



# Artificial Intelligence and Mobile Health for Early Detection of Diabetic Complications in Underserved Populations

Athare Nazri-Panjaki  <sup>1,\*</sup>, Sudabe Moodi <sup>2</sup>, Amirpouya Daneshvariyan <sup>1</sup>

<sup>1</sup> Pirogov Russian National Research Medical University, Moscow, Russia

<sup>2</sup> Birjand University of Medical Sciences, Birjand, Iran

\*Corresponding Author: Pirogov Russian National Research Medical University, Moscow, Russia. Email: athare.nazri@gmail.com

Received: 21 October, 2025; Accepted: 26 October, 2025

## Abstract

**Background:** Diabetes is a major health issue, particularly in underserved populations with limited access to healthcare. This paper explores how the combination of artificial intelligence (AI) and mobile health (mHealth) applications can facilitate early detection and management of diabetic complications in these communities. Utilizing AI and mHealth together provides a cost-effective solution to help reduce healthcare gaps in resource-limited areas.

**Methods:** The paper proposes three key ideas: (1) A simple retinal screening pathway using smartphone fundus imaging, analyzed on-device, to detect complications such as retinopathy and neuropathy; (2) a minimum viable dataset (MVD) that includes basic health data and a retinal image for risk assessment; and (3) a negative predictive value (NPV)-first approach to prioritize patients who need immediate care, thereby improving resource allocation. The manuscript also emphasizes the implementation of edge AI, federated learning, offline functionality, and model compression to ensure the system functions effectively in low-resource settings.

**Conclusions:** Finally, it recommends measuring success using metrics such as “time-to-action” and “intervention reach”, ensuring improved health outcomes and offering practical solutions for diabetes care in underserved communities, while providing a model for future healthcare improvements.

**Keywords:** Mobile Health Applications, Diabetes Care, Underserved Populations, Digital Health Technologies, Diabetic Complications

## 1. Background

In underserved populations, artificial intelligence (AI) integrated with mobile health (mHealth) applications can play a pivotal role in the early detection and management of diabetic complications. This perspective examines how such technologies may reduce healthcare disparities by enabling timely monitoring and intervention, particularly in settings where specialist access and longitudinal follow-up are limited.

Diabetes remains a global challenge, with the heaviest burden falling on communities experiencing delayed diagnosis and fragmented care. Unlike studies that assess AI methods or mobile platforms in isolation,

we emphasize their integration and field practicality for low-resource settings – where offline functionality, low total cost of ownership, and minimal training requirements are decisive. By highlighting scalable, cost-effective solutions, we outline how AI-enabled mHealth can meaningfully address inequities in detection and care escalation when resources are scarce (1, 2).

## 2. Methods

We advance three practice-oriented proposals to focus development and evaluation on what matters most in the field. First, a single-touch retinal triage pathway: Smartphone fundus imaging analyzed on-device as the entry point for complication screening.

Retinal microvascular change serves as a systemic barometer; when coupled with lightweight models, a single exam can stratify risk not only for retinopathy but also for co-morbid neuropathy and nephropathy, triggering context-appropriate next steps [tele-ophthalmology, foot exam, urine albumin-to-creatinine ratio (ACR)] even in clinics with intermittent connectivity. Second, a minimum viable dataset (MVD) for low-resource risk stratification: Age, sex, a brief symptom checklist, two vitals (blood pressure, weight), one retinal image, and – where available – step count or heart rate from commodity wearables. This parsimonious bundle enables useful stratification while respecting data minimization and device constraints. Third, negative predictive value (NPV)-first optimization for early screening: In constrained systems, the most valuable model safely rules out those who can wait. Calibration and thresholds should therefore prioritize high NPV in high-risk subgroups so that scarce specialty slots are reserved for those most likely to benefit (3-5).

Translating these proposals into durable services requires an implementation architecture specifically tailored to constraint: Edge AI and federated learning to protect privacy and reduce bandwidth demands; offline-first design with graceful synchronization for intermittent networks; model compression and quantization for on-device inference; and human-centered workflows that fit the routines of community health workers rather than the reverse. Beyond technical deployment, sustainability depends on routine device turnover plans, straightforward retraining schedules, and locally owned data governance (6-8).

### 3. Conclusions

Evaluation should move beyond single summary statistics to outcomes that reflect actual access and timeliness. We therefore recommend reporting (1) time-to-action from the first algorithmic signal to a documented clinical response, and (2) intervention reach – the proportion of high-risk individuals receiving a definitive action within 30 days – both disaggregated by sex, age, and other locally relevant strata (9). These measures align technology claims with patient-level benefit and equity.

