AI-Driven Health Applications in Africa: A Structured Literature Review with a Focus on Nigeria

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ABSTRACT

Nigeria's health system is often hindered by several challenges, such as inadequate resources like drugs and equipment at health facilities or a shortage of skilled personnel at Primary Health Centers (PHCs), especially in rural areas. As the prospect of Artificial Intelligence (AI) in the healthcare space grows, it is important to determine the current situation with its adoption in regards to solving some of the problems encountered in the Nigerian health system. This paper reviews the applications of AI technology in healthcare in Africa with a focus on Nigeria. Studies that integrated AI techniques to build solutions to target health domains, such as predicting infectious disease or an expert system for diagnosing and monitoring patients in African countries, were identified and studied. Using machine learning, neural networks, and other AI techniques, researchers have proven the benefits of AI integration into systems in Nigeria and other African countries to solve various health issues for local populations. While Nigeria has made commendable progress in applying AI in healthcare, significant opportunities remain. There is still room for the development of cost-effective AI tools that are tailored to local communities to enhance their engagement and health literacy. A critical barrier to the broader adoption of AI in healthcare in the Nigerian setting is the limited availability of high-quality health data. Therefore, there is a pressing need to develop comprehensive and standardized repositories of Nigerian health data that align with the FAIR (Findable, Accessible, Interoperable, and Reusable) data principles. Strengthening these foundational elements will be key in unlocking the full potential of AI in transforming healthcare delivery in Nigeria.

Keywords: Digital Health in Africa, Artificial Intelligence in Healthcare, Expert Systems in Medicine, Public Health Innovation, Machine Learning Applications

INTRODUCTION

The Nigerian primary healthcare system continues to face significant challenges and it is often hindered by a range of obstacles, such as inadequate funding and support from stakeholders, a shortage of skilled personnel, insufficient infrastructure, and scare essential resources like drugs, equipment, and vaccines at facilities (Kress et al., 2016; Ogah et al., 2024; Udenta & Udenta, 2019). Often affected are rural areas that have a shortage of functioning Primary Health Centers (Amedari & Ejidike, 2021). The health system ranks poorly in access, quality, and efficiency, contributing to high mortality rates and disease burdens (Obansa & Orimisan, 2013; Amedari & Ejidike, 2021). In addition to typical recommendations like investing in infrastructure, building capacity, and so on, Nigeria can leverage advanced technologies to enhance healthcare delivery and achieve better health outcomes (Umar et al., 2024). There is an opportunity to utilize technology such as Artificial

Intelligence (AI) to curb infectious diseases in low and middle-income countries like Nigeria, and augment the health system (Otaigbe, 2022).

Over the last two decades, AI in digital health has shown significant growth and potential across the globe with key technological trends like Machine Learning (ML), and deep learning applications in various domains like cardiology and congenital heart defects, promoting maternal and neonatal health, and so on (Khan et al., 2022; Thomford et al., 2020). However, implementation in clinical practice lags behind technological development due to challenges such as regulatory issues, system integration, and stakeholder involvement (Hummelsberger et al., 2023). To address these challenges, experts recommend developing national digital health strategies, creating supportive policy frameworks, and ensuring interoperability of digital health systems (Aerts & Bogdan-Martin, 2021). Despite obstacles, AI is expected to transform healthcare systems from reactive to proactive and preventive, particularly benefiting resource-limited settings (Thomford et al., 2020; Aerts & Bogdan-Martin, 2021).

The purpose of this review paper is to identify, explore, and synthesize existing literature on the development and deployment of AI-driven health applications across Africa, with a particular focus on Nigeria. As AI technologies continue to gain global attention for their potential to improve healthcare delivery, especially in low-resource settings (Khan et al., 2022), this review seeks to understand how these innovations are being applied in the African context, especially within Nigeria's unique healthcare landscape.

The specific objectives of this review are to:

1. Identify and categorize the types of AI-driven health applications currently implemented across Africa, especially in Nigeria.

2. Examine the key healthcare domains and medical challenges in Nigeria where AI technologies are being applied.

3. Analyze the common AI techniques and methodologies used in Nigerian health applications.

4. Highlight the major challenges and limitations faced by AI-driven health solutions in Nigeria and across the African continent.

