Bridging the Vision Gap: Role of AI in Diabetic Retinopathy Detection and Clinical Feasibility in Low Resource Settings

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DOI: https://doi.org/10.51584/IJRIAS.2025.100500058

Received: 09 May 2025; Accepted: 14 May 2025; Published: 10 June 2025

ABSTRACT

Diabetic retinopathy is the leading cause of vision loss worldwide, especially in low-resource settings and underserved or rural communities where routine screening is not widely available. Early detection prevents irreversible vision loss, but traditional screening methods require specialized personnel and equipment that are not universally available. These gaps can potentially be filled by artificial intelligence which allows early accurate and flexible detection of diabetic retinopathy. Deep learning models like convolutional neural networks and AI algorithms show similar sensitivity and specificity as human graders in diabetic retinopathy detection. Tools like IDx-DR and EyeArt which have been approved by authorities and adequate regulatory bodies, show promising results for adaptable screening. Integration with mobile and telemedicine platforms, in addition to innovations that improve data diversity and algorithm transparency will increase accessibility, accuracy and trust in artificial intelligence. This review takes a look at artificial intelligence in ophthalmology focusing on its use in diabetic retinopathy detection and also discusses implementation problems it faces like ethics issues and algorithmic bias, data quality and representation, data privacy concerns and limited digital literacy and sustainability in low resource settings. With all these barriers aside, integrating artificial intelligence with telemedicine platforms, mobile diagnostics, national health systems, and recommending policy and collaborations for artificial intelligence deployment can close the gap between diabetic retinopathy screening and eye care access in low resource settings. This paper concludes by recommending more investment, more teamwork across various professions and more inclusive policies to ensure artificial intelligence driven diabetic retinopathy screening technologies benefit all people particularly those most at risk of preventable blindness.

Keywords: Diabetic retinopathy, Artificial intelligence, Deep learning, Low-resource settings, Healthcare equity

INTRODUCTION

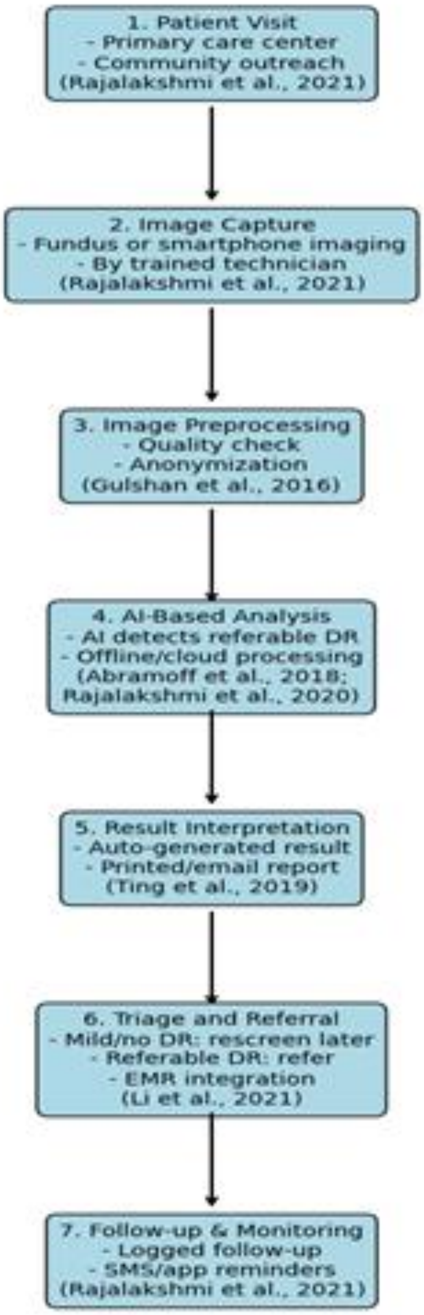
Diabetic retinopathy is one of the most common complications of diabetes mellitus and a leading cause of vision impairment and blindness worldwide, affecting more people who live in low- and middle-income nations that lack proper access to eye care (Teo et al., 2021). Diabetic retinopathy presently affects more than 103 million people worldwide and it is projected to reach 160 million by 2045 due to a growing global diabetes burden (International diabetes Federation, 2021). Early detection and prompt treatment are essential to avoid irreversible vision loss. However, to screen effectively traditional methods require specialized equipment and personnel that are often not available in resource constrained settings (Ting et al. 2019). Such a disparity highlights the need for new and scalable solutions to increase screening access and care equity.

