Artificial Intelligence in Neuroanesthesiology and Neurocritical Care

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Abstract

Artificial intelligence (AI) already influences almost every sector of our daily life, including the rapidly evolving technologies and datasets of healthcare delivery. The applications in medicine have significantly evolved over the past few decades and have shown promising results. Despite constant efforts to incorporate AI into the field of anesthesiology since its inception, it is still not commonplace. Neuroanesthesiology and neurocritical care is a discipline of medicine that deals with patients having disorders of the nervous system comprising a complex combination of both medical and surgical disease conditions. AI can be used for better monitoring, treatment, and outcome prediction, thereby reducing healthcare costs, minimizing delays in patient management, and avoiding medical errors. In this review, we have discussed the applications of AI and its potential in aiding the clinician's judgment in several aspects of neuroanesthesiology and neurocritical care, some of the barriers to its implementation, and the future trends in improving education in this field, all of which will require further work to understand its exact scope.

Keywords
► artificial intelligence
► machine learning
► neuroanesthesiology
► neurocritical care

Introduction

The official introduction of AI occurred during the 1956 Dartmouth Artificial Intelligence Conference. John McCarthy coined the term "artificial intelligence" in 1955, and is one of the "founding fathers" of artificial intelligence together with Alan Turing, Marvin Minsky, Allen Newell, and Herbert A. Simon.[1] Since then, there has been widespread implementation of AI in all sectors including healthcare[2,3] AI is defined as the development of computer systems to model intelligent behavior with minimal human intervention.

The application of AI in medicine has two main branches: 1) virtual branch and 2) physical branch.

The physical branch comprises highly repetitive work. It empowers the doctors to deliver faster and more accurate clinical care by offering them expertise and assistance. The virtual component is represented by Machine Learning (ML), mathematical algorithms that improve learning through experience.

Health Data Management

The health data are nowadays available in electronic health records (EHRs). The medical data include numerical information, laboratory test results, genetic tests, culture results, images, treatment information, administrative data, and health research information. Clinical data stored in EHR are both structured and unstructured[4,5] (►**Fig. 1**).

Structured Data

Structured data follow a prescribed data model and value set, constraining the users to only be able to choose

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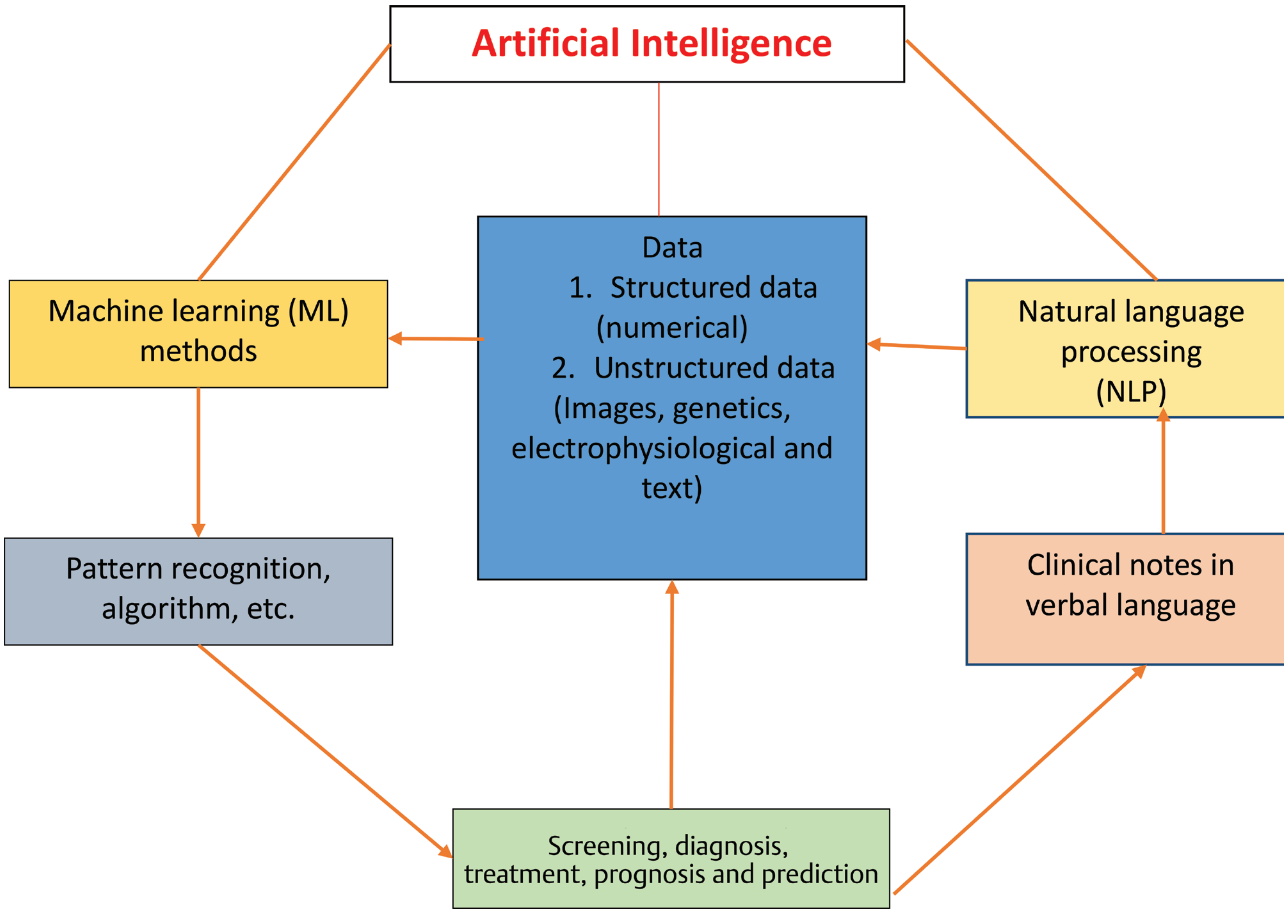

