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Improving community health-care screenings with smartphone-based AI technologies

Sreekar Mantena,
Department of Statistics and Department of Molecular and Cellular Biology, Harvard University, Cambridge, MA, USA

Leo Anthony Celi,
Laboratory for Computational Physiology, Massachusetts Institute of Technology, Cambridge, MA, USA

Division of Pulmonary, Critical Care and Sleep Medicine, Beth Israel Deaconess Medical Center, Boston, MA, USA

Department of Biostatistics, Harvard T H Chan School of Public Health, Boston, MA, USA

Salmaan Keshavjee,
Department of Global Health and Social Medicine and Center for Global Health Delivery, Havard Medical School, Boston, MA, USA

Division of Global Health Equity, Brigham and Women's Hospital, Boston, MA, USA

Andrea Beratarrechea
Institute for Clinical Effectiveness and Health Policy, Buenos Aires C1414CPT, Argentina

Non-communicable diseases cause the majority of global disease burden and mortality. However, in both high-income countries and low-income and middle-income countries (LMICs), a substantial number of patients remain unaware that they have these life-threatening conditions. Previous studies have found that approximately half of adult diabetes cases worldwide are undetected, and a considerable proportion of patients with hypertension, lung disease, and other chronic conditions remain undiagnosed.[1]

Early screening and diagnosis are crucial to enabling prompt treatment, preventing disease progression, and reducing morbidity and mortality. However, it is challenging to screen patients who might not have access to a physician or who live in rural areas that are a considerable distance from health-care facilities. In Tanzania, more than 80% of citizens will never see a doctor in their lifetime.[2] Even in many high-income countries such as the USA, a high proportion of the population is either uninsured or does not visit a primary care physician on a regular basis.[3]

A key barrier to screening underserved and under-resourced populations is poor access to appropriately sensitive diagnostic tools. Many diagnostic platforms are expensive, invasive,

andrea.beratarrechea@gmail.com .

or require trained health-care workers to operate, making them infeasible for deployment in resource-limited settings.

Smartphone-based artificial intelligence (AI) technologies present a potential solution to this challenge. By collecting data from smartphone sensors and leveraging machine learning algorithms to analyse these data, such technologies enable inexpensive mobile screening of many medical conditions. In the past decade, access to smartphones has risen sharply, and modern smartphones are powerful computing devices, with advanced microprocessors, touchscreen displays, high-resolution cameras, and sensitive microphones. AI, when combined with smartphone technology, has the potential to enable diagnostic tests previously only possible in hospital settings.

AI-empowered front-line health workers (including nurses, community health workers, and midwives) could non-invasively screen for a variety of conditions by leveraging a smartphone. When linked to care providers, these technologies could identify disease earlier and improve health outcomes.

For example, heart rate and blood pressure are important vital signs that need to be routinely monitored for patients with hypertension, heart disease, and arrhythmia. Using smartphone camera sensors, many research groups have built technologies that can accurately estimate these vital signs. By leveraging the photoplethysmography technique, smartphone applications can analyse videos of a patient’s fingertip to compute blood pressure, heart rate, and heart rate variability, obtaining readings concordant with those obtained using traditional cuff devices and electrocardiograms.[4,5] Newly developed machine learning models are capable of analysing videos of a patient’s face and processing changes in facial blood flow to detect atrial fibrillation with high sensitivity and specificity.[5] More than 1 billion people globally have hypertension, thus these platforms, once extensively validated, could make screenings more accessible and facilitate early treatment to prevent heart disease and stroke.

Even for conditions that typically require blood tests for diagnosis, smartphone AI technologies could enable non-invasive screening. For example, a smartphone application developed at Emory University (Atlanta, GA, USA) analyses images of fingernail beds to estimate haemoglobin levels.[6] In a pilot study, the application could detect anaemia with a sensitivity of 97% and accuracy was comparable to invasive point-of-care tests such as the HemoCue system (HemoCue; Ängelholm, Sweden), which cost more than US$500 per unit.[6] Anaemia affects over 2 billion people globally and these inexpensive smartphone platforms could facilitate early detection in LMICs where the burden of anaemia is highest.

Smartphone AI technologies also have the potential to complete initial assessments that can be used to refer patients to specialised care. A number of research groups have developed machine-learning algorithms that detect skin disease in images taken by smartphones. Researchers at Stanford University (Stanford, CA, USA) created a deep-learning platform that could identify malignant melanomas and keratinocyte carcinomas with performance that was comparable to certified dermatologists when grading clinical images.[7] Similarly, smartphone applications have been built to detect psoriasis and dermatitis with sensitivities and specificities of more than 90%.[7] These methods could profoundly increase access to routine skin disease screenings and enable front-line workers to triage these conditions early.

