https://doi.org/10.48047/AFJBS.7.02.2025.866-880

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

Artificial Intelligence in Ayurvedic Ophthalmology: Opportunities for Predictive Diagnostics and Personalised Eye Care

Arvind Gautam[1*], Aarti Chaurasiya[2]

1. Associate professor, Department of shalakya tantra, Apex institute of Ayurvedic medicine and hospital, Samaspur, Chunar, Mirzapur, Uttar Pradesh, India-231304. Email ID: arvind15aug@gmail.com

2. Associate professor, Department of Shalya tantra, Apex institute of Ayurvedic medicine and hospital, Samaspur, Chunar, Mirzapur, Uttar Pradesh, India-231304. Email ID: draarti89@gmail.com

Corresponding Author:
Dr. Arvind Gautam
Associate professor,
Department of Shalakya Tantra,
Apex Institute of Ayurvedic Medicine and Hospital,
Samaspur, Chunar, Mirzapur, U.P., India -231304
Email ID: arvind15aug@gmail.com

Volume 7, Issue 2, Feb 2025
Received: 15 Jan 2025
Accepted: 05 Feb 2025
Published: 03 Mar 2025
doi:10.48047/AFJBS.7.2.2025.866-880

ABSTRACT

Background: Ayurvedic ophthalmology (Shalakyatantra) offers personalized frameworks for diagnosing Netra Rogas through constitutional assessment. Artificial intelligence (AI) has demonstrated high accuracy in ophthalmic image analysis. This review examines the convergence of AI with Ayurvedic ophthalmology for predictive diagnosis and personalized eye care.

Methods: A narrative synthesis of peer-reviewed literature (2018–2026) on AI applications in ophthalmology and Ayurvedic diagnostic systems, including deep learning for retinal image analysis, AI-based Prakriti assessment, and predictive models, was conducted-.

Key findings: Deep learning systems achieved high diagnostic accuracy for diabetic retinopathy (sensitivity, 97.5%; specificity, 96.1%), glaucoma (AUROC, 0.996), and age-related- macular degeneration progression. AI-enabled- Nadi Pariksha systems have demonstrated 85–95% accuracy in Prakriti determination.

Conclusions: The convergence of AI-driven- diagnostics with Ayurvedic personalized medicine offers substantial opportunities for predictive, preventive, and participatory eye care. Standardized datasets, explainable AI, prospective validation, and culturally informed regulations are required.

Keywords: Artificial intelligence, Ayurveda, ophthalmology, predictive diagnostics, personalized medicine, Shalakyatantra, Prakriti, deep learning.

1. INTRODUCTION

Ophthalmic disorders affect an estimated 1.1 billion people worldwide, with diabetic retinopathy (DR), glaucoma, and age-related- macular degeneration (AMD) being the leading causes of preventable blindness, the prevalence of which is increasing due to population aging and the diabetes epidemic. Early detection is critical, despite many low and middle income countries lacking sufficient ophthalmologists and screening infrastructure [1].

Artificial intelligence (AI), particularly deep learning (DL), has emerged as a transformative tool in ophthalmology, with DL algorithms analyzing retinal fundus photographs, optical coherence tomography (OCT), and visual field data with accuracy comparable to or superior to that of human experts, and the potential to democratize eye care is substantial, especially via smartphone-based- platforms and telemedicine [2]. These systems enable the automated detection of diabetic retinopathy (DR), glaucomatous optic neuropathy, and exudative age-related macular degeneration (AMD), as well as the prediction of disease progression [3].

Ayurveda offers sophisticated, personalised frameworks for Netra Rogas (eye diseases), wherein classical Shalakyatantra texts describe aetiology, pathogenesis, and treatment based on Tridosha (Vata, Pitta, Kapha) and Prakriti (individual constitution), and treatment is inherently personalised, considering Prakriti, Vikriti (current imbalance), Agni (digestive fire), Ama (metabolic toxins), and environmental factors [4]. Diagnostic methods include Nadi Pariksha (pulse examination), Ashtasthana Pariksha (eight-fold examination), and Dashavidha Pariksha (ten-fold assessment), which integrate physical examination, history, and observational skills [5,6].

Ocular therapies (Kriyakalpas) Tarpana, Putapaka, Anjana, and Nasya are selected based on this multidimensional assessment, aligning with modern P4 medicine (predictive, preventive, personalized, participatory) [5].