By achieving these objectives, the review aims to provide a comprehensive overview of the current landscape, uncover gaps in research and implementation, and inform policymakers, researchers, technologists, and other stakeholders on future directions for AI in African healthcare.

The next section explains how the papers were searched and screened for the literature review. Section 3 explains the results of the review, with subsection 3.1 describing the types of AI-Health applications in Africa that were identified, subsection 3.2 highlighting the Healthcare Domains Targeted by AI in Nigeria, subsection 3.3 elaborating on the common AI techniques used in Nigerian health applications, and subsection 3.4 explaining the challenges to AI adoption in the African/Nigerian healthcare system that were identified. Section 4 discusses the patterns identified from the literature, the identified gaps from the current research and applications, and reflections on prospects for Nigeria.

METHODOLOGY

Search Strategy

For this systematic review, Google Scholar, PubMed, and AJOL were searched for studies between 2005 to November 18, 2024 by independent authors, using keywords "Africa", "Nigeria", "Health applications", "Knowledge Based Expert Human", "Natural Language Processing", "Public Human Health", "Neural Network", "Machine Learning" and "Deep Learning". After removal of duplicates and application of inclusion and exclusion criteria, 21 studies were included in this review (Fig. 1).

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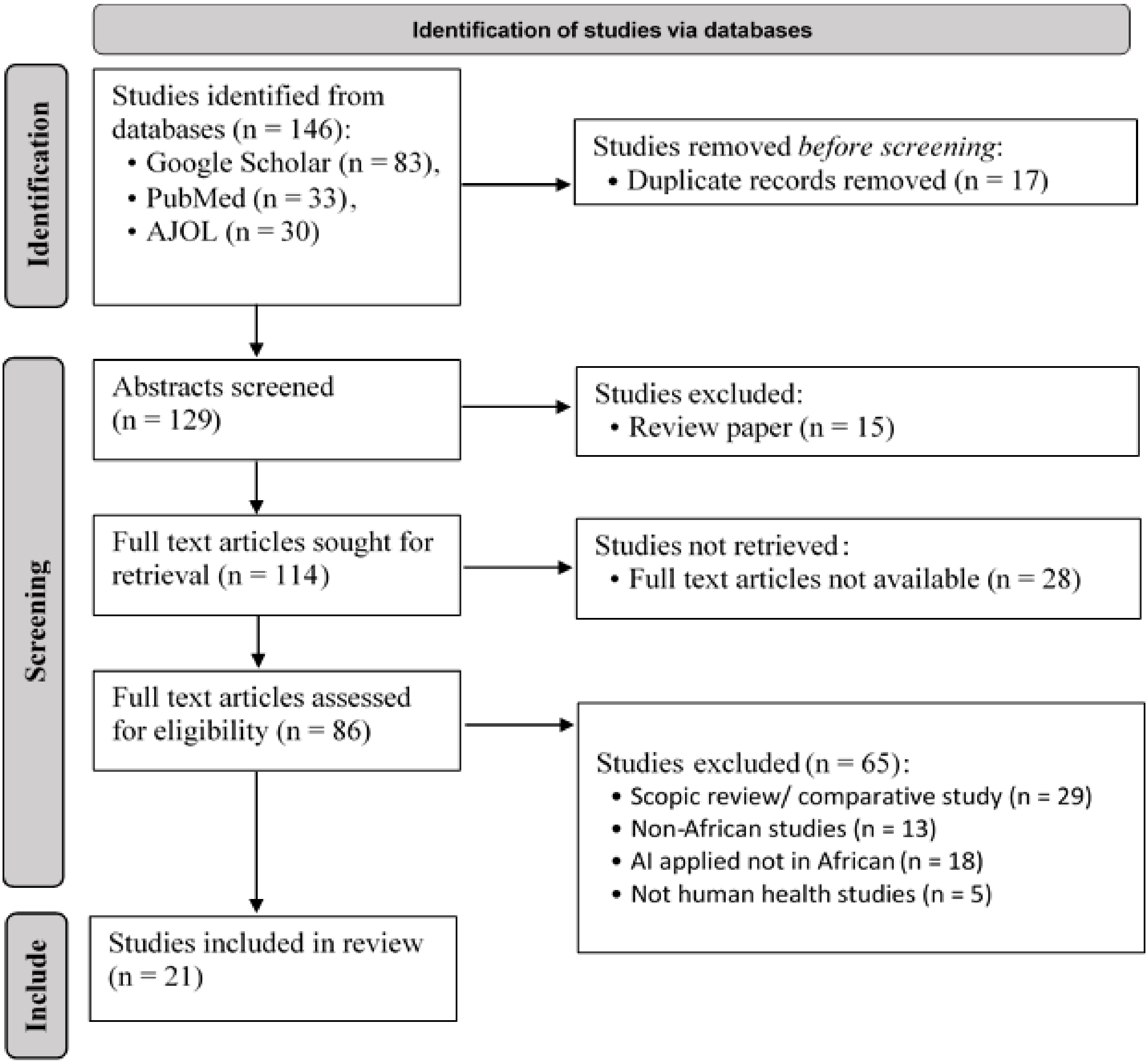