Taken together, AI-enabled mHealth can compress time to intervention, personalize surveillance, and

reallocate scarce expertise toward those most in need in underserved communities. By centering single-touch retinal triage, a MVD suitable for constrained environments, NPV-first calibration, and equity-aware evaluation, this manuscript contributes both immediate guidance for current programs and a reproducible framework for future development and governance of digital diabetes care in low-resource settings.

### Footnotes

**Authors' Contribution:** Athare Nazri-Panjaki conceived the idea, designed the review strategy, performed the literature search and analysis, drafted the initial manuscript, and lead all stages of writing, revision, and finalization. Sudabe Moodi contributed to refining the conceptual framework and provided critical feedback on the structure and clarity of the manuscript. Amirpouya Daneshvariyan assisted with supplementary literature checking and provided minor revisions to improve coherence. All authors reviewed the final version of the manuscript and approved it for the submission.

**Conflict of Interests Statement:** The author declares no conflict of interest.

**Data Availability:** The dataset presented in the study is available on request from the corresponding author during submission or after publication.

**Ethical Approval:** This study does not involve human or animal subjects. Therefore, ethical approval is not required.

**Funding/Support:** The present research received no funding/support.

### References

1. Okati-Aliabad H, Nazri-Panjaki A, Mohammadi M, Nejabat E, Ansari-Moghaddam A. Determinants of diabetes self-care activities in patients with type 2 diabetes based on self-determination theory. *Acta Diabetol.* 2024;61(3):297-307. [PubMed ID: 37855999]. <https://doi.org/10.1007/s00592-023-02186-w>.
2. Nazri-Panjaki A, Moodi S, Mohammadzadeh L, Abeyat A, Mohammadzadeh L, Fanaei M. Improving the Accuracy of Wearable Devices in Monitoring Blood Glucose: Lessons from Deep Learning and Real-Time Data Processing. *ADCES Pract.* 2025;13(5-6):16-8.

3. Rajalakshmi R, Arulmalar S, Usha M, Prathiba V, Kareemuddin KS, Anjana RM, et al. Validation of Smartphone Based Retinal Photography for Diabetic Retinopathy Screening. *PLoS One*. 2015;10(9). e0138285. [PubMed ID: 26401839]. [PubMed Central ID: PMC4581835]. <https://doi.org/10.1371/journal.pone.0138285>.
4. Bastawrous A, Giardini ME, Bolster NM, Peto T, Shah N, Livingstone IA, et al. Clinical Validation of a Smartphone-Based Adapter for Optic Disc Imaging in Kenya. *JAMA Ophthalmol*. 2016;134(2):151-8. [PubMed ID: 26606110]. [PubMed Central ID: PMC5321504]. <https://doi.org/10.1001/jamaophthalmol.2015.4625>.
5. Ruamviboonsuk P, Tiwari R, Sayres R, Nganhavee V, Hemarat K, Kongprayoon A, et al. Real-time diabetic retinopathy screening by deep learning in a multisite national screening programme: a prospective interventional cohort study. *Lancet Digit Health*. 2022;4(4):e235-44. [PubMed ID: 35272972]. [https://doi.org/10.1016/S2589-7500\(22\)00017-6](https://doi.org/10.1016/S2589-7500(22)00017-6).
6. 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. [PubMed ID: 33015372]. [PubMed Central ID: PMC7490367]. <https://doi.org/10.1038/s41746-020-00323-1>.
7. Mohnani P, Thümler C, Castillo AA, Tolba R, Bassi A, Simon A, et al. Recent advances in federated learning for digital healthcare systems. In: Imoize AL, Obaidat MS, Song HH, editors. *Federated Learning for Digital Healthcare Systems*. Cambridge, USA: Academic Press; 2024. p. 81-93. <https://doi.org/10.1016/b978-0-443-13897-3.00005-9>.
8. Singh R, Gill SS, Edge AI: A survey. *Internet of Things and Cyber-Physical Systems*. 2023;3:71-92. <https://doi.org/10.1016/j.iotcps.2023.02.004>.
9. Bresnick G, Cuadros JA, Khan M, Fleischmann S, Wolff G, Limon A, et al. Adherence to ophthalmology referral, treatment and follow-up after diabetic retinopathy screening in the primary care setting. *BMJ Open Diabetes Res Care*. 2020;8(1). [PubMed ID: 32576560]. [PubMed Central ID: PMC7312438]. <https://doi.org/10.1136/bmjdrc-2019-001154>.