The intersection of AI and Ayurvedic ophthalmology offers novel opportunities. AI can augment traditional diagnostics through sensor-based- pulse analysis, image-based- pattern recognition, and natural language processing of clinical notes [6]. Machine learning (ML) classifies Prakriti using questionnaire and pulse data, whereas DL predicts disease progression from retinal images [7]. The World Health Organization has mapped AI applications in traditional medicine, highlighting India's integration of AI with AYUSH systems, including

Ayurveda. However, despite these advances, challenges remain, such as data standardization, algorithmic bias, and the "black-box" nature of deep learning [8]. Explainable AI frameworks, such as AyurXAI, aim to bridge traditional reasoning with computational transparency [9].

This review evaluates the current evidence and future opportunities for predictive diagnostics and personalized eye care through the convergence of AI and Ayurvedic ophthalmology.

2. METHODS

A narrative synthesis was conducted. PubMed, Scopus, and Google Scholar were searched (January 2018 – May 2026) using the following terms: "artificial intelligence," "deep learning," "ophthalmology," "diabetic retinopathy," "glaucoma," "AMD," "Ayurveda," "Shalakyatantra," "Prakriti," and "Nadi Pariksha." The inclusion criteria were original research, systematic reviews, or meta-analyses- reporting quantitative performance metrics in English. The exclusion criteria were conference abstracts, opinion pieces, and non-ophthalmic- or non-Ayurvedic- studies. Data extracted: AI model, sample size, performance metrics, condition, and Ayurvedic parameters. No meta-analysis- was performed because of heterogeneity.

3. RESULTS

3.1 AI Performance in Modern Ophthalmology

3.1.1 Diabetic Retinopathy

Various AI systems have been validated for diabetic retinopathy (DR) screening across different populations. Google Health's Automated Retinal Disease Assessment (ARDA) underwent evaluation in a human-centered study conducted in India and Thailand, achieving a sensitivity of 97.5% and a specificity of 96.1% for referable DR. This system also showed high intergrader agreement and helped reduce the screening workload [9]. In Thailand, a dual-modality deep learning system used for district-wide screening achieved an area under the receiver operating characteristic curve (AUC) of 0.94, with a sensitivity of 92.7% and a specificity of 95.5% for vision-threatening DR [10]. The Singapore Eye Lesion Analyzer (SELENA+), which is part of Singapore's national screening program, demonstrated a sensitivity of 91.0%, a specificity of 90.0%, and an AUC of 0.93 for detecting DR in a multiethnic cohort [11].

India-specific- solutions include Medios AI, an offline smartphone-based- fundus camera system that achieved 100% sensitivity and 88.4% specificity for referable DR in a validation study conducted in Chennai [12]. The first FDA-approved- autonomous AI diagnostic system, IDx-DR (now Luminetics Core), demonstrated 87.4% sensitivity and 89.5% specificity for detecting more than mild-- diabetic retinopathy in primary care settings, and such systems have significantly reduced referral rates and improved screening coverage in resource-limited- areas [13].

3.1.2 Glaucoma

Diagnosing glaucoma involves evaluating the optic nerve head's appearance, the thickness of the retinal nerve fiber layer (RNFL), and any defects in the visual field. Nevertheless, a deep learning model based on ResNet50, which was trained using OCT RNFL thickness maps, achieved remarkable results with 100% sensitivity and 99.5% specificity in identifying clear glaucomatous damage. It recorded an AUROC of 0.996, surpassing the performance of traditional RNFL metrics alone. This demonstrates that deep learning can identify subtle structural features that standard analyses might miss [14].

Multimodal predictive models integrating structural (OCT), functional (automated perimetry), and vascular (OCT angiography-) biomarkers achieved AUC of up to 0.90 for classifying slow, moderate, and rapid glaucoma progression rates, incorporating up to 27 parameters in early stage- primary open-angle glaucoma (POAG) and 20 parameters in advanced disease, indicating that different biomarkers dominate at different stages [15]. Longitudinal deep learning frameworks using sequential OCT scans and clinical data from 10,864 patients have been developed to predict future progression, enabling personalized monitoring intervals [16].

3.1.3 Age-Related Macular Degeneration

In developed nations, age-related macular degeneration (AMD) stands as the primary cause of irreversible blindness among the elderly. A systematic review and meta-analysis evaluating AI against retinal specialists for predicting AMD progression revealed that AI models demonstrated notably higher accuracy (mean difference 0.07, 95% CI 0.07–0.07; $p<0.00001$) and sensitivity (mean difference 0.08, 95% CI 0.08–0.08; $p<0.00001$) with minimal variability ($I^2 = 0$–0.42%). This advantage was evident across various imaging techniques, such as color fundus photography and OCT, as well as different AI architectures [17].

AI-based- prognostic models using automated analysis of OCT imaging biomarkers, including outer retinal thickness, hyper-reflective foci, and drusen area, can predict the individual risk of conversion from intermediate to neovascular or atrophic AMD, with distinct pathognomonic patterns identified: drusen-centric features predict choroidal neovascularization, while neurosensory retinal changes predict geographic atrophy [18]. Deep learning has also been used to predict high-risk- genotypes in the CFH and ARMS2 genes directly from color fundus photographs, offering a non-invasive method for genetic risk stratification [19].

