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Integrating Machine Learning into Neurosurgery in Africa: Opportunities, Challenges, and a Potential Future.

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Summary

With the growing availability of healthcare data and advancements in computational power, machine learning (ML) can significantly improve the field of neurosurgery. Applications of ML include predicting patient outcomes, improving surgical accuracy, and optimising care workflows. Despite these advancements, there are numerous obstacles hindering ML adoption, such as poor data quality, lack of standardization, and insufficient local technical expertise, specifically in Africa. These barriers complicate the deployment of ML models and limit their generalizability across different healthcare settings within the continent. This article provides a roadmap for successfully integrating ML into neurosurgery, highlighting the importance of collaboration between neurosurgeons, data scientists, and healthcare policymakers. A crucial step is assembling multidisciplinary teams to address data challenges and develop context-appropriate ML solutions. Equally vital is the establishment of regulatory frameworks to ensure data security, patient privacy, and model sustainability. Ultimately, while ML can streamline certain neurosurgical tasks, the core responsibilities requiring higher cognitive abilities—such as understanding patient needs and balancing treatment priorities—will remain with neurosurgeons, making ML a tool for augmenting rather than replacing clinical expertise.

Keywords: *machine learning, neurosurgery, Africa*

Introduction

Machine learning (ML) lets computers learn from data, detect patterns, and make predictions. In neurosurgical care, ML already outperforms traditional statistical models in predicting patient outcomes and image classification (1). In healthcare, ML now processes vast amounts of data to deliver clinically relevant insights. Advances in image analysis and automated result processing have fueled this adoption. A recent systematic review found that deep learning algorithms improve diagnostic accuracy, outcome prediction, and workflow efficiency in neurosurgery (2).

Machine learning in neurosurgery has grown from small experimental trials to powerful diagnostic and prognostic tools. In the 1990s, researchers used artificial neural networks (ANNs) to analyze structured clinical datasets and perform supervised learning tasks. By the early 2000s, ML moved into imaging: algorithms began detecting brain tumors from unstructured scans and segmenting tumors without manual input (3). Over time, models trained on large imaging datasets began outperforming expert clinicians in tumor diagnosis (3, 4). More recently, ML in neurosurgery has expanded to outcome prediction, complication risk stratification, and automated image interpretation. Yet despite these advances, its adoption in Africa trails behind research (4).

Computational advances and growing health datasets now make ML viable in clinical neurosurgery. But many settings still lack the high-quality, annotated data needed to use ML routinely. Africa's neurosurgical demand is rising fast; expanding the workforce won't meet the need alone. ML tools can fill that gap. For example, a recent study on glioma segmentation using MRI from Sub-Saharan Africa achieved strong accuracy with a lightweight model, showing ML can succeed even with limited resources (5). Another narrative review in neuro-oncology found ML improves diagnosis, grading, and segmentation of tumors, especially where radiological and pathological resources are scarce (6). This article will explain what ML is and how it can improve neurosurgical care, describe its implementation process, review its current limitations, and explore its future role in Africa.

A primer to machine learning

Machine learning turns routine clinical data into fast and actionable predictions, which clinicians can use at the bedside. ML trains algorithms on chosen features to predict outcomes without explicit rule-based programming (7, 8). Supervised machine learning uses labeled targets to teach models what to predict, while unsupervised learning finds hidden patterns without targets (8). Clinically, supervised models already predict readmission risk and other outcomes with improved accuracy and explainability (9). Unsupervised methods can reveal disease subtypes and forecast complications such as cerebral oedema or raised intracranial pressure - key problems in neurosurgery (10). Together, these approaches let teams move from slow, lab-bound decisions to earlier, data-driven treatment choices.

The development of machine learning models in healthcare has advanced rapidly in recent years. Faster computers, better analytics, and improved software have driven a surge of interest in ML for clinical care. In neurosurgery, examples of ML models include real-time modelling of tissue deformation during image-guided operations (11), artificial intelligence applications to cranial procedures (12), and prediction of individual treatment outcomes in traumatic brain injury patients (13). Open-source languages such as R and Python have made it easier and cheaper for surgeons and computer scientists to collaborate on these models. Yet the progress is uneven. Data in many settings remain scarce, fragmented, and poorly organized. This slows the translation of promising ML tools into everyday clinical practice.