Fig. 1: PRISMA flow chart diagram of the search strategy

Inclusion & Exclusion Criteria

The titles, abstracts, and full texts of studies obtained from the search were used to screen and select studies against the eligibility criteria in Table 1:

Table 1: Study eligibility criteria

Included	Excluded
AI health applications developed in Africa	AI health applications developed for use in non-African countries
At least one AI technique was used during implementation	Scopic review and comparative study paper
Nigeria-focused studies	Non-African studies
At least one model or web-based system was implemented	Applications not focused on human health

Data Extraction Approach

The key information extracted from studies includes author, year, country, AI techniques used, models trained or systems developed, health application domain, and challenges encountered during the study.

RESULTS AND THEMATIC REVIEW

Types of AI-Driven Health Applications Implemented in African Countries

One application of AI that is prevalent in Africa is the prediction of infectious diseases and various outcomes, such as predicting undernutrition among under-five-year-old children in Ethiopia using ML algorithms like Extreme Gradient Boosted (XGB) Tree (Bitew et al., 2022), and airborne pulmonary tuberculosis (TB) in Ethiopia, using Genetic Programming, a variant of machine learning (Tarekegn et al., 2021).

Several studies across Africa favour the use of Neural Network (NN), a technique inspired by the structure of the human brain's neuron (Singh et al., 2013) for health applications. For instance, a study employed an Artificial Neural Network (ANN) model to predict the COVID-19 outbreak in South Africa and other countries across the globe (Niazkar & Niazkar, 2020). NN has some varieties that are suitable for processing image data. A notable example is a diagnostic tool known as CheXaid, developed using a deep learning algorithm to assist in diagnosing tuberculosis (TB). The tool utilizes clinical information and chest x-ray images from HIV-positive patients from hospitals in South Africa to assist clinicians as a web-based diagnostic assistant (Rajpurkar et al., 2020).

Many studies employ a combination of NN with other AI techniques to achieve their goals. For instance, one study conducted in Zambia found that AI model based on an ensemble consisted of a Convolutional Neural Networks (CNNs): an adapted VGGNet architecture and a Residual Neural Network (ResNet) architecture for classifying retinal colour fundus (the inside back of the eye) images showed similar outcomes compared to human graders for detecting referable diabetic retinopathy prevalence and systemic risk factors association with the disease (Bellemo et al., 2019). Another study in South Africa used an ANN model and a Multivariate Logistic Regression model to determine factors such as Systolic blood pressure and Partial pressure of oxygen in arterial blood that are associated with mortality in children admitted to pediatric intensive care units (Pienaar et al., 2022).

Also, in South Africa, Support Vector Machines (SVM), a kind of machine learning, and NN, were used with genome sequence data to predict CD4 cell (a type of white blood cell) count in Human Immunodeficiency Virus (HIV) positive patients to closely monitor the progression of the infectious disease in developing countries where the emergence of HIV drug resistance is evident (Singh et al., 2013). And in another study, a web-based health application that allows doctors to predict brain tumors using a CNN, and stroke using SVM, random forest, decision tree, and logistic regression was developed in Ghana as a contribution to help tackle these neurological diseases (Okae, 2024).