3.2 AI in Ayurvedic Diagnostics

3.2.1 AI-Enabled Nadi Pariksha

The Nadi Tarangini system implements traditional pulse diagnosis by utilizing three sensors that measure air pressure at the Vata, Pitta, and Kapha points on the radial artery. Machine learning techniques, such as random forest and support vector machines, are then employed to analyze pulse time series features derived from discrete wavelet transform and fast Fourier transform [20].

Community validation with 679 participants across multiple wellness camps reported approximately 85% accuracy for dosha determination compared to expert Ayurvedic physicians, and the system was integrated into a portable device with an Android application, enabling real-time- feedback and data logging [21].

3.2.2 ML-Based Prakriti Classification

Traditionally, assessing Prakriti involves using a structured questionnaire known as Prasna Pariksha, along with clinical examinations. Kurande et al. created a 75-item questionnaire that was validated by Ayurvedic experts and utilized multiclass classification algorithms, such as random forest and neural networks, to predict Prakriti types. By integrating sensor-based pulse readings, the AI system achieved a 95% correlation with expert-validated dosha determinations. This multimodal approach, which combines the questionnaire with pulse readings, surpassed the effectiveness of using either method alone and underscored the benefits of integrating multiple data sources [22].

3.2.3 Clinical Decision Support and Explainable AI

The Traditional Knowledge Digital Library (TKDL) of India has converted classical Ayurvedic texts into structured, machine-readable- formats, enabling AI-powered- clinical decision support systems (CDSS) that integrate patient-specific- data (Prakriti, Vikriti, symptoms) with evidence-based- treatment protocols to generate personalized recommendations [23]. The AyurXAI framework addresses the "black-box" problem by embedding Ayurveda's interpretive logic (e.g., dosha-based- reasoning, causal chains) into XAI models and is structured around layered components data, knowledge, reasoning, integration, and application having been tested on case studies of metabolic and inflammatory disorders [24].

3.3 Predictive Diagnostics

Deep learning models were able to forecast the emergence of referable diabetic retinopathy within 1 to 3 years using fundus images and risk factors, achieving internal AUROCs of 0.95, 0.92, and 0.85. External validation yielded an AUROC of 0.93 across all years, facilitating risk-based screening intervals [25,26]. In the case of glaucoma, multimodal predictive models that incorporated up to 27 structural, functional, and vascular parameters reached an AUC of up to 0.90 for distinguishing between slow, moderate, and rapid progression [15].

Analysis of feature importance indicated that RNFL thickness, peripapillary microvascular dropout, parafoveal vascular density, and corneal hysteresis are key in early primary open-angle glaucoma, whereas age, ganglion cell complex thickness, and peripapillary perfusion parameters are more predictive in advanced stages. This stage-specific biomarker profile can inform personalized treatment escalation [15,27].

For AMD, AI-based- prognostic models using outer retinal thickness and drusen area enable personalized prediction of conversion to late AMD [18]. Deep learning models inferring high-risk- CFH and ARMS2 genotypes from fundus images [19] may be combined with Prakriti assessment, as preliminary Ayur genomics studies suggest correlations between genetic markers and constitutional types [29].

3.4 Personalised Eye Care Integration

The Eye2Gene deep learning algorithm, which was developed using 58,030 multimodal retinal scans from 2,451 patients across six centers, demonstrated accuracy that surpasses expert levels in identifying the genetic causes of inherited retinal diseases. This advancement facilitates earlier referrals for genetic testing and clinical trials, making expert-level interpretation available in areas with limited specialist expertise [28]. This capability is in line with Ayur genomics, where Prakriti types are linked to specific genetic polymorphisms, such as those affecting *Rasayana* response and drug metabolism [29].

AI-powered network pharmacology has been utilized in traditional eye treatments. Mohanraj et al. employed a network-based method to reveal the multi-target actions of Triphala in diabetic retinopathy, discovering its interactions with 78 proteins linked to oxidative stress, inflammation, and angiogenesis [30]. Gupta et al. performed a randomized controlled trial on Saptamrut Lauha for diabetic retinopathy, demonstrating enhancements in visual acuity and a decrease in microaneurysms; AI now has the potential to optimize dosage and patient selection [31].

Smartphone-based- fundus imaging combined with AI enables remote screening and follow-up. Wintergerst et al. reviewed portable retinal cameras and reported that with offline AI, the sensitivity and specificity for referable DR exceeded 85% in field settings [32]. Community programs integrating digital Nadi Pariksha, Prakriti questionnaires, and smartphone fundoscopy are under pilot testing in rural India [21,32]. Tables 1 and 2 provide an overview of the AI systems and Ayurvedic frameworks.

