

Artificial Intelligence and Machine Learning for Neurological Disorders in Africa: Conceptual Framework for Implementation in Nigeria

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ABSTRACT

Background: Neurological disorders are a leading cause of disability and mortality worldwide, with sub-Saharan Africa experiencing a disproportionate burden due to the coexistence of communicable and non-communicable neurological diseases. In Africa, Nigeria bears the highest burden of stroke, and some neurological disorders, compounded by limited access to neurologists, neurodiagnostic facilities, and advanced imaging technologies which results in delayed diagnosis, poor clinical outcomes, and the risk of morbidity and mortality. Artificial intelligence (AI) and machine learning (ML) offer significant opportunities to improve neurological diagnosis, yet their implementation in Nigeria remains fragmented and lacks a context-specific framework. The objective of this study is to review current evidence on the burden of neurological disorders and AI/ML applications in neurological diagnosis in Nigeria and Africa, and to propose a practical implementation framework tailored to Nigeria's healthcare system.

Methods: A narrative literature review was conducted using PubMed, Scopus, Google Scholar, and African scientific databases to identify peer-reviewed studies published between 2016 and 2026. Eligible studies evaluated AI/ML applications for the diagnosis or prediction of neurological disorders in African populations or addressed implementation challenges relevant to low- and middle-income countries. Evidence was synthesized to identify implementation priorities and how to develop a health system-based framework.

Results: Available evidence demonstrates that AI/ML models applied to magnetic resonance imaging, computed tomography, electroencephalography, and clinical datasets can improve the detection and risk prediction of stroke, epilepsy, dementia, and other neurological disorders, with reported diagnostic accuracies promising, but subject to dataset bias and local infrastructure limitations. Major barriers to the implementation of these models include fragmented health information systems, inadequate digital infrastructure, limited funding, algorithmic bias, and shortages of skilled personnel.

Conclusion: A nationally coordinated AI/ML implementation framework provides a feasible pathway for strengthening neurological diagnosis in Nigeria. Investment in digital health infrastructure, locally representative datasets, workforce capacity, and regulatory governance will be critical for translating AI innovations into equitable, scalable, and sustainable neurological care across Nigeria and other resource-constrained African settings.

Introduction

1.0 The Landscape of Neurological Disorders in Africa

Neurological disorders contribute significantly to the overall disease burden worldwide with the African continent bearing a considerable share of this burden¹. While the incidence and prevalence paradigms have risen concordantly, the burden of neurological disorders in

Africa, especially in the low-income countries remains underestimated^{1,2,3}. At this time, stroke, epilepsy, and dementia are the leading contributors to neurological disorders^{4,5}. Stroke, often caused by bleeding in the brain - hemorrhagic stroke is a more prevalent cause in the low- and middle-income class countries (LMICs). The stroke investigative research and educational network (SIREN) carried out a study that examined stroke patients across

African countries, the results show that very fewer adults patients are even aware of their blood pressure status before stroke eventually sets in^{6,7}. Tension-headache is another highly prevalent nervous system disorder globally^{8,9}. A critically important measure of the debilitating effects of neurological disorders is the associated mortalities and the disability-adjusted life years (DALYs), manifested as a profound drop in quality and healthy life expectancy, usually occur in the low- and middle-income class countries⁸. Around 15% of these disorders is quoted as the DALYs, which is a concise health metric that predicts disease burden which leads to palpable economic and human capital losses. Worthy of mention is that the burden of neurological disorders is associated with an infectious disease undertone in Africa; because of the interplay between infectious diseases such as neurocysticercosis, cerebral malaria, bacterial meningitis etc, and the immune system leading to some neurological disorders^{3,10}. The core symptoms of the common disorders, such as dementia, may be given gross attention in the diagnosis and management, while the underlying infectious agents or directly implicated epidemiological factors are subdued. In Sub-Saharan Africa, infections of the central nervous system are the most prevalent neurological disorders⁴. There exists a “meningitis belt” of Africa where bacterial meningitis is most prevalent, and contributes majorly to the overall worldwide burden^{11,12}. Furthermore, Aderinto and colleagues in 2023¹³ highlighted the gross underreporting of these neuroinfectious diseases, with the high prevalence and considerable ability of these disorders to pose a significant epidemiological and economic burden¹³. This is in addition to an increasingly profiled burden of neurological diseases of infectious origin in Africa. On one hand, the epidemiological status of first-world countries currently follows a lower incidence of neuroinfectious diseases, such as bacterial meningitis or neurocysticercosis; on the other hand, the status of the LMICs in Africa displays a much higher incidence^{14,15}. This reflects the disparity of the two healthcare systems in combating infectious and communicable diseases over the years. Data on mortality and morbidity remain sparse in the developing regions of Africa and even in certain regions of the world. Hence, there is a pressing need to carefully delineate the epidemiology of these diseases in Africa, paying attention to key incidence and risk factors, prevalence patterns, diagnostic pointers, and burden profiles. The gap in treatment strategies between the majority of Africa and the rest of the developed world remains huge. This further complicates the already ingrained ideology of the local populace such that the neurologist or health practitioner is viewed through the lens

of an all-knowing, all-sufficient personality, coupled with the belief that certain neurological disorders are spiritual or outworldly^{16,17}. Moreover, the medical and health training does not necessarily reflect the peculiarity of the healthcare needs of the population in LMICs.

1.1 Growing burden of Neurological disorders in Africa

Neurological disorders are a growing global health challenge, affecting 42% of the world's population, with over 435 million disability adjusted life years (DALYs) and 11.8 million deaths in 2021¹. The top neurological diseases associated with loss of health were stroke, neonatal encephalopathy, migraine, Alzheimer's disease (AD) and other dementias, diabetic neuropathy, idiopathic epilepsy, neurological complications linked with autism spectrum disease, and other nervous system disorders¹⁰. About 53% of African countries recorded an increase; these were among the 102 WHO member states that provided information for the global status report on neurology, and Nigeria (the most populous African country) carries a higher burden². In low and middle-income countries, access to diagnosis, treatments, care, and rehabilitation is limited, accounting for 80% of disability-adjusted years, due to the high cost of treatment, alongside poor financial and social protection. In 2019, a report noted an increase in new cases and deaths. In Africa, 33% of population experience some loss of nervous system health¹⁸. In 2018, Komolafe et al. reported that the most diagnosed neurological disorders at the Obafemi Awolowo Teaching Hospital in Nigeria over eight years, between 2003-2005 and 2010-2014 includes episodic and paroxysmal disorders such as epilepsy, cerebrovascular diseases, headaches, and sleep disorders¹⁹. A similar study conducted in Sudan revealed stroke, epilepsy, headache, movement disorder, peripheral neuropathy, and dementia²⁰. In LMIC, a substantial diagnostic gap occurs in neurological diseases such as dementia, resulting in an underestimation of the true burden of these diseases². The paucity of data due to a lack of clinical registries or infrastructure to aid data collection and a large diagnostic gap leads to the underestimation of the actual burden of neurological disorders. Consciously, the pendulum appears to be swinging in the direction of a rise in the tide of neurodegenerative conditions, such as Parkinson's disease and Alzheimer's disease in Africa²¹. With Nigeria in focus, neurological diseases—including stroke, epilepsy, neurodegenerative disorders, neuropathies, and CNS infections remain a major and growing public health burden where stroke alone accounts for over 160,000 deaths annually, with an estimated prevalence of 1.14 per 1,000 population²². Epilepsy affects approximately 4–6 per 1,000 Nigerians; one of the highest

rates in Africa²³. Despite this burden, Nigeria faces severe shortages of neurologists, neurodiagnostic equipment, and diagnostic imaging capacity. Artificial intelligence (AI) and machine learning (ML) offer transformative potential for improving early diagnosis, triage, and management of neurological diseases. Studies have shown that AI/ML can address Nigeria's diagnostic challenges by automating interpretation of Magnetic Resonance Imaging (MRI), Computer Tomography (CT) scan, Electroencephalograph (EEG) clinical data; supporting non-specialist clinicians in rural and peri-urban areas; reduce diagnostic delays; improving triage for urgent referrals; enhancing early detection of stroke, flagging abnormalities as early symptoms, epilepsy, dementia, and neuropathies. Pilot studies in Nigeria suggest that deployment and implementation of AI/ML for neurological use is feasible, Aribisala and colleagues (2025) showed a 80% accuracy of ML models in predicting stroke risk using the SIREN clinical datasets in an African based study including participants from Nigeria²⁴. Similarly, EEG datasets have been used to train ML models for epilepsy detection with an accuracy of 85–90%²⁵.

