



Artificial Intelligence Applications in Clinical Neurosurgery

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Abstract

An emerging area of computer science is artificial intelligence (AI), which involves creating machines capable of learning, reasoning, and solving problems in the same way as humans. There is increasing use of machine learning techniques in the medical field, along with image recognition, language processing, and data mining, ranging from automated image analysis to disease prediction. Neurosurgery is frequently regarded as a pioneer in developing disruptive and innovative technologies that have significantly altered the course of acute and chronic disorders, such as epilepsy and brain tumors. Artificial intelligence platforms have been developed in recent decades to contribute to the paradigm shift in brain tumor surgery. Artificial intelligence platforms can result in safer and more effective brain tumor surgery. Artificial intelligence will soon be used to evaluate, analyze, and provide high-quality medical care. Robots will also become more prevalent in neurosurgery. Hence, physicians must keep up with this revolution to personalize patient care and deliver meaningful outcomes. For neurosurgeons to continue providing high-quality care in the future, they must understand artificial intelligence and utilize it effectively.

Keywords: Precision Medicine, Neurosurgery, Brain Neoplasms, Artificial Intelligence, Wearable Electronic Devices, Epilepsy

1. Context

The healthcare industry faces unprecedented challenges due to an increasing patient population and a longer life expectancy. Consequently, in recent years, the healthcare industry has experienced a shortage of human resources. Nevertheless, relying solely on human capital to meet the rising demand for healthcare services is insufficient (1). According to estimates, approximately 13.8 million people worldwide receive neurosurgical treatments annually (2). However, more than five million low- and middle-income individuals have untreated neurosurgical diseases each year, despite an increase in the number of neurosurgeons to more than 50,000. Therefore, the world needs 23,000 neurosurgeons to fix the neurosurgical shortage, particularly in developing nations. However, educating neurosurgeons is competitive, time-consuming, and costly and requires highly devoted trainers and specialized surgical equipment (3-7).

Therefore, technology has paved the way for human-machine interaction to resolve this issue in the 21st century. With the advent of artificial intelligence (AI), com-

puters can mimic and surpass human intelligence (1). As a result, neurosurgeons can provide their patients with the best possible health care through AI during diagnostic and prognostic procedures and in supporting them during surgical procedures. Aside from creating, analyzing, and storing clinical data, AI is also important for reducing expenses in neurosurgery (8).

Neurosurgery, where technology and medicine are intertwined, can benefit from AI and machine learning since high-tech medical equipment and complex information systems are frequently used in neurosurgery. Furthermore, neurosurgeons have been at the forefront of adopting innovative technology to provide superior patient treatment since Kwoh et al. performed the first modern robotic technique for computed tomography (CT)-guided stereotactic brain surgery in 1988 (9). It is well known that inside and outside operating rooms, neurosurgeons use various noninvasive imaging methods, including CT scans and magnetic resonance imaging (MRI) (10, 11). As AI improves the quality of these high-resolution radiological images, invasive diagnostic procedures can be minimized,

complications can be identified, and better care can be provided. Additionally, neurosurgery produces a lot of diagnostic and therapeutic data, making it an ideal candidate for machine learning. Accordingly, this article discusses artificial intelligence applications in neurosurgery, particularly concerning epilepsy, brain tumors, and patient evaluation.

2. Patients Evaluation

Due to time constraints and fatigue, primary care physicians may encounter difficulties getting complete medical histories from their patients (12). Data are collected via paper questionnaires or interviews during a patient visit, and the information is then manually recorded in the electronic health record (EHR). Lack of time or training results in missing or poor-quality data (13). Consequently, information gaps can lead to inaccurate diagnoses and a failure to address issues that affect 18 million Americans annually (14).

Thanks to recent technological advancements in AI and natural language processing, AI-based conversational bots can extract meaningful information about a person's personal and family history before the visit (15). Chatbots, avatars, and voice assistants are some of the conversational agents that mimic human communication through text or voice (16). These agents have been used in healthcare to screen, triage, counsel, and manage chronic conditions and train healthcare professionals. Some benefits have been reported, including improving patient engagement, reaching large populations, and supporting populations with poor health literacy (17). For instance, telemedicine for routine monitoring and follow-up visits could benefit people who live in remote areas without access to specialists and reduce the cost and time required to travel to them. In addition, such a patient-centered approach can lead to more frequent and punctual visits (8). It is also beneficial for geriatric patients, given that they are more likely to experience a more significant number of chronic conditions, which may require constant monitoring. However, traveling back and forth to clinics for every issue can be exhausting and not always necessary. Additionally, some of these individuals may have physical or cognitive disabilities, leading to a lower referral rate or the inability to explain their symptoms clearly in short sessions. Consequently, this might result in misdiagnosis (18).