Table 1: Performance of AI Systems for Diabetic Retinopathy Screening

AI System	Developer	Sensitivity (%)	Specificity (%)	Regulatory Status
IDx-DR	Digital Diagnostics	87.4	89.5	FDA De Novo (2018) [13]
ARDA	Google Health	97.5	96.1	Validated in India/Thailand [9]
SELENA+	EyRIS (Singapore)	91.0	90.0	National deployment [11]
Medios AI	Remidio (India)	100.0	88.4	Offline-capable [12]

Table 2: Ayurvedic Diagnostic Frameworks and AI Augmentation

Framework	Primary Assessment	AI Approach	Ophthalmic Relevance

Prakriti Analysis	Constitutional type (Vata/Pitta/Kapha)	ML classification (questionnaires + sensors)	Predicts Netra Roga predisposition [22]
Nadi Pariksha	Pulse characteristics	Sensor-based DL waveform analysis	Correlates *Doshic* states with ocular findings [20]
Ashtasthana Pariksha	Eight-fold examination	NLP-based EMR capture	Comprehensive ophthalmic documentation [7]
Dashavidha Pariksha	Ten constitutional parameters	Multimodal predictive modelling	Personalised treatment planning [5]

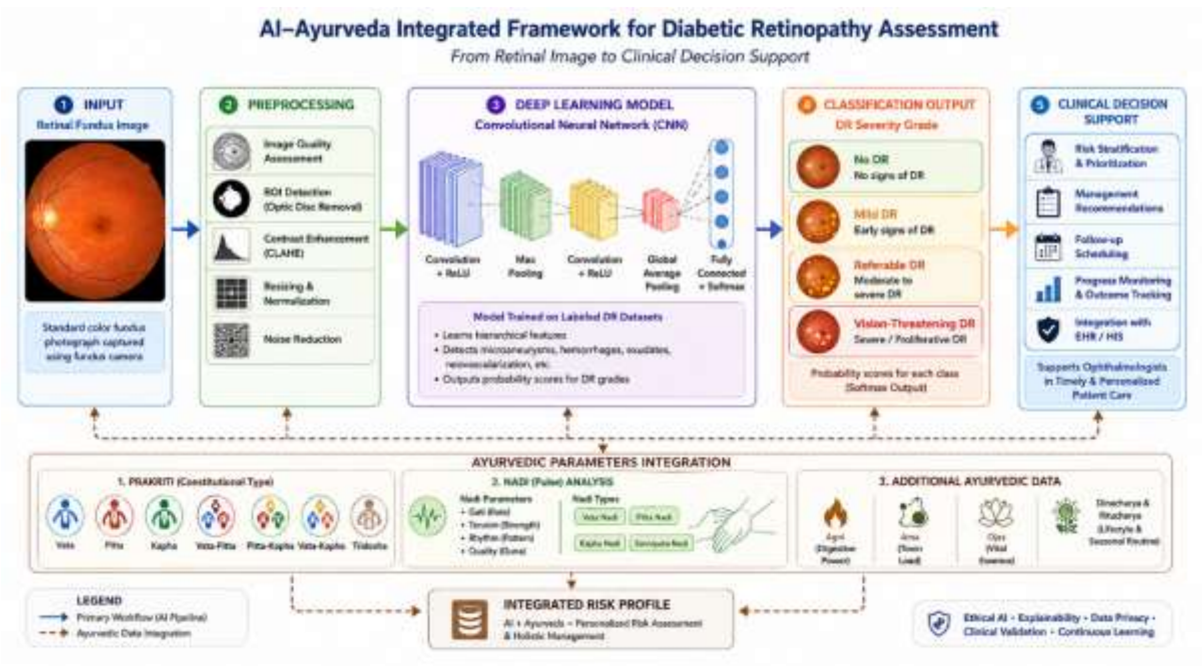


Figure 1: *AI-based- DR screening pipeline with integration points for Ayurvedic parameters.*