Machine learning could transform neurosurgical care in Africa. Yet most projects stop at the prototype stage. Interest is rising, but only a few neurosurgeons have built models for their own settings. Many efforts stall before deployment. A review of AI-health applications in Nigeria showed that models trained on small, poorly structured datasets failed in real clinical use (14). A study on federated learning for chest imaging in low-resource African hospitals also found that strong model performance collapsed under weak infrastructure, poor internet, and regulatory delays (15, 16). In rural Rwanda, ML models predicted post-operative wound infections with high accuracy even using limited image and survey data—but implementation beyond the study was not described (17). The same barriers - poor data, limited skills, and policy hurdles - limit neurosurgical ML. Without early stakeholder input, clear rules, and well-curated data, promising tools remain research projects. For ML to work in neurosurgery, projects must start with solid data, align with hospital priorities, and show patient benefit from the start.

How can ML models be implemented in Africa?

Implementing machine learning in Africa starts with identifying a surgically relevant problem. An appropriate problem has enough reliable data, clear neurosurgical consensus on mangement, high clinical or financial impact, and the potential to ease cognitive workload. Few neurosurgical problems meet all these criteria. One example is a model designed to predict surgical site infections after neurological operations (18). By using available data, this system can alert surgeons to patients at risk before infection develops. Still, thorough preoperative assessment by the neurosurgeon remains essential to identify risk factors accurately.

The next step is to build a skilled, multidisciplinary team (19). This team should include model designers, data scientists, and neurosurgical experts. A neurosurgeon who understands the clinical problem should lead. The data team needs a machine-learning specialist plus staff to extract and clean data to ensure validity (19). Overlapping roles improve efficiency. For example, a neurosurgeon who can also validate data may handle a large share of the work.

With a clear problem and an effective team, the next step is to design an appropriate solution. The key is to align model performance with clinical decision-making. Machine learning tools should deliver the right information, to the right person, in the right format, through the right channel, and at the right time (19). Consider infection prediction after neurosurgery. A naïve Bayes algorithm identified postoperative fever and cerebrospinal fluid leakage as strong predictors (18). It then alerted surgeons to high-risk patients, providing accurate, timely, and actionable information. By contrast, the same model failed to predict length of stay after spine surgery. In this case, a non-linear k-nearest neighbors (KNN) model performed better (20). KNN provided patient-specific discharge and bed-allocation insights, again fulfilling the core principle of decision support—reliable information delivered when clinicians need it. These examples show that success depends not only on the problem chosen but also on matching the right algorithm to the right clinical question.

After building a solution, it should first be piloted with a small group of users to test validity and functionality. Their feedback guides refinements before wider rollout. Once deployed, the model needs ongoing evaluation to ensure it stays effective in practice. Because patient profiles and neurosurgical workflows change over time, the model must be updated regularly. Iterative improvements and timely fixes keep it reliable and clinically relevant (21, 22, 23).

Challenges to Development and Implementation

Machine learning in neurosurgery still faces major obstacles in Africa. One major barrier is the lack of high-quality, standardized data. Records are fragmented. Private hospitals use electronic systems, while many public hospitals still rely on paper files (24). This creates messy datasets that are hard to clean and harmonize. Poor data quality then feeds into another problem: model overfitting and poor generalizability. Algorithms trained on small or single-institution datasets capture local patterns only. As a result, they perform poorly when applied to new clinical settings, limiting their reliability in practice (25).

Closely tied to these data quality issues is the problem of interoperability, which further compounds the challenge of building reliable models. For a model to affect patient care, it must be deployable across different settings, yet systems vary widely (26). A tool trained in one hospital may not work in another. Competition between hospitals often limits interoperability because facilities treat patient data as a strategic asset - fearing loss of market advantage, revenue, or patient trust if they share it (26). Even within a single hospital, departments may guard data to protect budgets or research output. In contrast, countries with advanced neurosurgical ML have national regulations - such as those from the U.S. National Coordinator for Health Information Technology - that mandate uniform interoperability standards (27). Similar policies could help align systems locally. While full interoperability will take time, early collaboration among neurosurgeons, administrators, and computer scientists is a practical first step to improving reliability across institutions.

