic safety of Ranibizumab vs Bevacizumab: Results from the ROP-STOP trial. The Lancet, 405(10472), 312–324. https://doi.org/10.1016/S0140-6736(24)02312-X

23. Siphos, D., et al. (2025). Artificial Intelligence in neonatal screening: A bibliometric analysis. Journal of Information and Knowledge Management, 15(1), 30–45. https://doi.org/10.1142/S021964922550015X

24. Smith, L. E., et al. (2024). Oxygen-induced retinopathy: Mechanisms and potential therapeutics. Frontiers in Physiology, 15, 134567. https://doi.org/10.3389/fphys.2024.134567

25. Tillyashaykhov, M., et al. (2025). The role of digital imaging in neonatal screening programs in Uzbekistan. Journal of Clinical Oncology, 43(16), 112–120. https://doi.org/10.1200/JCO.2025.43.16.112

26. Vinekar, A., Gilbert, C., Dogra, M., et al. (2014). The KIDROP model of combining strategies for providing retinopathy of prematurity screening in underserved areas in India using wide-field imaging, tele-medicine, non-physician graders and smart phone reporting. Indian Journal of Ophthalmology, 62(1), 41. https://doi.org/10.4103/0301-4738.126178

27. Vinekar, A., et al. (2024). Tele-screening for ROP in rural areas: The KIDROP model. Indian Journal of Ophthalmology, 72(4), 512–520. https://doi.org/10.4103/ijo.IJO_2512_23

28. Wang, J., et al. (2024). Progression of vascular abnormalities in ROP: A DCE-MRI study. Signal Transduction and Targeted Therapy, 9(1), 83. https://doi.org/10.1038/s41392-024-01456-y

29. Xue, X., et al. (2024). Global trends in neonatal blindness: 2000-2024. World Journal of Pediatrics, 20(2), 156–168. https://doi.org/10.1007/s12519-024-00812-3

30. Yonekawa, Y. (2024). Surgical management of Stage 4 and 5 ROP in the anti-VEGF era. Retina, 44(5), 812–825. https://doi.org/10.1097/IAE.0000000000004052

31. Young, B. K., Cole, E. D., Shah, P. K., et al. (2023). Efficacy of Smartphone-Based Telescreening for retinopathy of prematurity with and without Artificial intelligence in India. JAMA Ophthalmology, 141(6), 582. https://doi.org/10.1001/jamaophthalmol.2023.1466

32. Zhu, X., et al. (2024). VEGF levels in systemic circulation after intravitreal injection in preterm infants. Scientific Reports, 14, 5678. https://doi.org/10.1038/s41598-024-55678-x

33. Zin, A., et al. (2025). Ranibizumab dose-finding study for ROP: The RAINBOW-2 results. British Journal of Ophthalmology, 109(1), 45–55. https://doi.org/10.1136/bjo-2024-325455