Fig. 1 The cycle of medical data generation through medical health records, NPL to ML to clinical treatment and prediction. ML, machine learning; NPL, natural language processing.

predetermined values. Computers can readily process structured data. Data sent by medical devices to EHRs are usually structured data.

Unstructured Data

Unstructured data do not follow a predefined set of values, allowing users to instead enter narrative information about data using their own words. This means recording data provides the user with the most freedom for recording an entry, but because the same clinical event could be documented in myriad ways, computers cannot easily process unstructured data, making errors more likely. These data have to be converted to computer readable data through the natural language processing (NLP) methods.[5,6]

Machine Learning Algorithms

Machine learning (ML) can be classified as follows[4,7-9]:

1. Unsupervised
2. Supervised
3. Deep learning
4. Reinforcement learning

Unsupervised Machine Learning

Unsupervised learning is a ML technique, where the model works on its own to discover information and the outcomes of the model are not defined.

It performs more complex processing tasks compared with supervised learning but becomes unpredictable compared with other ML techniques and is less accurate.

Clustering, association, and principal component analysis (PCA) fall into unsupervised techniques. Clustering finds out the structure and pattern in data and identifies different groups, whereas association establishes the relationship in the datasets from the given database. PCA is mainly used for the dimension reduction of data.

Supervised Machine Learning

The input and output variables are provided in a supervised learning model. Thus, specified data are used to train algorithms, and a link is established between input and output variables in a supervised learning model. These techniques are highly precise.

The supervised learning techniques are regression and classification. Classification separates the data, whereas regression fits the data.