Often, low and middle-income countries (LMICs) face challenges with a shortage of medical services available to patients, an insufficient number of well-trained healthcare professionals, and limited systems that store patient records, which may result in high rates of errors in patient diagnosis (Gebremariam et al., 2024). This has made the development of diagnostic tools necessary, such as in Ethiopia, a localized knowledge-based system for diagnosing pulmonary TB using microscopy results and chest x-rays (Tarekegn, 2016). This system receives inputs and generates diagnoses in Amharic, the Ethiopian national language, to let native users understand their diagnosis more easily. Another tool is the rule-based expert web application, a Maternal Expert System (MES) that uses fuzzy inference to diagnose maternal complications, developed to improve pregnancy outcomes and enhance intervention (Gebremariam et al., 2024). In Kenya, another MES in the form of an expert knowledge-sharing tool was developed for use in the Reproductive Health Division to aid in the diagnosis and treatment of Hypertension in Pregnant women (Gudu et al., 2012). These MES tools can assist medical officers, clinical officers, nurses, and other healthcare professionals, even in the absence of specialists, in managing pregnancy complications, providing counselling by sharing vital expert knowledge and education to pregnant women, as well as monitoring maternal health outcomes (Gebremariam et al., 2024; Gudu et al., 2012).

Furthermore, Natural Language Processing (NLP), another area of AI, has shown great potential for analyzing hospital records to gain new knowledge. For example, in a retrospective study conducted in South Africa, NLP was used to mine the text of verbal autopsy narratives to gain insights into mortality causes and prevalence of

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diseases (Mapundu et al., 2024). In another retrospective study, NLP was used to analyze electronic patient records for general and trauma surgery in LACE (Length of stay, Acuity of admission, Comorbidity, and Emergency department utilization) index scoring to predict trauma and surgical readmissions in a hospital in South Africa (Tokac et al., 2025).

Table 2: Summary of AI Applications in Healthcare Across Selected African Countries

Type of AI Application	AI Techniques	Health Domain	Country
Disease prediction	Extreme Gradient Boosted (XGB) Tree	Undernutrition in under-5 children	Ethiopia
Disease prediction	Genetic Programming	Airborne pulmonary tuberculosis (TB)	Ethiopia
Outbreak prediction	Artificial Neural Network (ANN)	COVID-19 outbreak	South Africa
Diagnostic tool (web-based)	Deep Learning (CheXaid)	TB diagnosis using chest x-ray and clinical info in HIV-positive patients	South Africa
Disease classification	CNN (VGGNet), Residual Neural Network (ResNet)	Diabetic retinopathy from retinal fundus images	Zambia
Mortality prediction in ICU	ANN + Multivariate Logistic Regression	Pediatric intensive care unit mortality	South Africa
Disease progression monitoring	Support Vector Machines (SVM) + Neural Networks	CD4 count prediction for HIV patients	South Africa
Diagnostic tool (web-based)	CNN, SVM, Random Forest, Decision Tree, Logistic Regression	Brain tumors, stroke	Ghana
Localized diagnostic support system	Knowledge-based system	Pulmonary TB diagnosis (Amharic interface)	Ethiopia
Maternal health diagnostic expert system	Rule-based expert system with fuzzy inference	Maternal complications diagnosis (MES)	Ethiopia
Maternal health decision support	Expert system	Hypertension diagnosis and treatment in pregnant women (MES)	Kenya
Health record text analysis (retrospective)	Natural Language Processing (NLP)	Mortality causes from verbal autopsies	South Africa
Health record analysis (retrospective scoring)	NLP using LACE index scoring	Trauma and surgical readmissions prediction	South Africa

Healthcare Domains Targeted by AI in Nigeria

In the last twenty years, AI has been applied in a diversity of target healthcare domains within Nigeria. This review identified AI research conducted by researchers in Nigeria using locally generated data to tailor solutions to Nigerian healthcare reality, such as the development of a rule-based expert system for diagnosing a range of fevers, a common and often misdiagnosed symptom (Tunmibi et al., 2013), use of digital stethoscope recordings with point of-care AI predictions for guided screening for cardiomyopathies (diseases of the heart muscles that makes it hard for the heart to pump blood) in an obstetric population, which could greatly improve maternal health outcomes (Adedinsewo et al., 2024). In another study, AI was used to predict possible cholera outbreaks in Yobe, a state in northern Nigeria (Ahmad Amshi et al., 2023). In the cardiovascular domain, a study used ML and other AI techniques to develop a predictive model for cardiovascular diseases (Babalola et al., 2024).