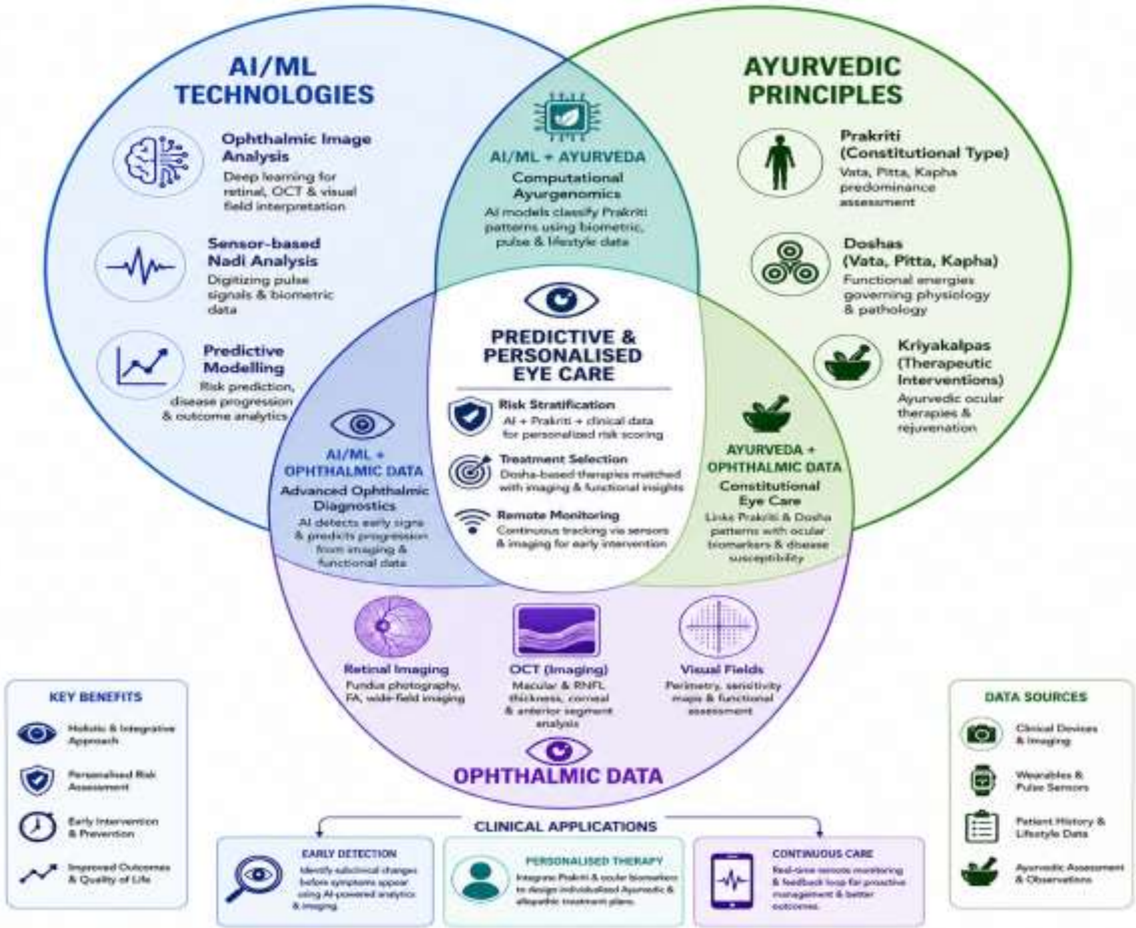
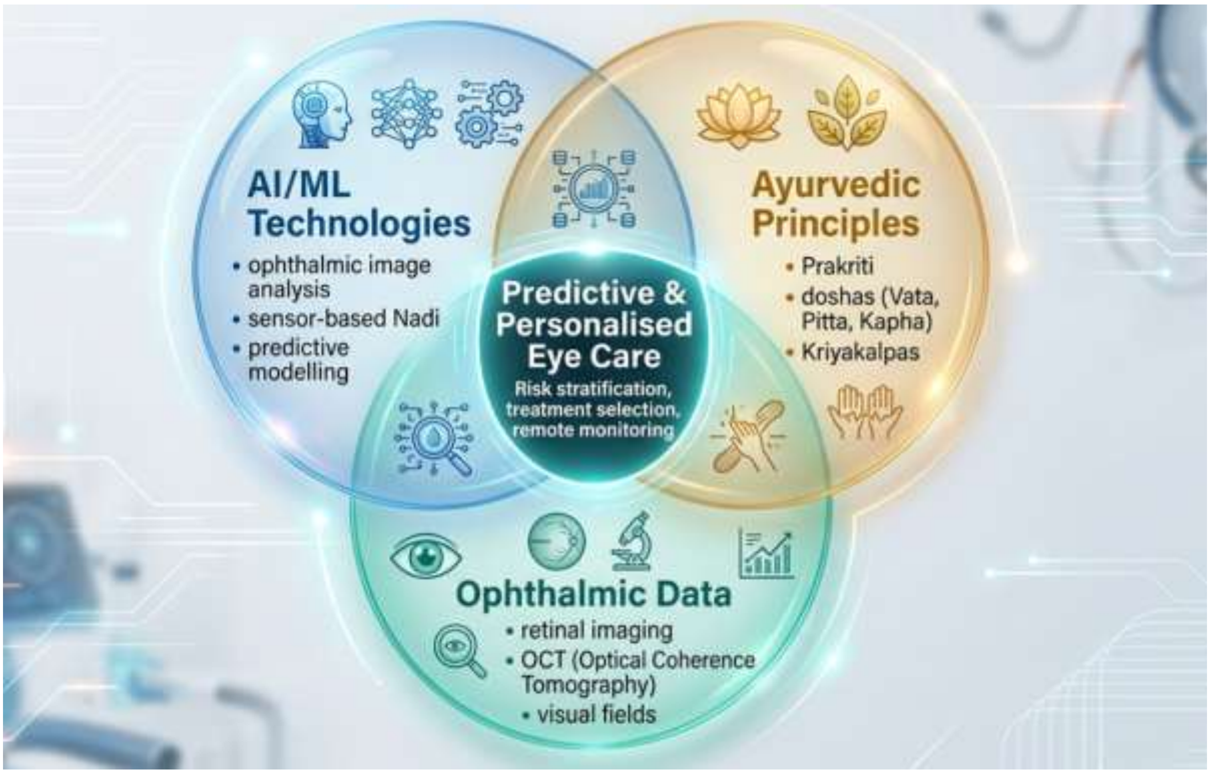