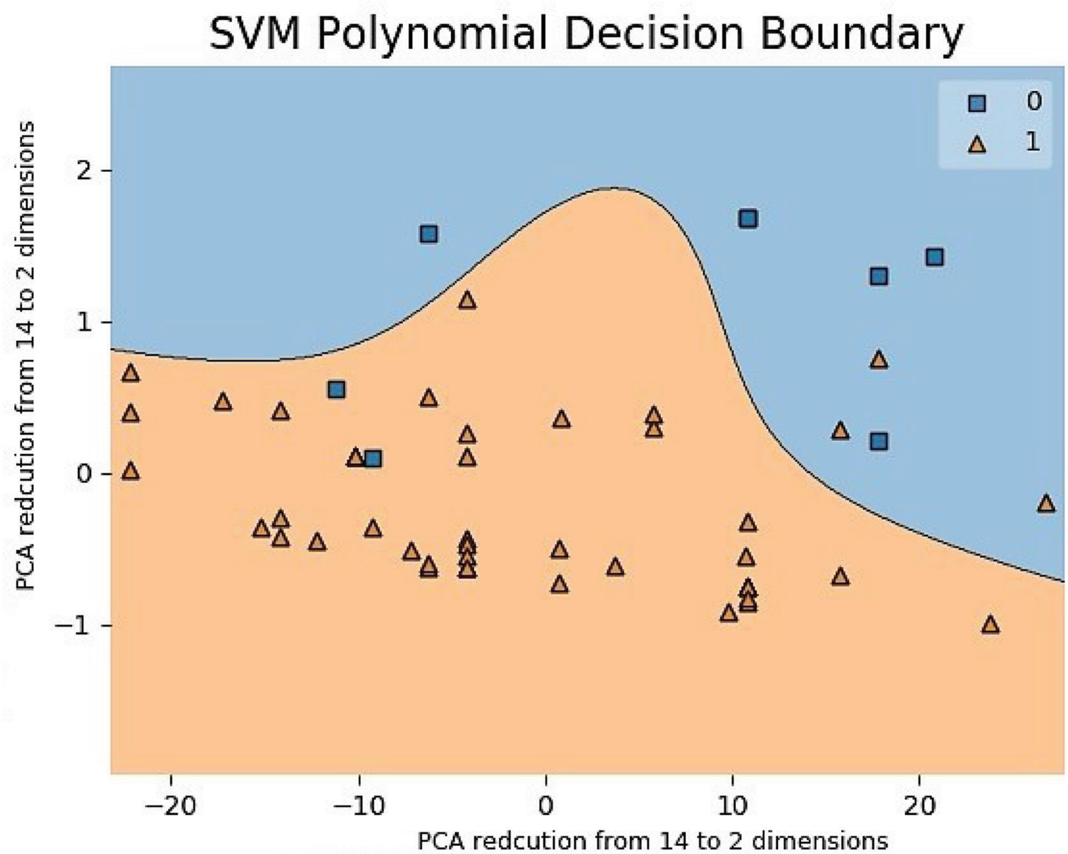

Fig. 2 Depiction of SVM classifying the data into two categories and data reduction by PCA. PCA, principal component analysis; SVM, supervised learning algorithm.

The following algorithms are used in supervised ML techniques: decision tree, random forest (RF), Naïve Bayes (NB), support vector machine (SVM), artificial neural networks (ANN), discriminant analysis, nearest neighbor, linear regression, and logistic regression. The SVM and ANN are frequently used in the medical field.

Support Vector Machine

This supervised learning algorithm classifies the data into two categories. The model is built from the data already sorted in two categories (►**Fig. 2**). This makes SVM a kind of nonbinary linear classifier. SVMs are used in text categorization, image classification, prediction, and handwriting recognition.

Artificial Neural Network

The neural network captures complex nonlinear relationships between input and outcome variables by multiple hidden layers (HLs) with prior specified functions. The weights are established through the input and outcome data; thus, the average error is reduced and the predictions become more accurate (►**Fig. 3**).

Deep Learning

Deep learning is a self-teaching system in which the existing data are used to train algorithms to find the patterns and then make predictions about new data. The ANNs with multiple layers of nodes create deep learning algorithms that mimic the network of neurons of the brain. This algorithm with multiple cycles defines patterns and improves the precision of predictions with each cycle (►**Fig. 4**).

Reinforcement Learning

Like deep learning, reinforcement learning is autonomous. But deep learning is learning from a training set and then applying that learning to a new dataset, while reinforcement learning is dynamically learning by adjusting actions, based on continuous feedback, to maximize a reward.[3,6-8]

Neuroanesthesiology and neurocritical care as a discipline is rendered difficult due to the inherent limitations in the assessment of patients with neurological injury. As neuroanesthesiologists, we work in operating rooms and intensive care units (ICUs), both being acute care settings, which demand vigilance, steady hands, and quick thinking.