However, successful implementation requires a context-specific framework grounded in Nigeria's health system realities, infrastructure constraints, and regulatory environment. There is a paucity of neurology-based research in Nigeria designed for implementation of AI and ML which are key aspects for reducing the burden of neurological disorders, improving diagnosis, disease prevention, and for tailored treatment. Robust policy recommendations that will inform treatment guidelines and implementation of AI/ML protocols are sorely lacking. Therefore, this review positions a comprehensive framework for implementing AI/ML based diagnostic systems for neurological diseases with Nigerian-based scientific evidence and aligned with global best practices.

2.0 Methods

A non-systematic narrative literature search was conducted on the use or adoption of artificial intelligence (AI) and machine learning (AI/ML) in the diagnosis and treatment of neurological disorders in Nigeria and broadly using African datasets. The review was carried out to provide a background on the gaps, challenges with diagnosis and current use and implementation of AI/ML applications in neurology in resource-poor settings across Africa. Multiple keywords were searched from databases including PubMed, Google Scholar, Scopus, and African Journals Online to identify peer-reviewed articles published between January 1, 2016 and May 30, 2026 which used AI/ML for diagnosis of Neurological disorders with

datasets from the African population. The individual keywords or phrases searched included but not limited to “Artificial intelligence”, “Neurological disorders” “Machine Learning”, “AI/ML”, “neurological conditions”, “Stroke diagnosis”, “Epilepsy diagnosis”, “Alzheimer's diagnosis” AI/ML in Africa”, “AI/ML” “neurological diagnosis” and “Nigeria”, “AI/ML in neurological disorders”. We combined the multiple search terms for a flexible literature search of articles relevant to the study. To produce a robust review, other articles that used AI/ML for neurological diagnosis, outcome prediction, or discussing challenges were also included as relevant to Nigerian context. The criteria for inclusion of a study were based on the focus on AI applications in neurological conditions in Africa, that it provides empirical evidence of AI's performance in diagnosing, treatment, or managing neurological disorders in African patients. We excluded systematic reviews and articles on AI/ML in neurological disorders using only non-African populations. The review also synthesized information on the challenges of AI/ML implementation in Africa and core African databases. Each article title and abstract was carefully reviewed by 2 authors; duplicate articles were removed, relevant articles were then selected and the information on AI/ML methods used, dataset, outcome on neurological disease was manually extracted to provide a comprehensive background on the use of AI/ML in neurology particularly in the African population.

2.1 Current practice for Diagnosis of neurological disease in Africa

Diagnosis of neurological disorders is based on clinical, laboratory, and radiological findings. Diagnosis of neurological diseases is important for swift treatment, disease progression evaluation, and improved treatment outcomes.

Stroke: Stroke is a health emergency and timely care is critical. Imaging such as Computed Tomography CT and Magnetic Resonance Imaging (MRI) scans are used in its diagnosis²⁶. On patient presentation to the hospital, the patient is evaluated for rapid recognition of Stroke symptoms 'FAST' (face- for facial droop, arm-weakness in either one or both arms, speech-slurred or strange speech, and time). The presence of these symptoms will necessitate an immediate CT scan if available or referred to a health care facility with a CT scan²⁶. A study conducted by Pires et al, 2026 revealed the citizens of Brazil had access to diagnostic services with 85% of the stroke units having neurologists available around the clock²⁷.

Epilepsy: A common clinical feature is seen among

different types of attack disorders; hence, the diagnosis of epilepsy is based on the ensemble of features, not on single features^{28,29}. The Electroencephalogram is used in diagnosis, identifying the type and treatment of epilepsy. This test is performed by a specialist and generates a large amount of data. Neuroimaging such as MRI and CT scan may also be used; however, CT scan is contraindicated in patients presenting at the emergency department after a typical seizure³⁰.

Migraine: The management of migraine misdiagnosis and poor treatment persist. The patient's medical history is crucial in the diagnosis of migraine. However, diagnostic aids such as headache diaries, headache calendars, three-item identity migraine questionnaires are not consistent. Further investigations such as neuroimaging, blood samples or lumbar puncture may be used to ascertain the secondary causes of headache³¹.

Alzheimer's disease: In 2021, 57 million people were estimated to have dementia, with about 60% of the patients living in low and middle-income countries³². AD presents with an asymptomatic phase characterized by neuropathologic changes such as amyloid beta (A β) deposition and pathologic tau. Alzheimer's disease can be diagnosed by measuring A β , tau, and the hybrid ratio (p-tau 181/A β 42, t-tau/A β 42, A β 42/40) biomarkers (core 1 biomarkers) in the cerebrospinal fluid, plasma, and neuroimaging³³. The amyloid PET, cerebrospinal fluid (CSF) A β 42/40, CSF p-tau 181/A β 42, and CSF t-tau/A β 42 are more accurate for diagnosis. Other biomarkers (Core 2 biomarkers) such as Neurofilament light chain and glial fibrillary protein, are used and have a non-specific process in the pathophysiology of AD, hence not used to alone to diagnose AD, but are highly associated with A β pathology, confirming AD pathology. A combination of both core 1 and core 2 biomarkers is used in the classification of the severity of the disease, providing information on the symptoms associated with AD, the progression rate in symptomatic patients, and informing the risk of short-term progression in asymptomatic patients³³.

Neonatal Encephalopathy: Majority of neonatal seizures and encephalopathy are subclinical³⁴, therefore confirmatory diagnosis is through EEG and Electrocardiogram (EKG) monitoring. Continuous EEG monitoring with neuroimaging is a more accurate method of diagnosis, however this requires highly skilled medical imagers and experienced neurologists; who are in short supply, the interpretation of the EEG reading is also time-consuming and expensive, thus adding to the diagnostics

challenge. Kissani et al., and other studies have reported a very low number of neurologists in Nigeria, hence the low availability of neurologists, poor access to MRI/CT/EEG further drives the high burden of neonatal encephalopathy and other neurological disorders in Nigeria^{35,36}. Other limitations such as poor imaging record keeping in neurological disorders further compounds the problem³⁶.