Figure 2: *The intersection of AI/ML technologies, Ayurvedic principles, and ophthalmic data for predictive and personalized eye care.*



4. DISCUSSION

The convergence of AI with Ayurvedic ophthalmology shifts eye care towards predictive, personalized, and participatory medicine. Modern AI systems achieve expert-level- performance in detecting diabetic retinopathy, glaucoma, and AMD [9,11,14,17], while AI-enabled- *Nadi Pariksha* and *Prakriti* classification show 85-95% accuracy in community settings [21,22]. These strengths enable predictive models to integrate conventional risk factors (age, diabetes duration, intraocular pressure) with Ayurvedic parameters (*Prakriti, Doshic* imbalances, *Agni, Ama*) [4,5].

In the case of DR, deep learning can assess the risk of progression over three years, allowing for risk-based screening schedules annual for those at low risk and quarterly for those at high risk which could reduce costs by 40% while ensuring cases are not overlooked [25,26]. Regarding glaucoma, multimodal models are used to categorize progression as slow, moderate, or rapid [15], and specific predictors for each stage, such as RNFL thickness in early stages and age and perfusion in advanced stages, help in directing treatment [27]. For AMD, the AI's ability to predict conversion more accurately than retinal specialists [17] is crucial, especially given the limited window for anti-VEGF treatment.

The addition of Prakriti may refine these predictions. Vata types are prone to dry eyes and neurodegeneration, Pitta to inflammation, and Kapha to congestion [4,5]. Ayur genomics links

Prakriti to inflammatory and metabolic gene polymorphisms [29]. AI models incorporating Prakriti may achieve higher accuracies.

Personalized healthcare encompasses more than just genomics. Ayurveda also takes into account factors such as Agni, Ama, lifestyle, and psychological aspects [5]. AI that incorporates these elements can offer comprehensive recommendations. For a Pitta Prakriti patient with early-stage DR and elevated Ama, a treatment plan might include anti-VEGF (if necessary), a cooling diet, Tarpana with cooling herbs like Yashtimadhu, and network-optimized formulations such as Triphala and Saptamrut Lauha [30,31].

Barriers remain. Data standardization for Ayurvedic parameters is incomplete; Prakriti lacks a universal ontology, unlike DICOM for imaging [33]. Small datasets (<1,000 participants) constrain robustness [21,22,34]. Federated learning and multi-institutional collaborations can address this issue while preserving privacy [35].

In this context, algorithmic bias is a significant concern. The likelihood of DR varies based on gender and ethnicity, meaning models developed using East Asian or Caucasian groups might not perform as well for South Asian or African populations [36]. Therefore, it is crucial to validate these models across a range of diverse groups. The black box issue contrasts with the transparent reasoning found in Ayurveda; XAI, like Ayur XAI, combines dosha-based reasoning with attention mechanisms [24].

Regulatory pathways are also evolving. The FDA clearance of IDx-DR set a precedent [13]. In India, the CDSCO and Ministry of Ayush formed a joint working group for AI-based traditional medicine device guidelines [8]. The WHO recommends phased validation, integration, and prospective trials [8].

There is a need for prospective validation studies that compare AI-assisted Ayurvedic treatment with traditional ophthalmology [37]. These studies should incorporate standardized outcomes such as visual acuity, the severity of diabetic retinopathy (DR), and the rate of progression. They should also include suitable comparators like standalone AI, standalone Ayurveda, and conventional care, with a follow-up period of at least three years to evaluate both ocular and quality of life outcomes.