Artificial intelligence (AI) has surfaced as a game changer in ophthalmology by delivering an increasingly automated and correct diagnostic modality. A number of well-trained AI algorithms applied on large datasets of retinal fundus images have demonstrated reliable performance in finding referable diabetic retinopathy. For example, the U.S. Food and Drug Administration FDA approved IDx-DR can autonomously read retinal images and give diagnostic outputs without the need for a clinician interpretation. (Gulshan et al., 2016;

Abramoff et al., 2018) AI has also shown promising results in diabetic retinopathy screening in low-income settings, however a few obstacles keep artificial intelligence based diabetic retinopathy screening from becoming universally applicable in low resource settings. They include image quality variability, regulatory uncertainties, digital illiteracy and data governance issues (Ting et al., 2020). All these issues must be addressed for AI to be safe, fair and sustainable in diabetic retinopathy screening.

In this review, AI is discussed for diabetic retinopathy detection with a focus on its clinical utility in low-resource settings. We review the evidence, challenges to implementation and practical recommendations for using AI to close the global vision care gap.

Flowchart: AI Assisted Diabetic Retinopathy Screening Workflow in Low Resource Settings



Artificial Intelligence Algorithms For Diabetic Retinopathy Detection

Artificial intelligence is a collection of technologies that allow machines to perform tasks traditionally performed by humans such as visual perception, decision-making and pattern recognition. For instance, in

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue V May 2025

ophthalmology, AI via machine learning (ML) and deep learning (DL) has tremendous potential for image-based diagnosis and clinical decision support. (Ting et al. 2019)

Artificial intelligence models for diabetic retinopathy detection mostly use deep learning architectures, most commonly convolutional neural networks (CNNs) for image classification tasks. CNNs can learn hierarchical representations of retinal features such as microaneurysms, hemorrhages and exudates from large image datasets (LeCun et al., 2015; Gulshan et al., 2016) In addition to CNNs, ensemble models based on predictions from several networks or classifiers have been used to increase robustness and model variance (Gargeya & Leng, 2017).

A number of AI systems for diabetic retinopathy screening have gotten regulatory approval. In 2018, IDx-DR became the first FDA-approved autonomous AI diagnostic system. It will analyze retinal images and output binary whether there is presence of more-than-mild diabetic retinopathy or not without an eye care professional input (Abramoff et al. 2018). A second system, EyeArt from Eyenuk Inc. in Europe has also been cleared by FDA and CE marked. Comparative studies have shown that AI systems can outperform human graders in diabetic retinopathy detection. For instance, Ting et al, in 2017 was able to compare deep learning system versus retinal specialists identified referable diabetic retinopathy, diabetic macular edema and other retinal pathologies and they were very similar. More importantly, AI models remove inter-grader variability and fatigue-related errors from human assessments.

Diagnostic performance of AI systems is normally measured in terms of sensitivity, specificity and area under the receiver operating characteristic curve (AUC). According to Gulshan et al., detecting referable diabetic retinopathy using a deep learning algorithm showed a 90.3% sensitivity, 98.1% specificity and AUC of 0.991 compared to expert ophthalmologists (Gulshan et al., 2016). Other high-quality studies with diverse populations have shown similar results (Ting et al. 2017).