Furthermore, medical technologies, such as wearable devices (WDs), are becoming increasingly crucial for personal analytics since they enable users to monitor their health, record physiological information, and schedule medications while monitoring their physical state. In addition, these technologies provide continuous medical data

for monitoring metabolism, detecting and treating diseases, and supporting people in living healthier lifestyles. Likewise, this technology has been successfully utilized in the assessment of motor function in neurodegenerative diseases such as Parkinson's disease (PD) and Huntington's disease (HD) by analyzing information regarding tremors, abnormal gait, bradykinesia, rigidity, and chorea (19). Besides WDs for detecting resting tremors in PD, vibrotactile stimulators are also used for reducing the severity of resting tremors (20). Another use of WDs is in stroke rehabilitation and recovery. For instance, it is possible to monitor and collect movement data unobtrusively using sensors such as an inertial measurement unit. These sensors can be used to determine a patient's motor deficits and determine treatment options. In addition to monitoring a patient's response to treatment by capturing data during daily life activities, the system will provide immediate feedback to enable patients to undergo more extensive training outside the clinic (21).

Moreover, technology, such as laptops equipped with cameras, can be used to track eye movements and irregularities or determine the underlying cause of the problem. For example, a patient with central nerve palsy caused by cerebral compression can be detected using eye-tracking technology in neurology while watching a movie or television. This method's repeatability and minimal danger make it suitable for many applications. However, it cannot replace the traditional invasive procedure (22-24).

Some smartphone applications have primarily been developed for cognitive change assessment to monitor dementia patients and record their wandering episodes. In addition, they may be able to aid in collecting information concerning potential risk factors for other cognitive disorders and early behavioral changes. For example, an app called "Ivitality" is designed to perform five digitally modified versions of traditional cognitive exams. Another instance is the "Delapp" app, designed to detect delirium in hospitalized patients (25).

Additional research could assist in developing suitable sensors for brain tissues that can detect chemical biomarkers that may cause neurological disorders, such as neurotransmitters. In addition, by collecting consistent and sustained data on vital signs, AI can predict clinical laboratory test results with less error (26).

3. Epilepsy Management

Epilepsy affects approximately 10% of the population at some point in their lives. Unfortunately, despite countless trials to cure epilepsy, antiepileptic drugs may be ineffective for about 30% of these patients. In addition, patients' treatment outcomes vary depending on their intrinsic

sic characteristics, such as seizure types and semiologies, brain lesions, or comorbid neuropsychological dysfunctions, as well as extrinsic factors, including treatment initiation stage and treatment conditions. Accordingly, choosing the proper treatment for each patient necessitates individualized approaches, which is essential for effectively assessing the patient's state (27-30). Hence, AI can contribute to the success of this procedure.

With the development of high-performance computing technology and multiple mathematical algorithms, researchers can analyze increasing data to tailor treatment plans for epileptic patients. There are two main areas of focus for these computational studies: The first is the development of machine learning algorithms derived from large quantities of information obtained from numerous patients to develop computational machines capable of performing specific tasks, such as predicting disease outcomes and automatic diagnosis. Secondly, biophysical in-silico platforms can replicate the individual patient's brain network dynamics using the patient's specific data, enhancing understanding of the pathophysiology and determining the best treatment. Therefore, integrating various types of patient data and analysis results into one platform using computational approaches is essential. These methods could suggest a new paradigm for precision medicine if successfully implemented (31).

Recently, AI-based approaches to epilepsy include automatic seizure detection and prediction, understanding the epileptogenesis, presurgical planning, optimizing the medical and surgical management, including the prediction of seizure freedom and delineation of epileptic networks, development of wearable electronic devices for people with epilepsy, and automated neuroimaging analysis (32, 33).

4. Automated Seizure Detection and Prediction

Applying machine learning to analyzing massive, complex datasets has sparked significant interest in the automated detection of seizures in electroencephalogram (EEG) recordings. Various methods, including the support vector machine (34, 35), k-nearest neighbor (36, 37), and deep learning classifiers (38, 39), have been utilized to accomplish this task. In addition, the same algorithm has also been used to predict seizure rates from EEG data using a restricted database, with prediction times up to several minutes (40, 41).