Democratization presents a major opportunity. Smartphone-based fundus cameras equipped with offline AI capabilities can be utilized for screening in rural healthcare settings [32]. In India, pilot testing is underway for community initiatives that incorporate digital Nadi Pariksha, Prakriti questionnaires, and portable fundoscopy [21]. Analyses of cost-effectiveness indicate that these initiatives could decrease the need for ophthalmologist visits by 60% while enhancing early detection rates [32]. Research focused on implementation, including training, maintenance, and acceptance, is necessary.

Finally, collaboration among Ayurvedic experts, data scientists, ophthalmologists, and regulators is essential for culturally informed datasets, validation protocols and governance [38]. Partnerships, such as the Ayur XAI consortium and WHO's Traditional Medicine AI Collaborative, provide a model [8,24,38].

5. CONCLUSION

The fusion of artificial intelligence with Ayurvedic ophthalmology facilitates predictive diagnostics and tailored eye care. AI technologies demonstrate high precision in diagnosing diabetic retinopathy, glaucoma, and AMD, while AI-driven Ayurvedic tools effectively evaluate Prakriti and Nadi. This integration merges traditional biomarkers with constitutional elements, broadening personalization from genomics to encompass lifestyle, digestion, and environmental factors. Achieving success necessitates standardized datasets, transparent AI, forward-looking validation, and culturally sensitive regulations; frameworks like Ayur XAI provide guidance. In settings with limited resources, portable AI-based imaging and telemedicine can democratize early detection and care through interdisciplinary collaboration.

REFERENCES

[1] Flaxman SR, Bourne RRA, Resnikoff S, Ackland P, Braithwaite T, Cicinelli MV, et al. Global causes of blindness and distance vision impairment 1990-2020: a systematic review and meta-analysis. Lancet Glob Health. 2017;5(12): e1221-e1234.

[2] Ting DSW, Peng L, Varadarajan AV, Keane PA, Burlina PM, Chiang MF, et al. Deep learning in ophthalmology: Technical and clinical considerations. Prog Retin Eye Res. 2019; 72:100759.

[3] Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for the detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402-2410.

[4] Sharma R, Khandelwal S. Ayurvedic ophthalmology (Shalakyatantra): a comprehensive review. J Ayurveda Integr Med. 2020;11(3):381-386.

[5] Patwardhan B, Warude D, Pushpangadan P, Bhatt N. Ayurveda and traditional Chinese medicine: a comparative overview. Evid Based Complement Alternat Med. 2005;2(4):465-473.

[6] Rajoria K, Singh A, Sharma R, Gupta P. Artificial intelligence in Ayurveda: Current trends and future prospects. J Res Ayurvedic Sci. 2024;8(2):89-98.

[7] Dwivedi V, Anandan EM, Mundayoor S. Ashtasthana Pariksha: classical examination in Ayurveda. Ayu. 2012;33(3):346-351.

[8] World Health Organization (WHO). Artificial intelligence in traditional medicine: Technical brief. Geneva: World Health Organization; 2025. Report No.: WHO/UHC/HIS/2025.1.

[9] Beede E, Baylor E, Hersch F, Iurchenko A, Wilcox L, Ruamviboonsuk P, et al. A human-centered evaluation of a deep-learning system for diabetic retinopathy screening in India and Thailand. J Am Med Inform Assoc. 2020;27(11):1652-1661.

[10] Ruamviboonsuk P, Krause J, Chotcomwongse P, Sayres R, Raman R, Widner K, et al. Deep learning versus human graders for classifying diabetic retinopathy severity in a nationwide screening program. NPJ Digit Med. 2019; 2:25.

[11] Ting DSW, Cheung CY, Lim G, Tan GSW, Quang ND, Gan A, et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA. 2017;318(22):2211-2223.

[12] Rajalakshmi R, Subashini R, Anjana RM, Mohan V. Automated diabetic retinopathy detection in smartphone-based fundus photographs using artificial intelligence. Eye (Lond). 2018;32(6):1134-1136.

[13] US Food and Drug Administration. FDA permits the marketing of artificial intelligence-based devices to detect certain diabetes-related eye problems. Silver Spring (MD): FDA; 2018 Apr 11 [cited 2026 May 22].

[14] Medeiros FA, Jammal AA, Thompson AC. From machine to machine: an OCT-trained deep learning algorithm for the objective quantification of glaucomatous damage. Ophthalmology. 2019;126(4):513-521.