Table 1: Performance Metrics of Artificial Intelligence Tools for Diabetic Retinopathy Detection

AI Tool	Sensitivity (%)	Specificity (%)	AUC	Key Notes	Citation
IDx-DR	87.4–90.0	89.5–96.0	~0.980	First FDA-approved autonomous AI system for diabetic retinopathy detection; does not require clinician input	Abramoff et al., 2018
EyeArt (Eyenuk Inc.)	>91.0	>91.0	~0.940	CE-marked and FDA-cleared; validated in large-scale real-world settings	Rajalakshmi et al., 2020
Google DeepMind Algorithm	90.3	98.1	0.991	High accuracy model trained on over 125,000 images; benchmark study for AI DR detection	Gulshan et al., 2016
Ensemble CNNs	~94.0	~98.0	~0.970	Uses multiple deep learning models to increase robustness and accuracy	Gargeya & Leng, 2017
Ting et al. Deep Learning System	~90.5	~91.6	0.936	Validated in multi-ethnic datasets across Asia; demonstrates high generalizability	Ting et al., 2017

Performance of AI Algorithms Across Demographic And Geographic Cohorts

Racial and Ethnic Variations in Retinal Features

There is a critical concern regarding generalizability across demographic cohorts. Most early studies, including those by Gulshan et al. (2016) and LeCun et al. (2015), were conducted on predominantly Western or Asian populations, which raises concerns about the applicability of AI systems to other ethnicities and regions. As AI models are often trained on datasets from specific populations, their performance can degrade when applied to underrepresented demographic groups. For example, darker-skinned individuals, who may exhibit different retinal features or suffer from different comorbidities (e.g., hypertension or cardiovascular disease), might experience lower diagnostic accuracy with AI systems initially trained on predominantly lighter-skinned cohorts. Gulshan et al. (2016) themselves noted that AI performance might be influenced by ethnicity, a factor that warrants careful attention in the validation of these systems across diverse populations.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue V May 2025

Gender and Age-related Disparities

In addition to ethnicity, gender and age also influence AI model performance. Ting et al. (2019) found that AI systems might perform differently based on the age and gender of patients, with potential for lower sensitivity in older populations or specific gender groups. For instance, elderly patients may exhibit more complex retinal pathologies that require more nuanced interpretation. Moreover, the potential overfitting of AI models to younger cohorts may limit their applicability to elderly populations, whose retinal features may differ due to age-related changes in the eye.

Feasibility and Implementation in Low-Resource Settings

The practical aspects of AI-based diabetic retinopathy screening tools in low resource environments such as technical and economic feasibility, interoperability with telemedicine and real-world applications are discussed below

Technical Feasibility

AI-driven diabetic retinopathy detection tools have different hardware and software requirements. Most of the systems work with digital retinal imaging, which requires desktop or portable fundus cameras and adequate lighting conditions. In low resource settings, inconsistent power supply, limited internet access and device maintenance issues may prevent implementation (Xie et al., 2020). Recent developments have tried to make these environments more adaptable. Alternatives include AI systems that can work offline, edge computing and smartphone-based imaging devices that reduce cloud computing and broadband internet usage. Some AI platforms work autonomously on embedded devices and are therefore better suited for rural or off-grid clinics (Rajalakshmi et al. 2021).

Economic Feasibility

AI-based diabetic retinopathy screening will eventually be economically workable despite initial investment on equipment and training. Dependence on eye care specialists and early detection rates are reduced by these systems which in turn reduces long-term costs of blindness and advanced eye care.

In India and Thailand, economic analyses have shown that AI-assisted screening may save money when applied to large populations, especially when rolled out as part of national non-communicable disease programs or telehealth systems (Ruamviboonsuk et al., 2019; Verma et al., 2021).