2.2 Accuracy with diagnosis and manpower shortage

Quality research with great insights usually precedes key diagnostic milestones. More research has to be conducted into unravel the incidence and prevalence burden of neurological disorders, especially in children, since they are mostly affected in Africa³⁷. This may aid in the mapping out of key diagnostic and preventive strategies from such research pointers. About 70% of people with at least one neurological disorder are residents in the poor regions of Africa³⁸. It is expedient to strengthen research qualitatively and quantitatively in Africa for excellent diagnostic capabilities, AI-driven or not. The trade-cultural health-seeking behaviour of individuals may reflect the collective mentality which spiritualizes and stigmatizes certain neurological conditions. They may be reluctant to seek the correct diagnosis and medical help. This is a very significant impediment that besets the diagnostic terrain in Africa, especially Sub-Saharan Africa³⁹. Culture and well-established traditions, that dictate the way of life and associate taboos to the occurrence or even unravelling of neurological disorders, have to be considered in designing diagnostic or treatment strategies. In fact, Western accepted and validated diagnostic tools may be insufficient in such African settings. Nigeria's scale for Autism, for instance, encompasses cultural ideologies and norms in the evaluation of autism spectrum disorder⁴⁰.

A closely related barrier to diagnostics is the out-of-pocket nature of diagnostic costs in Africa^{41,42}. Patients may have to prioritize getting drugs overpaying for neuroimaging services and diagnosis, which do not offer physical or palpable benefits, according to them. Clinicians and neurologists are then forced to play the role of the exceptional problem solver, by making use of presumptive diagnosis which are potentially error prone. It is a classic tale of people constrained by their environment which may lead to poor choices and healthcare dysfunction. It is important to know that many of the points above are intertwined; projecting a panacea to one may cause a ripple effect. For instance, effective policy recommendations will improve funding immensely, which will in turn make the environment more conducive for research, diagnosis, and management. Existing incentives will encourage neurologists to stay in the fragile pressure points and rural

areas⁴³. The paucity of neurologists in Africa is also partly due to the large-scale migration of the already threadbare specialists to the developed regions of the world. Instead, advocacy, collaborative research, and capacity building should be strengthened across borders¹³.

Neurology specialists are immensely insufficient in Africa, especially the LMICs⁴³. The ratio of neurologists to the wider population is both pathetic and concerning. The figure estimated for Africa is 0.03 per 100,000 people, well below the WHO's recommendation of 1 per 100,000 people³⁷. What happens when there is a lack of sufficient know-how and expertise to diagnose and manage neurological conditions optimally? The most daunting challenge posed to diagnostics generally in Africa is a lack of strong funding for research and management, a serious infrastructural deficit, and the chronicity of these because of the sheer lack of willpower from government and policymakers. This is more evident in the emerging field of neuroscience in Sub-Saharan Africa and Africa as a whole. The immensity of the burden of neuroinfectious diseases, such as neurosyphilis or HIV-related cognitive impairment^{13,44} succinctly typifies the lack of capacity to reduce communicable and infectious diseases to a bare minimum, in contrast to what obtains in the developed health systems of the world.

3.0 RESULT

3.1 Health Datasets for AI/ML infrastructures in Africa

African health datasets are majorly hosted within national health information systems, regional health observatories, and international health organizations. These datasets contain information on mortality trends, healthcare access, non-communicable diseases, and some neurological conditions. Although, epidemiological data is vast^{45,46,47} with respect to neurological disorders like Alzheimer's disease, Parkinson's disease, stroke, and epilepsy, data sources explored in Africa for developing diagnostic models include neuroimaging, clinical datasets, and electrophysiological recordings. The availability and digital⁴⁸ accessibility of high-quality, representative data are important factors that enhance the training, validation and deployment of artificial intelligence and machine learning systems⁴⁹. Thus, in a bid to improve and enhance the availability as well as usability of data at the continental level, the World Health Organization (WHO) Regional Office for Africa established an open-access platform, the WHO African Health Observatory and Regional Health Data Portal⁵⁰. Likewise, Open Data Africa provides datasets across socio-economic indicators, health, and demographics⁵¹.

These databases provide datasets on health systems, disease burdens, health system policy, and non-communicable diseases in which neurological disorders like stroke and epilepsy is a part. However, although these databases are useful in preliminary AI modelling, they still lack structure, imaging, and detailed epidemiological characteristics within African populations for clinical applications²⁵. Thus, due to the limited datasets in Africa, many researchers rely on global repositories such as Alzheimer's Disease Neuroimaging Initiative (ADNI), UK Biobank, PhysioNet EEG databases, and other international repositories. Although these datasets are valuable, they raise concerns of bias and generalizability because they are derived from non-African populations⁵². Isolated studies in Africa have documented phenomics data for stroke⁵³ and exome data for epilepsy⁵⁴, there is still a dearth of African-rich omics data integrated with neurological clinical imaging data for AI/ML applications.

3.2 African Datasets and Data infrastructure to support AI/ML implementation

Countries like South Africa, Rwanda, and Kenya are transitioning into digital healthcare systems which embrace electronic health record systems and national health data repositories. This method, although not without challenges in standardization, enhances AI integration⁵⁵. With collaboration, the Data Science for Health Discovery and Innovation in Africa (DS-I Africa) program, led by the National Institutes of Health, is actively developing platforms that emphasize data standardization and ethical governance, which are essential for scalable AI implementation⁵⁶. One of them is the **Open Data Africa**, which provides publicly available datasets across various sections like health, socio-economic indicators, and demographics⁵⁷. The **African Open Science Platform** is another initiative that encourages data sharing and transparency towards building a robust data ecosystem that is important for AI integration⁵⁸.

Several platforms support data access and utilization across Africa.

The WHO AFRO Open Data Portal possesses open-access data across the African region and enhances exploration of critical health issues, including communicable and non-communicable diseases. However, the site was still under processing at the time of exploration, 14th April, 2026⁵⁹.

The Integrated African Health Observatory (iAHO) is a strategic health intelligence platform based on three pillars: health information, data, analytics, and knowledge. It

provides reliable health information for the WHO Africa Region and promotes the utilization of high-quality data for action⁶⁰.

Observational Health Data Sciences and Informatics (OHDSI) Africa is an open-source interdisciplinary platform that brings out the value of health data through large-scale analytics, with its central coordinating centre at Columbia University⁶¹. **The Africa Health Data Space (AHDS)** is an accessible data space that supports strong, quality, and ethically governed AI-ready data. It contains about 20,000 patient records from 12 facilities across Uganda, Nigeria, Kenya, and Ethiopia⁶².

The African Index Medicus is a specialized database developed by WHO and African partners to improve access to health information and is a key resource for policymakers, researchers, health workers, and communities. **National Health Information Systems** (e.g., DHIS2-based systems) provide a comprehensive approach to data collection, reporting, analysis, and dissemination, enabling countries to monitor health outcomes and manage health programs effectively.

African Population and Genomics Initiatives: African countries are still behind in the genomic revolution targeted at understanding health and diseases in different populations and individuals at risk due to genetic or environmental factors. To tackle this challenge, the African Society of Human Genetics, the National Institutes of Health (NIH), and the Wellcome Trust brought together African scientists and stakeholders to outline research priorities and study designs needed to impact health in African populations. This led to the establishment of H3Africa in 2010⁶³.

3.3 Specialized Neurological Datasets

Although limited, there are emerging specialized databases that are relevant to neurological disorders in Africa. One of

them is the AfriMed-QA dataset, which was developed from clinically relevant information gathered from African medical students and practitioners, thus enabling the evaluation of AI systems in healthcare question-answering tasks. Another development in Africa is the emergence of localized neuroimaging datasets like the BraTS-Africa dataset, which aggregates magnetic resonance imaging (MRI) scans.