A similar study that used CNN to develop a model for predicting heart disease using data from a Nigerian hospital and Kaggle (Esan et al., 2024). The study showed that sometimes additional datasets are required for the development of AI models. Other research studies that used global data, inclusive of Nigerian data, include a study that used ML models for predicting the daily cases of COVID-19 in Nigeria and nine other

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African countries (Ibrahim et al., 2023). Another study created generalizable deep neural networks for image quality classification of cervical images in Nigeria, Costa Rica, the USA, and Europe to improve cervical cancer diagnosis, addressing one of the leading causes of female cancer morbidity and mortality in the world (Ahmed et al., 2025). And a Fuzzy-based expert system to diagnose coronary artery disease (Muhammad & Algehyne, 2021).

In some other studies, models were created by either Nigerian researchers or a research team with a Nigerian collaborator using data from international sources. For instance, a model was developed to accurately predict the likelihood of developing diabetes in patients (Edeh et al., 2022), deep CNN and X-ray photographs were used for the auto detection of the coronavirus disease (Hussein et al., 2024), and an AI-based ensemble learning model was developed to predict Hepatitis C disease in patients (Edeh et al., 2022). In the cognitive health domain, a study employed ML techniques to predict dementia (Fayemiwo et al., 2023). Another study used PulmoNet, an improved 26-layer CNN-based model, to predict pulmonary diseases (Abdulahi et al., 2024).

A research team outside Nigeria developed specialist hybrid models with asymmetric training for malaria prevalence prediction and found that their approach outperformed the current state-of-the-art stacked models on an open-source dataset containing 22 years of malaria prevalence data from Ibadan, a city in southwest Nigeria (Fisher et al., 2023). These categories of research show the breadth and direction of AI-driven health research in Nigeria or with Nigerian datasets.

Common AI Techniques Used in Nigerian Health Applications

This section highlights some of the common AI techniques or the adoption of AI used by the selected studies. For instance, one of the Nigerian research studies designed and developed a rule-based expert system for the diagnosis of fever, a common health symptom in many disorders among Africans. The system interacts with users in plain English based on some arranged rules. These rules, which are a typical collection of if/then rules, are extracted from experts in the medical field. Using these rules, a knowledge base was designed for the expert system. Some programming codes were also written in VB.NET to make deduction of new facts from rules in the knowledge base. (Tunmibi1 et al., 2013).

The study conducted by Esan et al., 2024, employs CNN, a deep learning approach for the prediction of heart diseases. The dataset for training and testing the model was obtained from a government-owned hospital in Nigeria and Kaggle, an online platform for data scientists and machine learning practitioners. The resulting system was evaluated using precision, recall, F1-score, and accuracy metrics. The results of the research obtained are: 0.94, 0.95, 0.95, and 0.95 for precision, recall, f1-score, and accuracy, respectively. This shows that the CNN-based model responded very well to the prediction of heart diseases for both negative and positive classes. The results obtained in the study were also compared to some selected machine-learning models like Random Forest, Naïve Bayes, K-Nearest Neighbors (KNN), and Logistic Regression, with results showing that the developed model achieved a significant improvement over the methods considered. Therefore, CNN is suitable for heart disease prediction than some state-of-the-art machine learning.

The research by Edeh et al., 2022 used four supervised machine learning classification algorithms, namely Random Forest, SVM, Naïve Bayes, and Decision Tree DT and an unsupervised learning algorithm (k-means) to identify diabetes in its early stages. The experiments were performed on two databases, provided by the UCI (University of California, Irvine) machine learning repository. Their results showed that the random forest and SVM algorithms outperformed other algorithms.

In the research study by Fisher et al., 2023, an alternative specialist hybrid approach that combines a linear predictive model that specializes in the linear component of the malaria prevalence signal and a Recurrent Neural Network (RNN) predictive model that specializes in the nonlinear residuals of the linear prediction, trained with a novel asymmetric loss. The ML models implemented were EN (Elastic Net), RF (Random Forest), SVR (Support Vector Regression), NN (Neural Network), and BiLSTM (Bidirectional Long Short-Term Memory). Their findings show that the specialist hybrid approach outperforms the current state-of-the-

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art stacked models on an open-source dataset containing 22 years of malaria prevalence data from Ibadan in southwest Nigeria.