Table 2. Economic and Operational Feasibility of AI Tools for DR Screening in Low-Resource Settings

AI Tool / Program	Economic Feasibility	Technical Requirements	Deployment Context	Citation
IDx-DR (USA)	Moderate start-up cost; high return on investment in long-term care	Fundus camera, local image processing, no internet required	Used in primary care settings in rural U.S.; autonomous and specialist-free screening	Abramoff et al., 2018
EyeArt (India, Europe)	Cost-effective when scaled nationally	Compatible with standard fundus cameras	Deployed in hospital and mobile DR screening units	Rajalakshmi et al., 2020
Aravind & Sankara Projects (India)	Very cost-effective for rural outreach	Smartphone-based fundus imaging; offline AI processing	Used to screen thousands in remote rural camps with minimal infrastructure	Rajalakshmi et al., 2021
Kenya & Ghana Mobile Programs	Feasible with NGO/donor support	Mobile fundus imaging and cloud-based AI platforms	Piloted in underserved African regions without local ophthalmologists	Tham et al., 2021
Thailand National DR Program	Demonstrated national-level cost savings	Integrated with public health screening and referral systems	Incorporated into national diabetic eye screening programs	Ruamviboonsuk et al., 2019

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue V May 2025

Integration with Telemedicine Infrastructure

AI algorithms also support telemedicine platforms as a triage tool for patients who need specialist attention. In this model, non-specialist personnel take retinal images and send them to AI-enabled platforms for immediate analysis and only abnormal or ambiguous cases are sent to an expert. This hybrid has expanded screening and reduced bottlenecks in rural and underserved areas (Li et al., 2021).

A second benefit is that AI in combination with electronic medical records and mobile health systems allows follow up and tracking referrals to be done in real time which makes continues care more efficient.

Task-Shifting and Workforce Efficiency

Task-shifting as an extension of diabetic retinopathy screening has become feasible due to the global shortage of ophthalmologists and optometrists especially in rural areas. AI tools let community health workers, nurses and technicians do screenings that used to be done only by eye care specialists. Studies show that with little training these cadres can screen large populations accurately using AI-enabled devices. (Ting et al., 2019) This re-allocation of tasks improves coverage, but also frees specialists to work on treatment and more complex cases.

Case Studies and Pilot Implementation

A few pilot studies have proven the feasibility of AI-based diabetic retinopathy screening in low-resource settings.

In India for example, AI-driven programs at Aravind Eye Care and Sankara Nethralaya used smartphone-based fundus photography and offline AI software to screen thousands of patients in rural camps with high accuracy and patient satisfaction (Rajalakshmi et al., 2021)

In Sub-Saharan Africa, Mobile retinal imaging and cloud-based AI platforms have been used in Kenya and Ghana to deliver diabetic retinopathy screening in areas without ophthalmologists (Tham et al., 2021).

In rural United States, primary care clinics in underserved regions, using AI systems such as IDx-DR have shown higher detection rates and shorter wait times for referrals (Abramoff et al., 2018)

These examples show that context-specific adaptation and policy support can improve diabetic retinopathy care in low-resource settings.

Stakeholders' Perspectives on AI Based Programs

Successful implementation of AI based diabetic retinopathy screening technologies depends not only on the availability of appropriate technology but also on the acceptance and engagement of key stakeholders like healthcare providers, patients, and policymakers, and by understanding and addressing their unique concerns, AI based programs can be designed to align with real world needs and limitations.

Healthcare providers

Healthcare providers especially those working in rural or underserved areas often recognize the value of AI-assisted screening in addressing specialist shortages and improving diagnostic capacity. Several studies have found that non-specialist personnel such as primary care physicians, nurses, and technicians are receptive to task-sharing models where AI tools assist with diabetic retinopathy screening (Ting et al., 2019). In India, healthcare workers in rural programs using smartphone-based fundus cameras and AI platforms reported increased efficiency and reach, particularly when dealing with high patient loads (Rajalakshmi et al., 2021). Despite these advantages, providers have voiced significant concerns. A common issue is the “black box” nature of many deep learning models. Surveys indicate that many clinicians prefer AI systems that provide explainable outputs or confidence scores to enhance clinical trust (Gichoya et al., 2022). Additionally, providers emphasize the importance of continuous validation of AI tools across local populations, warning that

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue V May 2025

without such adaptation, diagnostic accuracy may vary due to demographic and environmental differences.