The Nigerian Brain MRI dataset is another research dataset and represents one of the first MRI datasets from Africa. It contains clinical quality data from 93 individuals: 42 images from healthy subjects, 32 images from individuals diagnosed with age-related dementia, and 19 from individuals with Parkinson's disease. The individuals were recruited from multiple regions in Nigeria⁶⁴. However, this dataset is prone to diminished returns because of the low quality of the MRI scanners used in data collection. Studies like the Stroke Investigative Research and Educational Network (SIREN) also provide phenomic data for stroke in African population⁶⁴. Despite the emergence of localized datasets such as AfriMed-QA, BraTS-Africa, and the Nigerian Brain MRI dataset, the availability of large-scale, standardized neurological datasets in Africa remains limited. As a result, many AI models for neurological diagnosis continue to rely on well-established global repositories such as the Alzheimer's Disease Neuroimaging Initiative, OpenNeuro, and PhysioNet. While these databases provide high-quality neuroimaging and electrophysiological data, their limited representation of African populations raises concerns regarding model bias, reduced generalizability, and potential inequities in AI-driven healthcare applications.

3.4 Application of AI/ML for neurological diseases in Africa

Table 1 shows the studies that applied AI/ML on different neurological disease diagnosis or prediction and the limitations of its use in African or Nigerian context.

Table 1 Highlights of global AI/ ML applications in neurological research

Study	Disorder	Dataset/sample	AI/ML method	Diagnostic/predictive task	Key limitation
A. AI/ML Algorithms applied to different neurological disorders in Africa					
Jiao <i>et al.</i> , 2023 ⁶⁵	Memory impairment & Alzheimer's disease	Medical images	Radiomics, CNNs, YOLO	Classification and diagnosis of memory impairment and Alzheimer's disease; tumor detection and segmentation	Radiomics requires manual/pre-defined mathematical formulas.

Shaikh et al., 2025⁶⁶	Down syndrome	Varied data structures	AI-powered models	Detection and diagnosis of Down syndrome	Gross imbalance in datasets affecting final output and applicability.
McLaren et al., 2025⁶⁷	Epilepsy	EEG datasets	AI-powered models	Diagnosis of epilepsy	Requires training; legal, ethical, and privacy considerations.
Tomašev et al. 2019⁶⁸	Non-neurological (Acute Kidney Injury)	Patient health data	Deep learning	Early detection of asymptomatic atrial fibrillation	
Attia et al., 2019⁶⁹	Non-neurological (Atrial Fibrillation)	Normal electrocardiogram (ECG) signals	Deep learning	Early detection of asymptomatic atrial fibrillation	Asymptomatic nature of the condition.

B. AI/ML Algorithms applied to Neurological diseases with Nigerian dataset

Aribisala et al., 2025 ²⁶ .	Stroke	clinical and demographic data	Artificial Neural Networks (ANN), Ensemble Methods (Random Forest / XGBoost)	predicting occurrence, handling complex, non-linear relationships between risk factors	Specifically used on imbalanced health datasets.
Soladoye et al 2025 ⁷⁰	Stroke	CT scans and MRIs for large-scale datasets	Ensemble methods		Deep learning model outperformed traditional machine learning

4.0 Discussion

Development of Framework for Implementation of AI/ML for Neurological Diagnosis in Nigeria

Implementing AI/ML in neurological diagnosis is not simply a technical exercise. It is a journey that touches on data governance, clinical workflow, ethics, training, and sustainability. We derived a framework for implementing AI/ML for neurological diagnosis in Nigeria by adapting the five pillars established by WHO and the Federal government of Nigeria^{71,72,73} and we mapped it to the specific

use for neurological diseases in Nigeria, and a sustainability system; this directly addresses the healthcare needs in Nigeria, infrastructural limits, governmental policies and sustainability. The AI/ML framework below is presented as a narrative arc, a story of how Nigeria can move from aspiration to nationwide adoption. Firstly, there is the need to build the data foundations because every AI system relies on data. For Nigeria, this means creating a national neurological data ecosystem that includes MRI, CT, EEG, and clinical datasets across the country. Anonymized datasets must reflect Nigeria's population data including

ethnicity, geographic, and socioeconomic diversity which will be used to train the algorithms, govern and regulate applications under the Nigeria Data Protection Act⁷¹. These databases can be linked to anchor institutions like teaching hospitals, and thereafter expanded to other secondary and primary institutions. Strategies for implementation of similar digital health infrastructure for mental health have been outlined by the WHO working group of the Federal Ministry of Health⁷², outlined by a study by Adewuya et al (2026)⁷³. Secondly, Activate AI model development and training using the collated African datasets, this is especially necessary because AI models trained with European or Caucasian datasets perform poorly with African populations - as evident in many genomic databases. Models can be developed as hybrid models that combine medical imaging (which is highly used currently in Nigeria) with clinical parameters like blood pressure, glucose levels, or disease status - these are routinely taken as part of medical treatment in Nigeria; however for neurological conditions, specific clinical reports for stroke, epilepsy, EEG records, MRI or CT scan images etc can be imputed to train the model, using Digital Imaging and Communications in Medicine (DICOM) and European data format (EDF). These are standard file formats for handling, storing, and transmitting medical images from MRI, ECG; these training data can be used to compare with normal or healthy control group. The third and technical aspect is the integration into Clinical Workflows. Currently, fewer hospitals operate with the electronic clinical records (ECR). Improve adoption of ECR will make it easy to build AI into the clinical workflows and enabling inter-facility access to integrate into the Nigerian healthcare infrastructures. The integration step will also facilitate e-medicine whereby mobile applications can be deployed with mobile-based APIs that can guide clinicians through neurological assessments.

Operational framework for implementation requires training of the healthcare workforce such as Clinicians, radiographers, EEG technicians on the use of AI tools, to interpret outputs, and recognize limitations. Integration of AI/ML for neurological application into medical schools, nursing programs and biomedical programs curriculum is essential to train the next generation clinicians and medical experts. Establishment of ethical and regulatory guidelines through regulatory agencies like the Federal Ministry of Health to ensure effective and safe use of AI tools, and data protection agency for maintaining patients' data privacy is also non-negotiable. The benefits of AI/ML applications for neurology in Africa and Nigeria in particular are compelling. The sixth pillar integrates a sustainability

system through involvement of innovative start-up companies, private-public partnerships, and continuous improvement of the Nigerian health system through AI/ML applications. AI can dramatically improve diagnostic accuracy, reduce delays, and support clinicians in underserved areas. It can also generate new research insights and strengthen national surveillance systems. Figure 1 shows a schematic workflow for the integration of AI/ML in healthcare systems for neurological disorders and operable institutions.

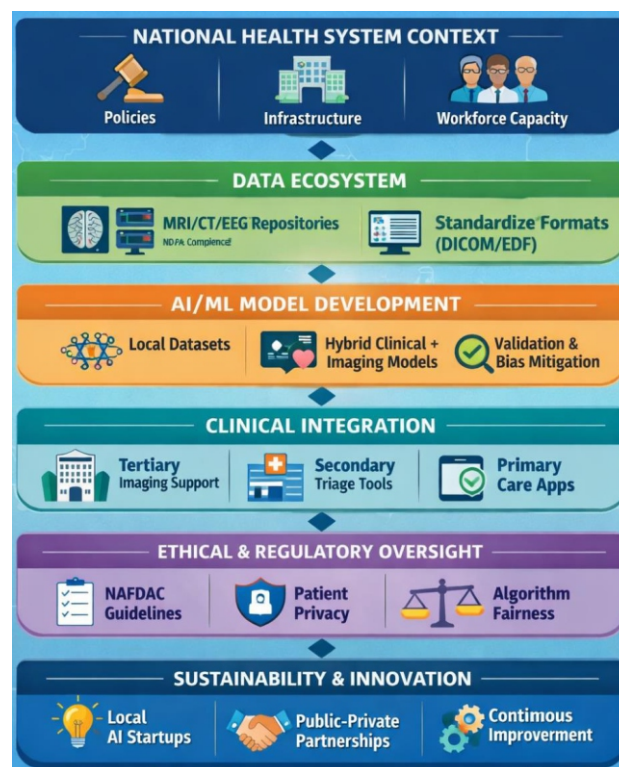


Figure 1. Schematic workflow for the integration of AI/ML in Nigerian healthcare systems.