As an alternative to EEG recordings, seizure detection using machine learning has been expanded to non-traditional data sources such as video recordings, surface electromyography (EMG), and mobile devices (EEGs). For

instance, a neural network technique was utilized to evaluate video recordings of neonates' bedside-recorded extremity movements, with a specificity and sensitivity of approximately 90% for detecting seizures in neonates (42). Likewise, the sensitivity and specificity were substantially enhanced when EEG data were added (43). Attempts have also been made to classify recordings of nocturnal seizures as tonic, tonic-colonic, or focal motor seizures using infrared camera data, infrared markers attached to anatomic landmarks for motion detection, and artificial neural networks (ANN) (44).

5. Application in Surgical Management of Epilepsy

Regarding epilepsy surgery, although it can increase the likelihood of seizure freedom for eligible patients with drug-resistant epilepsy from 10% to 67% (45), surgery remains underutilized or performed late in disease progression. This operation is likely underutilized due to its mortality and morbidity concerns, while both are comparable to knee and hip replacement surgeries (46). In epilepsy surgical planning and predicting surgical outcomes, especially following temporal lobectomy, machine learning approaches are increasingly applied as a tool for earlier intervention.

According to Grigsby et al., ANNs were used to encode clinical, electrographic, neuropsychological, imaging, and surgical data from 65 patients to predict the outcomes of anterior temporal lobectomy. According to the analysis, Engel I outcomes were predicted with an 80.0% sensitivity and 83.3% specificity, while Engel II outcomes were predicted with 100% sensitivity and 85.7% specificity (47).

Based on the hypothesis that machine learning algorithms could identify epilepsy surgery candidates early in the disease progression, Wissel et al. trained ML algorithms using n-grams extracted from free-text neurology notes, EEG and MRI reports, visit codes, medications, procedures, laboratories, and demographics. Two epilepsy centers were therefore equipped with site-specific algorithms. A total of 5,880 pediatric patients and 7,604 adults were grouped according to their surgical and nonsurgical diagnoses. The study revealed that AI-based models identified adult patients better than pediatrics eligible for surgery. However, it was possible to predict pediatric surgical patients 2.0 years before their presurgical evaluation (48). However, machine learning might not accurately predict long-term outcomes in some cases. Therefore, identifying the patient's epileptic network before epilepsy surgery is essential (49, 50).

6. Brain Tumors

Innovative AI applications in the disciplines of machine learning, natural language processing, computer vision, and robotics have the potential to revolutionize neurosurgical practice, which could have a significant impact on the management of brain tumors, including potential clinical uses of AI in the preoperative, intraoperative, and postoperative phases of brain tumor surgery.

Artificial intelligence might play an essential role in diagnosis, assessing, and planning as part of the preoperative stage of brain tumor management. The first thing to note about its role in diagnosis is that machine learning models, according to previous studies, can diagnose hematological disorders better than physicians (51). For example, Podnar et al. conducted a study that employed machine learning to identify minor differences in routine blood tests, which allowed for the early detection of brain tumors. Most notably, the machine learning algorithm demonstrated a decreasing trend in eosinophil and basophil counts and an upward trend in neutrophil counts and serum glucose among patients. In addition, their model has comparable sensitivity and specificity to CT and MRI, which were 96% and 74%, respectively (52). Hence, scientists believed this model could be utilized as a screening tool for intracranial malignancies; however, it failed to distinguish between primary and secondary brain tumors. In more recent research, Tsvetkov et al. revealed that glioblastoma in patients could be detected by differential scanning fluorimetry with a 92% accuracy using an AI-powered detection tool (53).

Neuroimaging, specifically MRI, has remained the gold standard in diagnosing brain tumors. Nonetheless, a lack of expertise in selecting appropriate MRI sequences can result in a loss of critical clinical findings, excessive medical expenses, or even patient injury. Machine learning has become increasingly crucial in treating brain tumors by automating sequence selections and assisting radiologists in diagnosis. According to Brown and Marotta a natural language processing ML system was developed to analyze MRI brain imaging requests and select the most clinically valuable sequences for MRI brain imaging (54). Radiomics also offers the capability of converting clinical imaging arrays into quantitative characteristics. By mining and validating them using machine-learning algorithms, quantitative imaging biomarkers can be developed for describing intratumoral dynamics (55).