Patients

Patients in low-resource settings often experience the most immediate benefit from AI-driven screening, especially in terms of accessibility and convenience. Studies in India and sub-Saharan Africa have shown high levels of patient acceptance when AI screening eliminates the need to travel long distances to urban eye hospitals (Rajalakshmi et al., 2021). In these cases, patients value faster results, shorter referral times, and early diagnosis, factors that are known to improve outcomes in diabetic eye disease. Nevertheless, patient apprehension toward non-human diagnostics persists. Qualitative interviews and community health reports reveal that some patients are hesitant to trust results generated by machines alone. Concerns range from accuracy and misdiagnosis to anxiety about data privacy particularly in regions where digital literacy is low or where prior experience with healthcare technology is limited (Ting et al., 2019). Building patient confidence will require education campaigns, clear data protection frameworks, and integration with existing trusted healthcare practices.

Policymakers

For policymakers, AI represents an opportunity to improve national health outcomes through scalable innovation, particularly within chronic disease management frameworks. In countries such as Thailand, India, and Kenya, government health agencies have begun integrating AI into broader public health initiatives, including diabetic care and blindness prevention programs (Verma et al., 2021). Policymakers acknowledge the long-term cost-saving potential of early detection and reduced burden on tertiary care facilities. However, practical and regulatory barriers are still remaining. Many low- and middle-income countries still lack formal regulatory pathways for AI approval, raising concerns about quality assurance and post-deployment monitoring. Policymakers further stress the importance of funding mechanisms, including public-private partnerships and insurance integration, to ensure sustainability beyond the pilot stage.

Long Term Sustainability Metrics and Funding Models

While AI-based diabetic retinopathy screening technologies have demonstrated strong diagnostic performance and pilot success, ensuring their long-term viability in low-resource settings requires good sustainability metrics and good financing strategies. Without dedicated frameworks to measure success and sustain investment, many promising AI implementations risk stagnation or collapse once external funding or research support ends.

Sustainability Metrics

To ensure continuity, long-term success of AI screening programs should be evaluated using multidimensional sustainability metrics, including:

Clinical Impact: Continuous monitoring of detection accuracy, referral rates, and reduction in vision impairment among screened populations. Longitudinal follow-up studies can assess whether early detection through AI translates into improved patient outcomes and treatment adherence (Verma et al., 2021).

Cost-Effectiveness: Cost-benefit analysis comparing AI-enabled screening versus traditional approaches in terms of cost per case detected, cost per quality-adjusted life year saved, and reductions in advanced disease management expenses. Studies in India and Thailand suggest AI solutions can be cost-saving when scaled nationally, especially as part of integrated non communicable disease programs (Ruamviboonsuk et al., 2019).

System Integration and Coverage: Metrics should capture integration with electronic medical records, interoperability with telehealth platforms, and uptake in rural and underserved clinics. Coverage indicators such as the number of screenings conducted per year, proportion of high-risk populations reached, and compliance with follow-up referrals are essential for national monitoring.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue V May 2025

Stakeholder Satisfaction and Engagement: Regular surveys of patients, providers, and administrators are crucial to measure satisfaction, trust in AI systems, and perceived utility in daily clinical workflows (Rajalakshmi et al., 2021).

Maintenance and Adaptability: Sustainability also depends on the system's ability to remain functional and up-to-date. Metrics include frequency of algorithm updates, ease of system maintenance, availability of local technical support, and the ability to adapt to evolving clinical guidelines or demographic changes.

Funding Models

To move beyond time-limited pilot projects, AI screening initiatives must adopt adaptable and diversified funding mechanisms. The following models are increasingly recognized as promising:

Public-Private Partnerships (PPPs): Collaborations between governments, tech companies, and healthcare providers can pool resources for development, deployment, and scaling. PPPs allow governments to access private sector innovation while offering companies access to clinical environments and data for refinement and validation (Ting et al., 2019).