4.2 Mapping an AI/ML framework matrix for stroke diagnosis in Nigeria

The matrix below maps out structural framework that outlines a precise implementation of an AI/ML model applicable for Nigerian health system for stroke diagnosis. It is noteworthy that models that predict risk for stroke prevention differs in that it uses patient risk factor data but models for stroke diagnosis require integrating localized diagnostic toolsets, deep learning, imaging datasets as predictive model for clinical implementation in Nigeria which is shown in Table 2

Table 2 AI/ML framework matrix for stroke diagnosis in Nigeria

Framework layer	Operational requirement	Implementation challenges	Stroke-specific AI/ML diagnosis
Clinical triage and time-to-treatment	Automated ischemic versus hemorrhagic stroke differentiation in less than 20 minutes of admission of a patient	Severe shortage of CT/MRI machines Shortage of radiologist reduces diagnostic workflow	Integrate an open-source stroke AI tool into web applications for medical officers who will utilize the stored cloud trained data to flag high-priority acute strokes
Low resource Infrastructure compatibility	High-fidelity processing of heavy medical imagery formats (DICOM)	Poor power infrastructure, and low bandwidth internet resources for cloud-based systems	Mandate offline AI design and compile deep learning models to execute directly on hardware laptops or low-power diagnostic PCs utilizing micro-frameworks rather than heavy cloud based resources.
Data curation	Nigerian data curated with diverse imaging databases	Electronic hospital records available and sharable across health institutions	Build standardized digital registries for clinical annotation in Nigeria
Workforce Capacity development and clinical integration	Targeted AI training across local neuro-clinical teams integrated into human work-flows	Low AI adoption in current clinical practice	Flexible AI-trainings and tools applicable for stroke diagnosis
Governance and Regulatory Alignment	Local medical device certification. • Clear diagnostic data protection compliance	A nationally unified explicit regional AI-integrated stroke diagnosis system with legal frameworks implemented	Mandate deployment using lightweight architectures. Align with international standards and technologies
Emerging AI-startups	specialized clinical data programs.	Private-public partnerships between health institutions and AI-hubs	Incentivize and promote collaborative development initiatives between tech accelerators and university hospitals.

4.3 Limitations of the Review and Economic Feasibility

A major limitation to this narrative review is the uncoordinated nature of healthcare data in Nigeria, especially as it pertains to the recency of artificial intelligence applicability. Data from local source are limited and may not be qualitative enough at times. Furthermore, the quantitative analysis strength of this study is not significant, with the notion that the qualitative emphasis will serve as an acceptable baseline for further studies and incorporation of artificial intelligence and machine learning in diagnostics. In addition, there are implementation challenges such as poor infrastructures, cost-effectiveness of AI/ML tools; many of which are not free to use, or existing can limit its deployment. Government funding of the health system does not currently cover AI integration, hence different institutions' adoption will depend largely on funding. AI/ML require some cloud infrastructure to maintain databases across institutions e.g. for real-time data sharing, these have heavy economic limits. The technological know-how as well as sustainability in the Nigerian health system needs to be inculcated into clinical curriculum, day-to-day clinical operations and active training to maintain smooth integration.

4.4 Conclusion

Although developments in dataset accessibility for AI and ML applications are encouraging, scarcity of data remains a serious challenge, as many healthcare systems in Africa are still not fully digitized and rely on paper-based documentation⁷⁴. Likewise, data fragmentation across institutions, incomplete data, and inconsistent information prevent integration and reduce usability in the development of AI-driven diagnostic tools. Open-access resources are readily available but often lack the granularity required for neurological AI applications, while controlled-access resources host highly valuable clinical datasets that are restricted due to legal and ethical concerns. Poor digital infrastructure in healthcare systems especially for rural areas may limit deployment. Also, algorithmic bias can cripple the implementation if models are trained on non-indigenous Nigerian neurological data, while high initial costs of integration, data privacy concerns, and clinician resistance may also slow adoption. These challenges are not insurmountable, but they require deliberate planning and sustained investment. We propose a framework that can mitigate these challenges, this comprises six strategic pillars: (i) development of standardized national health system for neurological diseases; (ii) creation of data ecosystem for AI models

using indigenous African data; (iii) AI/ML model development and validation; (iv) integration into electronic clinical workflows and tele-neurology services; (v) ethical, regulatory, and data governance mechanisms; and (vi) policy imperatives for sustainability and innovation. Conclusively, strengthening neurological care requires a systemic and integrated approach. AI/ML can substantially provide clinical decision-support technology when integrated properly into a structured health system rather than become a substitute for the role of neurologists, radiologists, for clinical judgment which are indispensable for diagnosis. AI/ML can empower non-specialist health workers or providers, provision of low-cost point of care diagnostics, public sensitization and education to combat stigma, consistent and sufficient funding for surveillance and health systems research.

References

1. Feigin VL, Vos T, Nichols E, Owolabi MO, Carroll WM, Dichgans M, Deuschl G, Parmar P, Brainin M and Murray C (2020) The global burden of neurological disorders: translating evidence into policy. *The Lancet Neurology*, 19 (3):255-265. [https://doi.org/10.1016/S1474-4422\(19\)30411-9](https://doi.org/10.1016/S1474-4422(19)30411-9)
2. World Health Organization (2025) Global status report on neurology. Available at: <https://www.who.int/publications/i/item/9789240116139>
3. Ngarka L, Siewe Fodjo JN, Aly E, Masocha W and Njamnshi AK (2022) The interplay between neuroinfections, the immune system and neurological disorders: a focus on Africa. *Frontiers in Immunology*, 12:803475. <https://doi.org/10.3389/fimmu.2021.803475>
4. Tekle-Haimanot R, Ngoungou EB and Kibru D (2018) Epidemiology of neurological disorders in sub-Saharan Africa. In *Neuroepidemiology in Tropical Health*, (pp. 129-141) Academic Press. <https://doi.org/10.1016/B978-0-12-804607-4.00010-1>
5. Logroscino G, Kalaria R and Preux PM (2024) Changing epidemiology of neurological diseases in Africa. *Neuroepidemiology*, 59 (4):291-293. <https://doi.org/10.1159/000539654>
6. Sarfo FS, Ovbiagele B, Gebregziabher M, Wahab K, Akinyemi R, Akpalu A, Akpa O, Obiako R, Owolabi L, Jenkins C and Owolabi M (2018) Stroke among young West Africans: evidence from the SIREN (Stroke Investigative Research and Educational Network) large multisite case-