Ibrahim et al., 2023 used ML models due to their nonlinearity and accurate prediction capabilities, including ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), SVM, and conventional Multiple Linear Regression (MLR) models to predict the COVID-19 pandemic in Africa. Both ML and MLR models were combined to produce better accuracy. The prediction efficiency of the ML models was enhanced using the novel ensemble approaches of combining ANN-E and SVM-E. The advantage of using ensemble approaches is that they provide collective benefits of all the standalone models, thereby reducing their weaknesses and enhancing their prediction capabilities. The results of the ensemble approaches demonstrated very high improvements in predicting the COVID-19 pandemic in Africa. Another study by Hussein et al., 2024 used a Custom-CNN to identify COVID-19 infection in chest X-rays. The Custom-CNN model consisted of eight weighted layers and utilized strategies like dropout and batch normalization to enhance performance and reduce overfitting. The approach achieved a classification accuracy of 98.19% and aimed to accurately classify COVID-19, normal, and pneumonia samples. Whereas the research study by Abdulahi et al., 2024 used a Deep Convolutional Neural Network (DCNN) founded image detection model, optimized with an image augmentation technique, to detect three different pulmonary diseases, namely COVID-19, bacterial pneumonia, and viral pneumonia.

Fayemiwo et al. 2023 developed models for the prediction of dementia through ML techniques and emphasized assessing the models' sensitivity performance. The dataset used in this study was obtained from the National Health and Aging Trends Study database (NHATS). Nine distinct experiments were conducted to determine which responses from either sample persons or proxy responses in the "word-delay," "tell-words-you-can-recall," and "immediate-word-recall" tasks. These tasks were essential in the prediction of dementia cases, and to what extent the combination of the sample person's or proxy's responses can be helpful in the prediction of dementia. Four machine learning algorithms, namely, KNN, decision tree, RF, and ANN, were used in experiments to build predictive models using data from NHATS.

Table 3: Overview of AI Applications in Healthcare Across Nigeria (2003–2025)

AI Application	AI Techniques Used	Healthcare Domain
Fever diagnosis expert system	Rule-based expert system (if/then rules in VB.NET)	General diagnosis (fevers)
Cardiomyopathy screening in obstetric patients	AI-assisted analysis of digital stethoscope recordings	Maternal cardiovascular health
Cholera outbreak prediction	Machine Learning	Infectious disease (Cholera)
Cardiovascular disease prediction	ML & AI techniques	Cardiovascular health
Heart disease prediction using hospital + Kaggle data	CNN, Random Forest, Naïve Bayes, KNN, Logistic Regression	Cardiovascular health
COVID-19 daily case forecasting	ANN, ANFIS, SVM, MLR, Ensemble Learning (ANN-E, SVM-E)	Infectious disease (COVID-19)
Cervical image quality classification	Deep Neural Networks	Cervical cancer diagnostics
Coronary artery disease diagnosis	Fuzzy-based expert system	Cardiovascular health
Diabetes prediction	Random Forest, SVM, Naïve Bayes, Decision Tree, K-Means	Chronic diseases (Diabetes)
COVID-19 detection via chest X-rays	Custom CNN (8 layers, dropout, batch normalization)	Infectious disease (COVID-19, Pneumonia)
Pulmonary disease detection	Deep CNN with image augmentation	Pulmonary health (COVID-19, bacterial & viral pneumonia)
Dementia prediction	KNN, Decision Tree, Random Forest, ANN	Cognitive health (Dementia)
Malaria prevalence prediction	Specialist hybrid model (Linear + RNN), EN, RF, SVR, NN, BiLSTM	Infectious disease (Malaria)

Challenges to AI Adoption in African/Nigerian Healthcare

Despite the growing interest and progress in the application of AI in healthcare in Nigeria and across Africa, several challenges hinder its full integration and impact within health systems.

A recurring challenge in many studies is the lack of adequate, diverse, and well-structured clinical datasets for training AI models. Public datasets often lack the size and population diversity needed to ensure model generalization across different demographic groups (Abdulahi et al., 2024). This limits the effectiveness and reliability of AI systems when applied in the African clinical settings.