AI can definitely assist us in making better clinical decisions and provide up-to-date medical information from journals, textbooks, and clinical practices. This results in early diagnosis, predicts outcome of the disease as well as treatment, provides feedback on treatment, and reduces errors. This greatly increases patient safety and saves costs. These traits allow AI systems to continuously monitor and treat neurocritical care patients in real-time. Early signs of

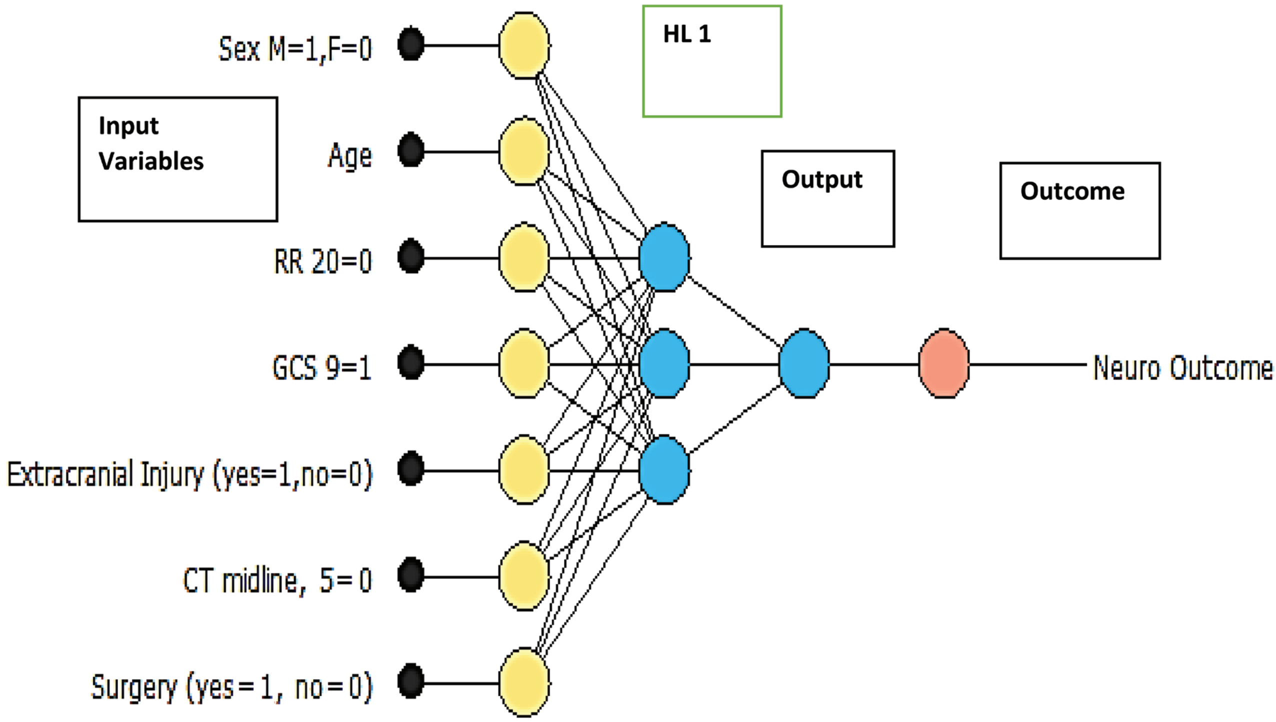

Fig. 3 A diagram representing ANN, showing the outcome of head injury; the input variables are sex (M–male, F–female), age, RR, GCS, extracranial injuries, CT scan of the midline shift, and whether surgery was performed in binary fashion. The HL is only one. ANN, artificial neural network; CT, computed tomography; GCS, Glasgow coma scale; HL, hidden layer; RR, respiratory rate.