- control study. *Stroke*, 49 (5):1116-1122. <https://doi.org/10.1161/STROKEAHA.118.020783>
7. GBD 2016 Stroke Collaborators (2019) Global, regional, and national burden of stroke, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. *The Lancet Neurology*, 18 (5): 439 - 458 . [https://doi.org/10.1016/S1474-4422\(19\)30034-1](https://doi.org/10.1016/S1474-4422(19)30034-1)
8. GBD 2019 Diseases and Injuries Collaborators (2020) Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, 396 (1 0 2 5 8) : 1 2 0 4 - 1 2 2 2 . [https://doi.org/10.1016/S0140-6736\(20\)30925-9](https://doi.org/10.1016/S0140-6736(20)30925-9)
9. Kuate Tegueu C, Dzudie Tamdja A, Kom F, Forgwa Barche B, Ebasone P, Magnerou M, Mbonda P, Doumbe J, Husøy A, Thomas H and Steiner TJ (2024) Headache in the adult population of Cameroon: prevalence estimates and demographic associations from a cross-sectional nationwide population-based study. *The Journal of Headache and Pain*, 25 (1):42. <https://doi.org/10.1186/s10194-024-01748-9>
10. GBD 2021 Nervous System Disorders Collaborators (2024) Global, regional, and national burden of disorders affecting the nervous system, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021. *The Lancet Neurology*, 23 (4): 344 - 381 . [https://doi.org/10.1016/S1474-4422\(24\)00038-3](https://doi.org/10.1016/S1474-4422(24)00038-3)
11. Davis LE (2018) Acute bacterial meningitis. *Continuum: Lifelong Learning in Neurology*, 24 (5) : 1 2 6 4 - 1 2 8 3 . <https://doi.org/10.1212/CON.0000000000000660>
12. Mazamay S, Guégan JF, Diallo N, Bompangue D, Bokabo E, Muyembe JJ, Taty N, Vita TP and Broutin H (2021) An overview of bacterial meningitis epidemics in Africa from 1928 to 2018 with a focus on epidemics “outside-the-belt”. *BMC Infectious Diseases*, 21 (1):1027. <https://doi.org/10.1186/s12879-021-06724-1>
13. Aderinto N, Alare K, AbdulBasit OM, Edun M and Ogunleke P (2023) Prevalence of neuroinfectious diseases and outcomes in Africa. *International Journal of Surgery: Global Health*, 6 (2) : e 1 0 4 . <https://doi.org/10.1097/GH9.000000000000104>
14. Singhal BS and Khadilkar SV (2014) Neurology in the developing world. In *Handbook of Clinical Neurology*, 121: 1773 - 1782 . <https://doi.org/10.1016/B978-0-7020-4088-7.00114-0>
15. Robertson FC, Lepard JR, Mekary RA, Davis MC, Yunusa I, Gormley WB, Baticulon RE, Mahmud MR, Misra BK, Rattani A, Dewan MC and Park KB (2018) Epidemiology of central nervous system infectious diseases: a meta-analysis and systematic review with implications for neurosurgeons worldwide. *Journal of Neurosurgery*, 130 (4):1107-1126. <https://doi.org/10.3171/2017.10.JNS17359>
16. Nweke MC and Kanayo EC (2019) The place of spiritual and traditional beliefs in stroke rehabilitation in sub-Saharan Africa: a scoping review. *Journal of Complementary and Alternative Medical Research*, 8 (2):1-16. <https://doi.org/10.9734/JOCAMR/2019/v8i230119>
17. Ned L, Kpobi L and Ohajunwa C (2022) Thinking about mental health and spirituality from the Indigenous knowledge systems frame of reference. *Disability Studies Quarterly*, 41 (4). <https://doi.org/10.18061/dsq.v41i4.8450>
18. GBD 2019 Stroke Collaborators (2021) Global, regional, and national burden of stroke and its risk factors, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet Neurology*, 20 (10): 795 - 820 . [https://doi.org/10.1016/S1474-4422\(21\)00252-0](https://doi.org/10.1016/S1474-4422(21)00252-0)
19. Komolafe MA, Owagbemi OF and Alimi TI (2018) The distribution and pattern of neurological disease in a neurology clinic in Ile-Ife, Nigeria. *Nigerian Journal of Clinical Practice*, 21 (11): 1520 - 1524 . https://doi.org/10.4103/njcp.njcp_230_16
20. Elsayed M, Hamid OAA, Tonga R, Elsadig SM, Ahmed MH, Ahmed M and Saeed MK (2021) The pattern of neurological disorders; revisited prevalence data of a dedicated neurology clinic in Sudan. *Case Reports in Clinical Medicine*, 10 (1 1) : 3 3 9 - 3 5 8 . <https://doi.org/10.4236/crcm.2021.1011043>
21. Kelechi WE, Soyemi T, Mayowa S, Ede NS, Ubalaeze SE, Iloanusi CA, Agbo CE, Suzan IO, Augustine IC, Clinton IO, Akpowowo CK, Oyebola GF, Nndoumele C and Olabisi PL (2025) Building healthcare capacity for neurodegenerative disease management in Nigeria: challenges and opportunities. *Journal of*