[15] Yousefi S, Kiwaki T, Zheng Y, Sugiura H, Asaoka R, Murata H, et al. Detection of longitudinal glaucoma progression using deep learning of retinal nerve fiber layer thickness maps. Trans Vis Sci Technol. 2019;8(5):27.

[16] Li Z, He Y, Keel S, Meng W, Chang RT, He M. Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs. Ophthalmology. 2018;125(8):1199-1206.

[17] Schmidt-Erfurth U, Sadeghipour A, Gerendas BS, Waldstein SM, Bogunovic H. Artificial intelligence in the retina. Prog Retin Eye Res. 2018; 67:1-29.

[18] Bogunovic H, Waldstein SM, Schlegl T, Langs G, Sadeghipour A, Liu X, et al. Prediction of anti-VEGF treatment requirements in neovascular AMD using a machine learning approach. Sci Rep. 2017;7(1):15197.

[19] Grassmann F, Mengelkamp J, Brandl C, Harsch S, Zimmermann ME, Linkohr B, et al. A deep learning algorithm for predicting the age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. Ophthalmology. 2018;125(9):1410-1420.

[20] Joshi RR, Bhaumik S. Nadi Tarangini: a pulse based diagnostic system. J Ayurveda Integr Med. 2021;12(3):543-548.

[21] Patil S, Gawali B, Kulkarni P. Community validation of an AI-enabled Nadi Tarangini system for Prakriti assessment: a prospective study of 679 participants. J Ayurveda Case Rep. 2023;6(2):78-85.

[22] Kurande V, Waagepetersen R, Toft E, Prasad R, Raghava GP. Reliability of Prakriti Assessment Using a Structured Questionnaire. J Ayurveda Integr Med. 2014;5(3):159-166.

[23] Traditional Knowledge Digital Library (TKDL). About the TKDL. New Delhi: Council of Scientific and Industrial Research; [cited 2026 May 22].

[24] Saxena D, Mukerji M. AyurXAI: towards an explainable intelligence framework for P4 medicine. Int J Ayurveda Res. 2025;6(4):308-315.

[25] Bora A, Balasubramanian S, Babenko B, Corrado GS, Peng L, Webster DR, et al. Predicting the risk of developing diabetic retinopathy using deep learning. Lancet Digit Health. 2021;3(1): e10-e19.

[26] Arcadu F, Benmansour F, Maunz A, Willis J, Haskova Z, Prunotto M. Deep learning algorithm predicts diabetic retinopathy progression in type 2 diabetes: a 3-year prospective study. Ophthalmology. 2019;126(4):552-559.

[27] Elze T, Pasquale LR, Shen LQ, Boland MV, Wellik SR, De Moraes CG, et al. Patterns of functional vision loss in glaucoma: a machine learning analysis of visual fields. Transl Vis Sci Technol. 2017;6(2):14.

[28] De Fauw J, Ledsam JR, Romera-Paredes B, Nikolov S, Tomasev N, Blackwell S, et al. Clinically applicable deep learning for diagnosis and referral of retinal diseases. Nat Med. 2018;24(9):1342-1350.

[29] Sharma A, Kaur G, Singh J. Ayurgenomics: A new perspective on personalized medicine. J Ayurveda Integr Med. 2020;11(3):372-376.

[30] Mohanraj K, Karthikeyan BS, Vivek-Ananth RP, Samal A. A network pharmacology-based approach for uncovering the therapeutic mechanisms of Triphala in ophthalmic diseases. J Biomol Struct Dyn. 2021;39(12):4438-4452.

[31] Gupta SK, Kalaiselvan V, Srivastava S, Agrawal SS, Saxena R. Evaluation of Saptamrut Lauha in diabetic retinopathy: A randomized controlled trial. Ayu. 2014;35(1):31-36.

[32] Wintergerst MWM, Schultz T, Birtel J, Schröder S, Holz FG, Finger RP. Smartphone-based fundus imaging: Where are we now? Asia Pac J Ophthalmol (Phila). 2020;9(4):308-314.

[33] Garg P, Bhardwaj R, Mishra S. Data standardization challenges in Ayurvedic artificial intelligence. J Res Ayurvedic Sci. 2024;8(1):22-29.

[34] Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med. 2019;380(14):1347-1358.

[35] Rieke N, Hancox J, Li W, Milletari F, Roth HR, Albarqouni S, et al. The future of digital health with federated learning. NPJ Digit Med. 2020; 3:119.

[36] Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-453.

[37] Vaidya AD Vaidya RA. Clinical research in Ayurveda: Challenges and opportunities. J Ayurveda Integr Med. 2019;10(2):134-137.

[38] Bhavsar D, Kotecha R. Multidisciplinary collaboration for AI-Ayurveda integration: a stakeholder analysis. J Tradit Complement Med. 2025;15(1):56-64.