Government Subsidies and National Insurance Schemes: Integrating AI-based diabetic retinopathy screening into publicly funded healthcare or universal health coverage schemes (e.g., Ayushman Bharat in India or UCS in Thailand) ensures financial protection and equitable access for vulnerable populations. Subsidies can support hardware procurement, staff training, and software maintenance in rural facilities (Li et al., 2021).

Philanthropic and Donor Funding: International development agencies and global health organizations such as WHO, the Gates Foundation, or USAID can provide seed funding for AI implementation in low-income regions. These funds often focus on technology transfer, capacity building, and monitoring frameworks.

Results-Based Financing (RBF): Under this model, funding is disbursed based on predefined performance indicators such as screening volumes, detection rates, or reductions in advanced-stage diabetic retinopathy diagnoses. RBF models create accountability and incentivize efficiency in service delivery (Gichoya et al., 2022).

Social Impact Bonds (SIBs): These innovative financing instruments allow private investors to fund AI screening initiatives upfront. If performance targets are met (e.g., reduced blindness rates or improved access), investors are repaid by governments or donors with interest. This model is particularly relevant for chronic disease prevention programs

CHALLENGES AND BARRIERS

AI has many challenges even in low-resource settings where there is growing enthusiasm for diabetic retinopathy detection with artificial intelligence. Understanding such barriers will enable responsible, fair and effective AI-driven screening programs.

Ethical issues and Algorithmic Bias

The biggest ethical issue with AI in healthcare is algorithmic bias. AI models that are trained mostly on datasets from high-income or homogeneous populations may perform poorly in diverse or underserved communities. That may result in misdiagnoses, delayed referrals, or unnecessary anxiety that compounds health inequities (Char et al., 2018). Also, the lack of transparency sometimes called AI's "black box" character raises questions about accountability and trust. Informed consent, transparency, and clinician responsibility are needed when using autonomous or semi-autonomous AI systems (Gerke et al., 2020).

Data Quality and Representativeness

For AI models to be reliable, it is highly dependent on training data quality, diversity and volume. Low-quality images, especially from outdated or low-resolution fundus cameras, can reduce algorithmic accuracy. And many current models are trained on datasets that do not include patients from Africa, Latin America, or Southeast Asia (Gichoya et al., 2022). This underrepresentation increases the risk of performance discrepancies when these tools are deployed in low resource/multicultural settings, thereby limiting its broad and generalized used and clinical utility.

Digital Literacy shortfalls

In low resource settings there is often limited digital literacy. Even if hardware is available, healthcare workers may lack digital literacy to operate AI-enabled devices or troubleshoot basic problems (Beede et al., 2020). Implementation thus depends on the technology as well as on adequate training/technical support and system integration.

Regulatory, Legal and Data Privacy Issues

The regulatory landscape for AI in healthcare is fragmented and evolving. Though some AI systems like IDx-DR have received FDA approval, in many countries there are no clear regulatory pathways for approving and monitoring AI tools (Topol, 2019). Also, data privacy laws especially biometric health data are very localised. Patient data protection laws in low-resource countries may be weak and patient data may be misused or accessed illegally (Tsamados et al., 2022). International standards like GDPR or HIPAA are important but often get ignored.

Sustainability and Scalability

Many AI pilots work in the short term but fail at scale. Main challenges are maintenance of equipment's, algorithm updates, personnel training, and financial sustainability beyond initial funding.

In order to be sustainable, AI programs must be included in national health systems and financed by proper financing methods such as public-private partnerships, government subsidies or insurance reimbursement schemes (Ting et al., 2019) And even the best technologies may not deliver immediate or lasting benefits without strategy in planning.

RECOMMENDATIONS AND FUTURE DIRECTIONS

To make the most of AI in diabetic retinopathy screening especially in low resource settings a multi-faceted approach is needed. Current AI tools are diagnostically accurate and offer flexible solutions, but they can succeed only with proper policies, fair design, continuous validation, and sustainable implementation frameworks. Key recommendations and future research areas to promote its success are discussed here in this section.