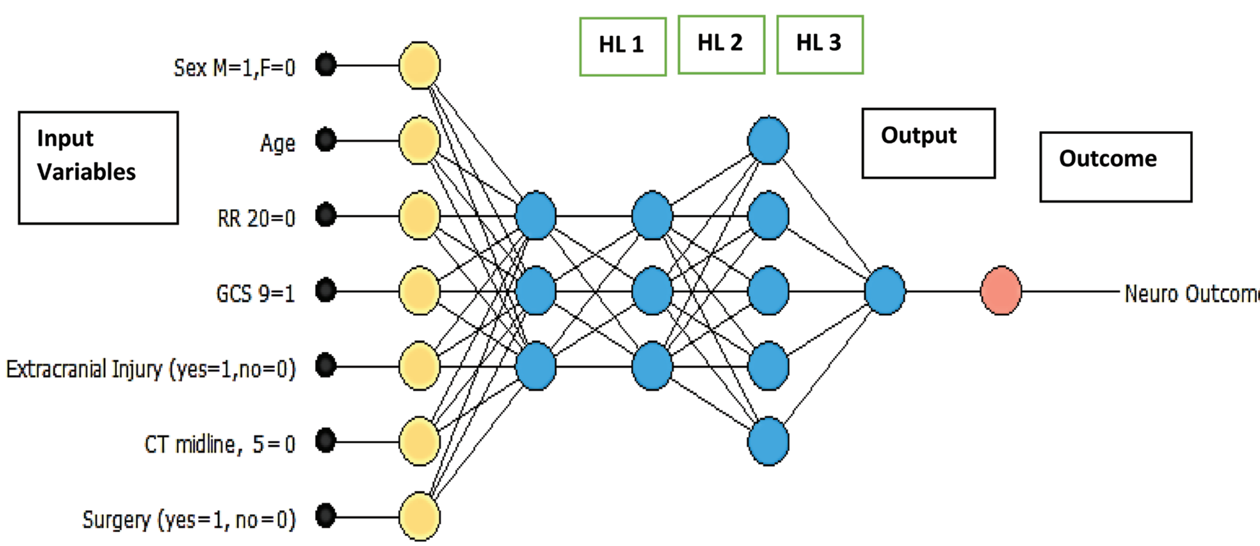

Fig. 4 Depiction of deep learning of ANN with the following input variables: sex (M–male, F–female), age, RR, GCS, extracranial injuries, CT scan of the midline shift, and whether surgery was performed in the binary fashion with three hidden layers of nodes and the head injury outcome. ANN, artificial neural network; CT, computed tomography; GCS, Glasgow coma scale; HL, hidden layer; RR, respiratory rate.

neurological deterioration could be detected more promptly and appropriate measures taken more quickly, thereby improving patient outcomes. AI can also help patients in areas where neurocritical care is not available,[10] as they take over more of the basic patient management, by analyzing the data and titrating treatments in real-time, reducing possible delays in patient care and optimizing the patient's condition till he/she is transferred to a higher center with neurocritical care facility.

In this review, we have discussed the applications of AI in neuroanesthesiology and neurocritical care, the barriers to its implementation, and the future trends in this field.

Applications in Neuroanesthesiology and Neurocritical Care

AI creates a potential system to manage the neuroanesthesiology and neurocritical care patient with minimal or no supervision, freeing the clinician to focus attention elsewhere.[11-13] Some potential parameters include anesthetics/analgesics, antiepileptic drugs (AEDs), blood pressure, glucose, fluids/electrolytes, neuromuscular blockade, and ventilator settings.[14-25] The applications of AI in our field can be broadly discussed under five categories (1) predictive analytics, (2) imaging, (3) smart devices, (4) Administration, and (5) research and education.

Predictive Analytics

Much of the work in critical care using AI has focused on predictive analytics. Improvement in the prediction of adverse events such as hypotension has been shown using advanced ML models in critical care environments.[26] ML methods can predict the risk of postinduction hypotension.[27,28] These models enables detection and intervention up to 15 minutes before an event and have been generalized for use in the multicenter clinical environment.[29] Predictive therapeutic interventions to prevent hypotension using AI have also been constructed for fluid resuscitation.[30] By combining models for early hypotension detection and therapeutic intervention, there is potential to prevent or minimize patient deterioration and the subsequent development of multisystem organ dysfunction.

Sepsis remains one of the largest causes of mortality in the ICU. Sepsis algorithms become more important and these interpretable models can predict sepsis 4 to 12 hours before clinical recognition.[31]

ML models can also help in the prediction of hospital-acquired infections such as central line-associated blood stream infection and *Clostridium difficile* infections.[32]

Prediction of prolonged mechanical ventilation is useful for early tracheostomy, ventilator weaning, and rehabilitation. Use of AI to identify patients who will require > 7 days of mechanical ventilation has been shown to improve outcomes.[33] Teams are also using AI to aid ventilator weaning by targeting the success of extubation. Kuo et al[34] used neural networks to create a model with an accuracy of 80% and improved on traditional prediction by rapid shallow breathing index.