- Public Health Research*, 14 (2): 22799036251350957. <https://doi.org/10.1177/22799036251350957>
22. Adeloye D, Ezejimofor M, Auta A, Mpazanje RG, Ezeigwe N, Ngige EN, Harhay MO, Alemu W and Adewole IF (2019) Estimating morbidity due to stroke in Nigeria: a systematic review and meta-analysis. *Journal of the Neurological Sciences*, 402: 136-144. <https://doi.org/10.1016/j.jns.2019.05.020>
 23. Ezeala-Adikaibe BA, Orjioko C, Ekenze O, Ijoma U, Onodugo O, Molokwu O, Chime P, Mbadiwe N, Aneke E, Onyekonwu C, Okudo G, Okwara C, Onyebueke G and Ulas I (2016) Prevalence of active convulsive epilepsy in an urban slum in Enugu South East Nigeria. *Seizure*, 35:100-105. <https://doi.org/10.1016/j.seizure.2015.12.010>
 24. Aribisala BS, Edward D, Ogbole G, Akpa OM, Ayilara S, Sarfo F, Olabanjo O, Fakunle A, Macaulay BO, Yaria J, Akinyemi J, Akpalu A, Wahab K, Obiako R, Komolafe M, Owolabi L, Osaigbovo G, Okekunle AP, Singh A, Ibinaye P, Osawata O, Sunday A, Chukwuonye I, Jenkins C, Tiwari HK, Ogah O, Laryea RY, Lackland DT, Arulogun O, Ajala O, Akinyemi R, Ovbiagele B, Sammet S and Owolabi M (2025) Predicting stroke with machine learning techniques in a sub-Saharan African population. *Neuroscience Informatics*, 5(3): 100216. <https://doi.org/10.1016/j.neuri.2025.100216>
 25. Owolabi MO, Leonardi M, Bassetti C, Jaarsma J, Hawrot T and Makanjuola AI (2022) The neurology revolution. *The Lancet Neurology*, 21(11):960-961. [https://doi.org/10.1016/S1474-4422\(22\)00394-5](https://doi.org/10.1016/S1474-4422(22)00394-5)
 26. World Health Organization (2025) Stroke fact sheet. Available at: <https://www.who.int/news-room/fact-sheets/detail/stroke>
 27. Pires AP, Martin KC, Secchi TL, Silva GS, Rebello LC, Bezerra DDC, de Freitas GR, Oliveira-Filho J, Miranda-Alves M, Kuster GW, Bazan R, Lange MC, de Carvalho JJF, Mont'Alverne FJA, Fiorot JA Jr, Zetola VF, Magalhães PSC, Rieder CRM, Nasi LA, Nogueira RG, Moro CC, Barbosa LA, Borelli WV, Pontes-Neto OM and Martins SCO (2026) Assessing the quality of stroke services in Brazil using the World Stroke Organization roadmap. *Cerebrovascular Diseases*, 55(1): 72-82. <https://doi.org/10.1159/000546276>
 28. Singh K and Malhotra J (2021) Cloud based ensemble machine learning approach for smart detection of epileptic seizures using higher order spectral analysis. *Physical and Engineering Sciences in Medicine*, 44(1):313-324. <https://doi.org/10.1007/s13246-021-00970-y>
 29. Akyol K (2020) Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection. *Expert Systems with Applications*, 148: 113239. <https://doi.org/10.1016/j.eswa.2020.113239>
 30. Jones KEA, Howells R, Mallick AA, Paul SP and Dey I (2023) NICE guideline review: epilepsies in children, young people and adults NG217. *Archives of Disease in Childhood - Education and Practice Edition*, 108(6):416-421. <https://doi.org/10.1136/archdischild-2022-324427>
 31. Eigenbrodt AK, Ashina H, Khan S, Diener HC, Mitsikostas DD, Sinclair AJ, Pozo-Rosich P, Martelletti P, Ducros A, Lantéri-Minet M, Braschinsky M, del Rio MS, Daniel O, Özge A, Mammadbayli A, Arons M, Skorobogatikh K, Romanenko V, Terwindt GM, Paemeleire K, Sacco S, Reuter U, Lampl C, Schytz HW, Katsarava Z, Steiner TJ and Ashina M (2021) Diagnosis and management of migraine in ten steps. *Nature Reviews Neurology*, 17(8):501-514. <https://doi.org/10.1038/s41582-021-00509-5>
 32. World Health Organization (2025) Dementia fact sheet. Available at: <https://www.who.int/news-room/fact-sheets/detail/dementia>
 33. Jack CR Jr, Andrews JS, Beach TG, Buracchio T, Dunn B, Graf A, Hansson O, Ho C, Jagust W, McDade E, Molinuevo JL, Okonkwo OC, Pani L, Rafii MS, Scheltens P, Siemers E, Snyder HM, Sperling R, Teunissen CE and Carrillo MC (2024) Revised criteria for diagnosis and staging of Alzheimer's disease: Alzheimer's Association Workgroup. *Alzheimer's & Dementia*, 20(8):5143-5169. <https://doi.org/10.1002/alz.13859>
 34. Ramantani G, Schmitt B, Plecko B, Pressler RM, Wohlrab G, Klebermass-Schrehof K, Hagmann C, Pisani F and Boylan GB (2019) Neonatal seizures-are we there yet? *Neuropediatrics*, 50(5):280-293. <https://doi.org/10.1055/s-0039-1693149>
 35. Kissani N, Liqali L, Hakimi K, Mugumbate J, Daniel GM, Ibrahim EAA, Yewnetu E, Belo M, Wilmshurst J, Mbelesso P, Ragab AH, Millogo A, Massimo L and Naji Y (2022) Why does Africa have the lowest number of neurologists and how to cover the gap? *Journal of the Neurological*

- Sciences*, 434:120119. <https://doi.org/10.1016/j.jns.2021.120119>
36. Howlett JR, Harlé KM, Simmons AN and Taylor CT (2025) Bayesian deconvolution for computational cognitive modeling of fMRI data. *NeuroImage*, 312:121213. <https://doi.org/10.1016/j.neuroimage.2025.121213>
 37. Frimpong M, Mohamed S, Ibukun MO, Owusu YA and Wireko AA (2026) Paediatric neurological care in Sub-Saharan Africa: current status and future directions. *Brain and Development*, 48 (1):104490. <https://doi.org/10.1016/j.braindev.2025.104490>
 38. World Health Organization (2022) Global health observatory data repository: MRI units per million population. Available at: <https://www.who.int/data/gho/data/indicators/indicator-details/GHO/total-density-per-million-population-magnetic-resonance-imaging>
 39. Elliot VL, Morgan D, Kosteniuk J, Froehlich Chow A and Bayly M (2019) Health-related stigma of noncommunicable neurological disease in rural adult populations: a scoping review. *Health & Social Care in the Community*, 27 (4):e158-e188. <https://doi.org/10.1111/hsc.12694>
 40. Bakare MO, Frazier TW, Karpur A, Abubakar A, Nyongesa MK, Mwangi PM, Dixon P, Khaliq I, Gase NK, Sandstrom J, Okidegbe N, Rosanoff M, Munir KM and Shih A (2022) Brief report: validity and reliability of the Nigerian Autism Screening Questionnaire. *Autism*, 26 (6):1581-1590. <https://doi.org/10.1177/13623613221080250>
 41. Odunyemi A, Islam MT and Alam K (2024) The financial burden of noncommunicable diseases from out-of-pocket expenditure in sub-Saharan Africa: a scoping review. *Health Promotion International*, 39 (5): daae114. <https://doi.org/10.1093/heapro/daae114>
 42. Ofori B, Twum S, Yeboah SN, Ansah F and Sarpong KAN (2024) Towards the development of cost-effective point-of-care diagnostic tools for poverty-related infectious diseases in sub-Saharan Africa. *PeerJ*, 12: e17198. <https://doi.org/10.7717/peerj.17198>
 43. Charway-Felli A (2023) African neurology: a targeted and unified approach to interregional collaboration. *Journal of the Neurological Sciences*, 455:120877. <https://doi.org/10.1016/j.jns.2023.120877>
 44. Thakur K and Zunt J (2015) Tropical neuroinfectious diseases. *Continuum: Lifelong Learning in Neurology*, 21 (6):1639-1661. <https://doi.org/10.1212/CON.0000000000000248>
 45. Alfin JD, Mahmud MR, Yusuf AS, Binitie OP, Joseph SD, Bot GM and Yiltok SJ (2021) Acute traumatic spinal cord injury; does a low Tesla magnetic resonance imaging features correlates with neurological status and predict early outcome? *Nigerian Journal of Medicine*, 30 (6):637-644. https://doi.org/10.4103/njm.njm_41_21
 46. Nwazor E, Chukwuocha I, Ajuonuma B, Obi P and Madueke O (2024) A 2-year review of stroke admissions and short term out-come predictors in a teaching hospital, Southeast, Nigeria. *Nigerian Medical Journal*, 65 (2):185-194. <https://doi.org/10.60787/nmj-v65i2-442>
 47. Arravalli T, Chadaga K, Muralikrishna H, Sampathila N, Cenitta D, Chadaga R and Swathi KS (2025) Detection of breast cancer using machine learning and explainable artificial intelligence. *Scientific Reports*, 15:26931. <https://doi.org/10.1038/s41598-025-12644-w>
 48. Nomhwange T, ENEGELA J, and Ishaku A (2026) The utilization of artificial intelligence (AI) and machine learning (ML) for health in Nigeria: a rapid review. *Journal of Medical Artificial Intelligence*, 9: 2026. <https://doi.org/10.21037/jmai-2025-1-227>
 49. Bataliack S, Mbondji E, Karamagi H and Janaushek L (2024) Health data digitalization in Africa: unlocking the potential. AHOP Policy Briefs. Brazzaville: WHO Regional Office for Africa. Available at: <https://ahop.aho.afro.who.int/download/health-data-digitalization-in-africa-unlocking-the-potential>
 50. World Health Organization (2025) Global status report on neurology. Available at: <https://www.who.int/publications/i/item/9789240116139>
 51. World Health Organization Regional Office for Africa (2024) Framework for integrating country and regional health data in the African Region (AFR/RC74/7). Available at: <https://www.afro.who.int/sites/default/files/2024-07/AFR-RC74-7%20Framework%20for%20integrating%20country%20and%20regional%20health%20data%20in%20the%20African%20Region.pdf>