In addition to blood marker tumor screening and optimizing imaging sequences, ML algorithms have been applied to various tasks related to diagnosing and assessing brain tumors. A few examples are as follows:

- Identifying and quantifying the molecular expression

of brain tumors

- Detecting metastases within the central nervous system
- Distinguishing primary from metastatic lesions
- Determining the grade of the tumor
- Predicting the presence of genetic mutations

A further benefit of this technology is that it can accurately predict the surgery outcome and stratify the risk before surgery to design a specific treatment plan (56). According to Ko et al., an ML platform could accurately predict the progression and recurrence of meningiomas using only radiological data (57).

As AI technology, particularly computer vision, is rapidly developing, machine learning systems may also play a significant role in treating intraoperative brain tumors. The project will benefit some areas, including intraoperative tumor identification, workflow analysis, robotic surgery, and risk detection (56).

Given that residual peripheral tumor tissue is the leading cause of tumor recurrence in brain tumors, more extensive tumor resection is associated with longer survival time in brain tumors, particularly glioma and GBM (58). Although several imaging modalities are utilized as guidance tools during brain tumor surgery, these imaging techniques have distinct limitations. As an example, the intraoperative neuronavigation system uses preoperative image information derived from CT or MRI to guide surgery in real time; however, due to the phenomenon of brain shift, the accuracy of tumor margin delineation decreases as the surgical procedure progresses (59-62). Integrating deep learning platforms with hyperspectral imaging (HSI) can address this issue for the intraoperative identification of brain tumors. Besides, HSI combines intraoperative imaging with spectroscopy to provide detailed information about the surrounding structures both spatially and molecularly (63, 64). The method was employed by Fabelo et al. as a deep learning platform for the analysis of HSIs of six GBM patients, which included a neural network containing three convolutional layers. Backgrounds were identified with 98% accuracy, while tumor tissue was detected with 42% accuracy. The authors also reported that the system had an 88% sensitivity to categorize images as tumor-free and a 100% specificity, which indicated that this technology performed well when classifying normal tissues (58, 63).

An exciting new application of artificial intelligence is intraoperative workflow analysis, which uses computer vision combined with machine learning platforms to analyze how steps, phases, instruments, gestures, anatomy, and pathology are executed during an operation. The AI-based workflow analysis can provide numerous advantages, including improved intraoperative surgical plan-

ning and routing, accurate identification of anatomical structures, identification of risks early, standardization of phases and steps, the creation of operative notes, and contributions to simulations and training programs. In addition, this technology is expected to significantly reduce surgical errors, complications, and operation times within the next few years and enhance surgeons' awareness of potential risks (65-67).

Due to the outstanding data-assimilation capabilities of AI systems, the postoperative phase could profit in various ways, including predicting complications and recurrence, bioinformatic early warning systems, and individualized follow-ups and treatments. Primary spheres of influence include inpatient, outpatient, and oncology care.

In patients with brain tumors, postoperative complication development is influenced by many static and dynamic factors, which can be assessed most effectively using AI techniques. Greater integration of AI in brain tumor surgery could prevent or mitigate postoperative complications such as surgical site infection, venous thromboembolism, adverse drug events, pressure ulcers, falls, and hypoglycemia. These avoidable postoperative problems cause many patients to suffer needlessly. Artificial intelligence can help reduce these common problems (56).

7. Conclusions

Artificial intelligence benefits neurosurgeons as it can be utilized before, during, and after a surgical procedure. A combination of humans and computers can use artificial intelligence to improve healthcare delivery by better matching patients with appropriate procedures, increasing intraoperative activities, providing postoperative follow-ups, and improving access to treatment by leveraging the most recent advances in AI technology. Hence, AI may eventually pave the way for personalized medical care. Precision medicine predicts health outcomes, prognoses disease processes, prevents diseases, reduces surgical complications, and develops numerical models to analyze clinical data. There are applications for AI in both personalized and precision medicine. However, additional research, funding, and interdisciplinary collaboration are required before AI can be widely applied in neurosurgery.

Footnotes

Authors' Contribution: P. S. conceptualized the study and prepared the initial draft. S. K., F. M., A. A., and G. R. took responsibility for the construction of the body of the manuscript. S. S. supervised the manuscript. P. Sh. and M. Sh. revised the manuscript and prepared the final draft.

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