AI has also been implemented in specialized ICUs such as in neurointensive care for early and accurate risk assessment of seizures in critically ill patients.[35]

Predictive ML models for patient trajectories[36] and ICU readmission have been developed and have shown higher predictive values than the conventionally used stability and workload index for transfer score or the modified early warning score criteria for early deterioration.[37]

Mortality is a common outcome in medical studies, and prediction capabilities related to it have been studied extensively using ML and NLP. Use of NLP enables inclusion of the traditionally difficult-to-use clinical notes. Weissman et al[38] showed the ability to use unstructured data such as clinical notes, and terms such as "poor prognosis," by using various NLP techniques. Using neural networks, classification algorithms can be constructed for identification of the most important terms in physician notes, which then can be used to construct ML models to predict outcomes such as mortality in the surgical ICU.[39] One such model, called Early Mortality Prediction for Intensive Care Unit patients, has been shown to outperform traditional scoring systems such as acute physiology and chronic health evaluation (APACHE) and sequential organ failure assessment (SOFA) despite missing values within the training datasets. The area under the curve (AUC) is 0.82 ± 0.04 compared with the traditional scoring systems which range from 0.54 to 0.65.[40] This model has not only focused on prediction accuracy, but has also attempted to generate earlier prediction by hours using multimodal data. The benefits of such models once again lie in triage, early intervention, and appropriate treatment recommendation to minimize risk to the patient and provide for cost-effective care.

Harnessing meaningful information from EHR data and data registries is expensive, can be of limited value, and is utilized primarily for retrospective research analysis. As we have seen from the above examples, ML provides a more cost-effective way to carry out retrospective research and, in constructing models, can provide real-time or prospective guidance to clinicians.[41]

Machine-learning models have been developed for predicting mortality following trauma in motorcycle riders. ANNs have been used to predict outcome following head injury.[42,43]

The occurrence of symptomatic cerebral vasospasm (SCV) after aneurysmal subarachnoid hemorrhage (aSAH) is a morbid and common problem. A simple ANN model was found to be more sensitive and specific than multiple logistic regression (MLR) models in prediction of SCV in patients with aSAH.[44] ML has been used to predict outcome in intracranial aneurysms treated with flow diverters.[45]

Hollon et al[46] sought to build a predictive model using supervised ML to accurately predict early outcomes of pituitary adenoma surgery. These results provide insight into how predictive modeling using ML can be used to improve the perioperative management of pituitary adenoma patients.

Stroke is one of the major causes of disability and death worldwide. It is estimated that up to 80% of strokes can be prevented if one can identify or predict the occurrence of stroke in its early stage.[47] AI-based methods offer several advantages in improving prediction performance for stroke treatment, prognosis, and functional outcome prediction. This helps neurophysicians to identify high-risk patients and guide treatment approaches, leading to decreased morbidity. Several AI-based techniques are being investigated to develop automated platforms for precisely predicting prognosis and the functional outcome. Park et al[48] have proposed a Bayesian network model for the prediction of poststroke outcomes with the available risk factors. They also introduced an online "Yonsei stroke outcome inference system" for predicting functional independence at 3 months and mortality within 1 year in patients with stroke using the Bayesian network model.

The timely diagnosis of stroke is crucial for good functional recovery and minimizing mortality. AI offers technology solutions with high-precision and accuracy for the diagnosis of stroke, its severity, as well as prediction of functional outcomes.[49]

Recently, in diagnostic neuroradiology, there has been an interest in adopting AI and ML techniques[50,51] and in the prediction of the outcome in patients postneurointerventional procedures.[52,53] Two recent studies[52,53] have used ANN modeling and supported vector machine algorithms in prediction of the final Modified Rankin Score (mRS) with relatively good accuracy and precision. The accuracy of outcome prediction, using supervised ML algorithms has shown promising results, especially in the prediction of final outcome as good or bad as well as the probability of requiring retreatment in future, with the potential for incorporation of larger multicenter datasets, which will further improve predictive accuracy.[54]