Improve Data Diversity and Algorithm Transparency

Future AI models need datasets that are representative of different ethnicities, geographic regions and clinical presentations. This reduces algorithmic bias and ensures fair performance across populations (Gichoya et al., 2022). Collaboration to share data and federated learning might yield large, diverse datasets without compromising data privacy (Rieke et al., 2020). Also, explainable AI can increase clinician trust and patient acceptance by making AI decisions transparent and interpretable (Holzinger et al., 2019).

Strengthen Regulatory and Ethical Governance

With the use of AI in healthcare, we need clear regulatory pathways and ethical oversight. Governments and international bodies need standards for AI approval, auditing, accountability and post-deployment monitoring. Guidelines should also provide for informed consent, data ownership and patient autonomy especially in vulnerable populations. (Gerke et al. 2020) Creating globally harmonized but locally adapted regulatory frameworks will foster innovation and protect public health.

Integrate AI in National Health Systems and Telemedicine Platforms

To be expansive and sustained, AI-based diabetic retinopathy screening should be integrated in national public health strategies like non-communicable disease programs and universal eye health initiatives. Integration with tele-ophthalmology platforms, electronic health records and referral networks is critical for workflows and proper implementation (Li et al., 2021).

Support Local Innovation and Capacity Building

Helping local developers, researchers and institutions in low-resource settings build AI solutions may promote context-appropriate technologies and ownership of implementation strategies. Public-private partnerships and funding should focus on open-source tools, affordable hardware and local training (Rajalakshmi et al., 2021). Long-term training and ability building of healthcare workers and personnel in digital literacy, image acquisition and AI ethics is necessary for long term adoption and quality control.

Expand Pilot Projects into Longitudinal Studies

Most of the evidence on AI for diabetic retinopathy screening comes from pilot programs and cross-sectional studies. Longitudinal evaluations are needed for patient outcomes, referral compliance, system-level cost-effectiveness, and long-term sustainability (Verma et al., 2021) These studies should also examine how AI implementation influences clinical decision making, workforce efficiency and patient satisfaction.

Policy that favour AI Deployment

Governments and international health organizations need to develop clear regulatory frameworks and national AI strategies for low-and middle-income communities. Policies must cover AI validation standards, data security, ethical oversight, reimbursement and training of healthcare workers, among others (Wang & Preininger, 2019). Public health policies should also prioritize infrastructure development like broadband internet and power supply for AI deployment in remote areas.

Partnership Models: Public-Private Partnerships and Government Health Programs

AI will use partnership models in diabetic retinopathy detection including public-private partnerships, non-governmental organizations, academic and national health systems. Such models can pool resources, expertise and funding to co-develop, test and evaluate AI tools. (Rajalakshmi et al., 2021) AI-based diabetic retinopathy screening could be adapted to government-funded screening initiatives like national diabetes or blindness prevention programs for fair access and viability.

CONCLUSION

In this review, we have shown how AI can help reduce the global burden of diabetic retinopathy in underserved and low-resource settings with limited access to routine eye screening. Demonstrating how quickly AI technologies are improving especially deep learning algorithms like convolutional neural networks having shown diagnostic performance when compared with human graders. Regulated systems like IDx-DR and EyeArt are significant for clinical adoption. However, converting these advances into action especially in resource-constrained settings face various limitations like data bias, infrastructure deficits, ethical issues, and regulatory uncertainties which we must fully address to successfully use AI in diabetic retinopathy screening.

Future directions have to be focused on making AI systems more inclusive and explainable, also combining mobile health and electronic record platforms, public-private partnerships, and national health programs to have long lasting impact and make it more sustainable. In the end, using AI for broad screening for diabetic retinopathy will only succeed if there is favourable policy to support it and, ethical governance.

If applied correctly, AI may one day transform global eye care delivery and accessibility, so no one is left behind in the fight against blindness from diabetic retinopathy.

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