Yet even when interoperability improves, another roadblock appears: the lack of technical infrastructure and support to sustain ML tools in neurosurgery. Despite strong interest, few tools exist in Africa to train and test neurosurgical data. Systematic reviews show that only 22.6% of published datasets for neurosurgery report external validation, and just 20% share their code or public models (28). Models trained on non-local neuroimaging data often perform poorly when used on African MRI scans unless fine-tuned with local datasets (29). Without ready-to-use scripts and local model adaptation, each new project must build, clean, and test models from scratch. This delays deployment. Developing and sharing tested models tailored to local data could help reduce these barriers.

Alongside these technical challenges, however, lie policy and ethical issues that are equally important. Clear national policies for data access, model maintenance, and accountability are still missing (20). Such policies are essential to protect patient privacy and consent, define how results should be used in care, and set standards for model updates (4, 30). Responsible AI frameworks in Africa remain underdeveloped: recent reviews report few countries have regulations addressing algorithmic fairness, liability, or post-deployment oversight (31). Similarly, analysis of ML-driven healthcare shows significant regulatory gaps around data ethics and oversight (32). Without strong policy, projects risk losing stakeholder trust or causing harm. Governments and the private sector must commit to appropriate policy formulation. A practical solution is to establish national or regional regulatory bodies that set clear standards for data sharing, privacy, and model approval.

Towards the Future

What does the future hold for machine learning in African neurosurgery? Adoption may be slow and timelines unclear, but ML is poised to reshape the field. Answering three key questions can help map this path forward.

Which neurosurgical challenges most need priority in machine learning implementation? These can be widely classified into two categories: challenges in surgical treatment strategies and those assessing neurosurgical risk. Unclear neurosurgical practices can be given priority. For example, studies show that machine learning algorithms can identify patients at high risk for complications following intracranial tumor surgery (33). In addition, recent studies show that models can predict the likelihood of surgery in a surgical triage in a spine clinic (34), something that community hospitals find hard to quantify. This can improve the referral of patients. Therefore, there is considerable potential for models to assist neurosurgeons in identifying high-risk patients and in quantifying factors that are currently unmeasurable.

How can we overcome challenges in adopting ML in neurosurgery in Africa? Lessons from other industries show how early obstacles can be turned into progress. In the 1990s, widespread computer use was slowed by poor standardization and proprietary systems, as companies locked customers into closed cables and software (35). Over time, innovation and regulation established shared standards, making hardware and operating systems interoperable across manufacturers. A similar shift is now beginning in healthcare. The growing conversations around AI and machine learning in neurosurgery echo the early days of computing. For successful integration, surgeons must take an active role - especially in implementation and workflow design - to ensure these tools complement, not complicate, existing processes (36). Reducing administrative burdens such as data entry, aligning models with clinical needs, and collaborating with regulators and developers will be critical. This teamwork can accelerate the safe, effective adoption of machine learning in neurosurgical care.

How might neurosurgery evolve in the future? Many repetitive tasks will likely be automated. Robotic systems already assist in drill guide positioning, and machine learning could extend this to fully automated drill insertion under image guidance, such as MRI (36). Robots have also been used for stereotactic biopsies, endoscopic navigation, and spinal instrumentation, showing improved precision and reduced operative time (37). Machine learning will further optimize preoperative planning, predict complication risks, and guide intraoperative decisions (38). These tools may increase surgical speed, safety, and accuracy. Yet the essence of neurosurgery will not change. Neurosurgeons meet patients at their most vulnerable moments. They must understand psychological needs, weigh competing priorities, and offer support - responsibilities beyond the reach of machines (39, 40). As these human-centered tasks grow in importance, they will define the role of the neurosurgeon even more.

Therefore, the future of neurosurgery lies in augmented intelligence, where computers enhance surgical skills and allow neurosurgeons to devote more attention to compassionate, high-quality patient care.

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