Nigeria has yet to fully implement a comprehensive national digital health policy or strategy to guide the integration of AI and digital health solutions into the health system. The absence of such a policy framework hinders coordinated implementation, regulation, and monitoring of AI-driven health initiatives (Owoyemi et al., 2020).

Some AI approaches, such as genetic programming, are computationally intensive and require significant processing power, making them difficult to apply to large datasets in resource-constrained environments (Tarekegn et al., 2021). Similarly, neural networks (ANNs), which are well-suited for discovering non-linear patterns and complex relationships, are underutilized due to limited access to electronic health records and the small size of available datasets (Pienaar et al., 2022).

Translating AI systems, particularly expert systems, into local languages presents another barrier. For example, adapting medical knowledge into Amharic for use in Ethiopia proved difficult due to both linguistic and cultural complexities (Tarekegn, 2016; Gebremariam et al., 2024). Nigeria, with its linguistic diversity, may face similar challenges in developing culturally and linguistically appropriate AI health tools.

The development and deployment of AI-based expert systems (e.g., Maternal Expert Systems) are often expensive, requiring investment in both software and hardware components, as well as skilled personnel. These costs can be prohibitive in low-resource settings (Gebremariam et al., 2024).

DISCUSSION

Over the past few decades, AI techniques have proved to be useful tools in aiding researchers in Africa to solve health issues, from the prediction of diseases, assisting doctors, and other healthcare staff in identifying early risks in patients to monitoring of patients with a particular infectious disease like Malaria, TB, and HIV were drug resistance maybe a crucial factor in patient management.

For Nigeria, AI holds immense potential to address challenges in the healthcare system, particularly through low-cost, scalable interventions. Mobile health (mHealth) applications, specifically Android applications leveraging AI Application Programming Interfaces (APIs), are especially promising for frontline healthcare workers and patients in low-resource settings. These tools, when developed using open-source platforms and supported by national infrastructure, can provide real-time diagnostic support, triage assistance, and public health surveillance.

However, several systemic limitations continue to hinder the broader adoption of AI in Nigerian healthcare. Chief among these is the lack of accessible, high-quality, and representative clinical datasets. Nigerian researchers often resort to using publicly available datasets from outside the country, which limits the relevance and generalizability of their models to the local population.

To address the challenge with datasets, policymakers should support the creation of a National Health Data Repository governed by FAIR (Findable, Accessible, Interoperable, and Reusable) principles. This effort could include legislation that mandates anonymized clinical data collection across public hospitals, teaching hospitals, and PHCs, ensuring data interoperability through adherence to international standards such as HL7 (Health Level Seven) FHIR (Fast Healthcare Interoperability Resources), and incentivizing collaboration between public health institutions, universities, and tech startups to share and contribute to a national AI-ready data infrastructure.

Additionally, researchers and AI developers in Nigeria could be supported through grant schemes, fellowships, and other funding for AI-for-health research, with a focus on underrepresented regions and diseases, promoting open-source AI models and tools built with local datasets to foster reproducibility and capacity building and encouraging the localization of AI tools, including the development of NLP models for indigenous languages like Hausa, Yoruba, and Igbo to improve patient comprehension and engagement, especially in rural communities.

Finally, the absence of a national policy on AI in healthcare is a key barrier. Nigeria should develop a National AI for Health Strategy, aligned with WHO's guidance on digital health, that clearly outlines standards for ethical AI development and deployment, data privacy and patient consent, public-private partnerships for innovation, and AI regulation, testing, and clinical validation frameworks.

CONCLUSION

AI applications are enhancing healthcare systems across Africa, improving diagnostics, disease prediction, and health outcomes, particularly in areas burdened by infectious diseases and resource constraints. Nigeria has made commendable progress in adopting AI for healthcare, but efforts remain fragmented and under-resourced.

To fully realize the benefits of AI in Nigeria's healthcare system, a coordinated and well-supported national strategy is essential. Policymakers need to prioritize the establishment of FAIR-compliant health data repositories, enact supportive AI governance policies, and incentivize research and innovation in AI applications tailored to the Nigerian context.

For researchers, focusing on developing AI models using localized data and languages, engaging in interdisciplinary collaborations, and contributing to open datasets and tools will be critical in driving forward sustainable digital health transformation.

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