52. Gianattasio KZ, Bennett EE, Wei J, Mehrotra ML, Mosley T, Gottesman RF, Wong DF, Stuart EA, Griswold ME, Couper D, Glymour MM and Power MC (2021) Generalizability of findings from a clinical sample to a community-based sample: a comparison of ADNI and ARIC. *Alzheimer's & Dementia*, 17 (8):1265-1276. <https://doi.org/10.1002/alz.12293>
53. Akpalu A, Sarfo FS, Ovbiagele B, Akinyemi R, Gebregziabher M, Obiako R, Owolabi L, Sagoe K, Jenkins C, Arulogun O, Adamu S, Appiah LT, Adadey MA, Agyekum F, Quansah JA, Mensah YB, Adeoye AM, Singh A, Tosin AO, Ohifemen O, Sani AA, Tabi-Ajayi E, Phillip IO, Isah SY, Tabari NA, Mande A, Agunloye AM, Ogbole GI, Akinyemi JO, Akpa OM, Laryea R, Melikam SE, Adinku D, Uvere E, Burkett NS, Adekunle GF, Kehinde SI, Azuh PC, Dambatta AH, Ishaq NA, Arnett D, Tiwari HK, Lackland D and Owolabi M (2015) Phenotyping stroke in sub-Saharan Africa: Stroke Investigative Research and Education Network (SIREN) phenomics protocol. *Neuroepidemiology*, 45 (2):73-82. <https://doi.org/10.1159/000437372>
54. Ademuwagun IA, Adam Y, Rotimi SO, Syrbe S, Radtke M, Hentschel J, Lemke JR and Adebisi E (2025) Exome sequencing in Nigerian children with early-onset epilepsy syndromes. *Epilepsia Open*, 10 (1):222-232. <https://doi.org/10.1002/epi4.13106>
55. Abiodun OA, Ajiboye PO, Salihu MO, Sulyman D, Akinsulore A, Obayi O and Salihu HB (2025) Psychiatrists' and trainees' knowledge, perception, and readiness for integration of artificial intelligence in mental health care in Nigeria. *BMC Psychiatry*, 25 (1):685. <https://doi.org/10.1186/s12888-025-07135-1>
56. National Institutes of Health (2021) NIH awards nearly \$75M to catalyze data science research in Africa. Available at: <https://www.nih.gov/news-events/news-releases/nih-awards-nearly-75m-catalyze-data-science-research-africa>
57. Open Data for Africa (2025) Open Data for Africa data portal. Available at: <https://dataportal.opendataforafrica.org/ydixvvd>
58. Motshegwa T (2025) The African Open Science Platform: implementing the African Open Science Vision. *Open Conference Proceedings*, 5. <https://doi.org/10.52825/ocp.v5i.1427>
59. World Health Organization Regional Office for Africa (2025) Disease Prevention and Control (DPC) data portal. Available at: <https://dataportal.afro.who.int/>
60. World Health Organization Regional Office for Africa (2025) Integrated African Health Observatory (IAHO). Available at: <https://aho.afro.who.int/about-us/af>
61. Observational Health Data Sciences and Informatics (2025) OHDSI Africa. Available at: <https://www.ohdsi.org/>
62. Africa Health Data Space (2025) Africa Health Data Space. Available at: <https://aun.mu.edu.et/ahds/>
63. Adoga MP, Fatumo SA and Agwale SM (2014) H3Africa: a tipping point for a revolution in bioinformatics, genomics and health research in Africa. *Source Code for Biology and Medicine*, 9:10. <https://doi.org/10.1186/1751-0473-9-10>
64. Wogu E, Filima P, Caron B, Deabler D, Herholz P, Leal C, Mehboob MF, Kim S, Gosain A, Flexwala A, Hayashi S, Akintoye S, Ogoh G, Godwin T, Eke D and Pestilli F (2025) A labeled clinical-MRI dataset of Nigerian brains. *Scientific Data*, 12 (1):518. <https://doi.org/10.1038/s41597-025-04743-0>
65. Jiao F, Wang M, Sun X, Ju Z, Lu J, Wang L, Jiang J and Zuo C (2023) Based on tau PET radiomics analysis for the classification of Alzheimer's disease and mild cognitive impairment. *Brain Sciences*, 13 (2):367. <https://doi.org/10.3390/brainsci13020367>
66. Shaikh MA, Al-Rawashdeh HS and Sait ARW (2025) A review of artificial intelligence-based Down syndrome detection techniques. *Life*, 15 (3):390. <https://doi.org/10.3390/life15030390>
67. McLaren JR, Yuan D, Beniczky S, Westover MB and Nascimento FA (2025) The future of EEG education in the era of artificial intelligence. *Epilepsia*, 66 (6):1838-1842. <https://doi.org/10.1111/epi.18326>
68. Tomašev N, Glorot X, Rae JW, Zielinski M, Askham H, Saraiva A, Mottram A, Meyer C, Ravuri S, Protsyuk I, Connell A, Hughes CO, Karthikesalingam A, Cornebise J, Montgomery H, Rees G, Laing C, Baker CR, Peterson K, Reeves R, Hassabis D, King D, Suleyman M, Back T, Nielson C, Ledsam JR and Mohamed S (2019) A clinically applicable approach to continuous prediction of future acute kidney injury. *Nature*, 572 (7767):116-119. <https://doi.org/10.1038/s41586-019-1390-1>
69. Attia ZI, Noseworthy PA, Lopez-Jimenez F,

-
- Asirvatham SJ, Deshmukh AJ, Gersh BJ, Carter RE, Yao X, Rabinstein AA, Erickson BJ, Kapa S and Friedman PA (2019) An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. *The Lancet*, 394 (10201):861-867. [https://doi.org/10.1016/S0140-6736\(19\)31721-0](https://doi.org/10.1016/S0140-6736(19)31721-0)
70. Soladoye AA, Aderinto N, Popoola MR, Adeyanju IA, Osonuga A and Olawade DB (2025) Machine learning techniques for stroke prediction: a systematic review of algorithms, datasets, and regional gaps. *International Journal of Medical Informatics*, 203:106041. <https://doi.org/10.1016/j.ijmedinf.2025.106041>
71. Federal Republic of Nigeria (2023) Nigeria Data Protection Act, 2023 (Act No. 37). Federal Republic of Nigeria Official Gazette No. 119, Vol. 110. Lagos: The Federal Government Printer. Available at: <https://ncc.gov.ng/media/801/view>
72. Federal Ministry of Health, Nigeria (2025) Statement by Nigeria: agenda item 13.2, mental health and social connection. Seventy-eighth World Health Assembly. Available at: <https://apps.who.int/gb/statements/WHA78/PDF/Nigeria-13.2.pdf>
73. Adewuya AO, Abdulmalik J, Abimbola S, Oladipo O, Shettima F, Dahiru A and Fasawe A (2026) Fidelity and feasibility of a pilot implementation of adapted WHO digital interventions to scale up mental health in Nigerian primary care: a mixed-methods process evaluation. *Cambridge Prisms: Global Mental Health*, 13: e65. <https://doi.org/10.1017/gmh.2026.10131>
74. World Health Organization (2016) Global diffusion of eHealth: making universal health coverage achievable. Report of the third global survey on eHealth. Geneva: World Health Organization. Available at: <https://iris.who.int/bitstream/handle/10665/252529/9789241511780-eng.pdf>