Smartphone AI technologies have also been used in ophthalmology to aid diagnosis. Diabetic retinopathy is the leading cause of preventable blindness globally, and fundus cameras that image the interior surface of the eye are typically required to diagnose this condition. However, conventional desktop fundus cameras are expensive, non-portable, and unavailable in many resource-limited settings. In the past 5 years, inexpensive smartphone lens addons have been developed that enable fundus imaging with a smartphone. Combining smartphone fundus imaging with machine learning algorithms has shown great promise for identifying individuals with diabetic retinopathy, and clinical studies have demonstrated sensitivities of more than 95%.[8] The majority of patients with diabetic retinopathy have no symptoms until irreversible visual impairment occurs, thus early detection by smartphone AI technology could be an important tool to prevent blindness and enable prompt referral to an ophthalmologist for further evaluation and treatment.

In addition to image processing, smartphone platforms can also screen for respiratory and neurological disease by analysing microphone-captured audio data. For example, birth asphyxia is one of the top three global causes of mortality in newborn babies, and due to the high costs of blood gas analysers, conventional diagnosis of birth asphyxia is challenging in low-resource settings. A team working in Montreal and Nigeria developed a smartphone application that analyses sound recordings of newborn babies crying to detect birth asphyxia with a sensitivity of 85%.[9] This application could be leveraged by midwives to non-invasively screen newborn babies at risk for asphyxiation. Previous studies have established the potential of auditory biomarkers in diagnosing neurodegenerative diseases. By using machine-learning algorithms to analyse patient voice samples, smartphone applications have been able to detect Parkinson's disease with high accuracy.[10] Leveraging these technologies, front-line health workers could readily screen community members with vocal symptoms of neurodegenerative diseases and refer them to a specialist.

In the past decade the use of AI technologies in medicine has grown exponentially. However, the majority of the literature has focused on the applications of AI within the traditional hospital environment. Smartphone-based AI screening by frontline health workers provides an opportunity to increase early detection of disease in the community and to target high-risk populations and those who do not have access to primary care.

In many LMICs, frontline health workers such as community health workers form the core of health-care systems, educating community members, and screening and triaging patients. These front-line health workers have been restricted by the services they can provide, and most only use smartphones for rudimentary data storage and communications purposes. Smartphone AI technologies could advance the capabilities of community health workers by empowering them to screen for a variety of medical conditions. Since the analysis is fully automated by AI, these platforms could be readily deployable and user-friendly, requiring minimal training.

However, it should be noted that there are considerable challenges associated with deploying AI technologies in health care, particularly in under-resourced settings. High-quality labeled datasets are required to train supervised machine learning algorithms. Algorithms trained on datasets collected in high-income countries might not be generalisable for deployment in other settings. Building models using non-representative data can introduce algorithmic bias, particularly towards minority ethnic groups. Therefore, it is vital to collect data from the target population to train and assess model performance. Building shared data repositories where researchers can externally validate and refine models could be a powerful tool in enabling rapid development and reproducibility.

Furthermore, in the past decade, many mHealth innovations have not advanced into clinical practice or achieved their anticipated impact despite governmental and philanthropic investment, largely due to low levels of adoption and a poor understanding of end-user needs. For smartphone-based AI technologies to meaningfully improve clinical care and avoid so-called pilotitis, such technologies must be thoughtfully integrated into a framework for care delivery. Investments should be made to train front-line health workers and clinicians, and mobile applications should securely transfer data between smartphone devices and existing digital health infrastructure to enable longitudinal care. Smartphone-based screenings are not intended to replace evaluation by a trained clinician. The results of these screenings should be used to triage patients to appropriate health-care providers. Patients who are identified as at risk need to have access to pathways of follow-up diagnosis and treatment, and health systems might need to build capacity to provide this care. Implementation research is required to study the barriers to deployment and effectively scale these interventions.

Overall, community-based screenings could substantially reduce morbidity from many diseases that benefit from early detection. Smartphone-based AI technologies hold promise for improving the diagnosis of diseases in resource-limited settings if they are carefully integrated into health systems. Empowering community health workers with smartphone AI technologies could bring preventative screening and diagnosis to low-resource settings.

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