Imaging

Point-of-care ultrasound for assessment of cardiac function, volume status, and vasopressor/inotrope management has witnessed increasing utilization in care of critically ill patients. Deep learning models have been developed that can enable fast and accurate classification of cardiac anatomy on echocardiograms.[55] Innovations such as these are likely to propel clinicians into a newer era of enhanced integration of various imaging techniques to generate more accurate diagnosis and treatment methods. Automated analysis of medical imaging is a prominent area in ML applications. ML models have been implemented in the reading of radiographic images, including X-rays and computed tomographic scans, and have reported increasing accuracy for clinical diagnosis.[56]

Within the ICU, models have been developed to provide surveillance for lines and tubes to assess proper device positioning.[57] In addition, waveform analysis from ventilator data has been used to create models to detect patient–ventilator asynchrony that match clinical experts.[58] Thus far, the primary use of ML waveform analysis has been to either automatically screen waveforms such as electrocardiograms and electroencephalographs, which cannot be monitored constantly by clinicians. The goal of these models is to improve time to early intervention.[59,60] The tools developed for waveform detection could also be used to reduce the burden of alarms plaguing ICUs. One of the Joint Commission International goals is to reduce alarm fatigue among care providers, which can conceivably be achieved using modern AI techniques.[61]

Smart Devices

Medication delivery and titration is a key component of patient care in the ICU and requires a large amount of clinical resources. Smart pumps exist for medication titration, and these devices can be further utilized for their abilities to provide closed loop management. In future, increased utilization of closed loop infusions will hopefully decrease manual labor while possibly enhancing consistency in steady-state drug delivery. Models using unsupervised learning have been trialed for clinical applications, including use in vasopressor drug delivery in the ICU.[62] Similarly, for tight glycemic control, AI-based artificial pancreas systems have been developed for use in the ICU.[63]

Administration

Triage from emergency departments is a complicated task and includes identification of high-risk patients who need to be promptly admitted to the ICU. AI models have been developed that can help triage trauma patients, thereby leading to appropriate and timely resource utilization.[64,65] Similarly, identification of cohorts of patients with similar clinical needs has been postulated to provide a framework for future organizational innovations in the ICU and provide better cost-effective care.[66]

Research and Education

Considerable research has been generated in all areas of AI. AI in medical education is still in its infancy. In the future, it is likely that basic understanding of AI and its applications will be required in clinical practice and thus will be part of educational curricula to facilitate better understanding, interpretation, and implementation.

Anesthesiologists and intensivists work at the junction of many disciplines: surgery, medicine, biology, pharmacology, mathematics, and physics, and are well-placed to embrace modeling. They have access to knowledge and expertise of enormous breadth and have experience of a huge array of induced and pathological states, and are comfortable with biological science, physical science, numbers, technology, and medicine. Anesthesiologists and intensivists, above all, have clinical contact, a real understanding of real-world relevancy and empathy for the issues of importance. In addition, they have skills in managing teams of individuals, collaborating and coordinating their efforts toward a single goal. All that is required of the researcher who wants to use modeling is to get an idea of what may be achieved and find a suitable question to answer. Contact with an expert will be enormously helpful during the researcher's early forays into AI.

Limitations and Future Trends

AI technologies have great potential for assisting future neuroanesthesiologists and neurocritical care physicians. However, significant hurdles remain before they can be used routinely in the operating room and ICU. One of the most significant challenges is creating adequate regulatory mechanisms to ensure the patients under the care of AI are safe and protected. When an AI independently decides to intervene on a patient and causes an adverse event, who is then held accountable? Furthermore, patient autonomy might be challenged because the AI system can administer care in an automated fashion without involving the patient in the decision-making process. The patient–doctor relationship can become more "distant," as these AI systems take over more of the basic patient management. As this technology becomes more widespread, these challenges need to be addressed before AI can play any role in patient care.

Conclusions

As a specialty, neuroanesthesia and critical care should continue to create and refine real-time evidence-based, individualized, clinical decision supportive tools and guidelines. One of the future clinician's greatest challenges will be validating the safety and efficacy of these systems. The revolution in AI is so much that there may be a risk of technological collusions such as cloud and edge computing to even surpass human intelligence in the years to come. The challenge for healthcare professionals, in particular, is the willingness to accept technology and the transformation that is inevitable. Effective clinical governance to ensure patient safety is vital for digital health.

Conflict of Interest
None declared.

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