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Editorial

Artificial intelligence in neurocritical care

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ABSTRACT

Background: Neurocritical care combines the management of extremely complex disease states with the inherent limitations of clinically assessing patients with brain injury. As the management of neurocritical care patients can be immensely complicated, the automation of data-collection and basic management by artificial intelligence systems have garnered interest.
Methods: In this opinion article, we highlight the potential artificial intelligence has in monitoring and managing several aspects of neurocritical care, specifically intracranial pressure, seizure monitoring, blood pressure, and ventilation.
Results: The two major AI methods of analytical technique currently exist for analyzing critical care data: the model-based method and data driven method. Both of these methods have demonstrated an ability to analyze vast quantities of patient data, and we highlight the ways in which these modalities of artificial intelligence might one day play a role in neurocritical care.
Conclusions: While none of these artificial intelligence systems are meant to replace the clinician's judgment, these systems have the potential to reduce healthcare costs and errors or delays in medical management.

1. Introduction

Neurocritical care involves the management of extremely complex cases with the inherent limitations of clinically assessing patients with brain injury. Multimodality monitoring (MMM) has created a wealth of data in the setting of neurocritical care [1]. Ventilation, intracranial pressure, hemodynamics, body temperature, fluid intake-output, serial neurological examinations, and other neurophysiologic parameters are examples of some of the information that may be gathered with MMM. While MMM has transformed care by centralizing patient data, more exciting is the prospect of implementing artificial intelligence (AI) in automating basic care utilizing data accumulated by MMM. Recent advances in AI have made it possible for AI to move from the experimental realm and become integrated into the actual clinical setting. AI systems that demonstrate ambient intelligence interact with humans and are embedded, context aware, personalized, adaptive, and anticipatory. Using these traits, an AI with ambient intelligence could be used for continuous real-time monitoring as well as treatment of neurocritical care patients. Early signs of neurological deterioration could be detected more quickly and appropriately managed, improving patient outcomes. Additionally, AI could reduce costs and help patients in remote areas where the expertise of a neurocritical care physician may not be present [2]. In this article, we review the promise of existing technologies in shaping automated care and discuss the future potential directions towards a more integrated AI system in neurocritical care.

2. Promise of artificial intelligence

AI systems have made great progress in the realm of data analysis of high resolution neurocritical care data as well as algorithmic decision making [2]. Alongside advances in this decision making, there has also been the development of technology that allow for these decisions to constantly be informed by the patient's health status [3]. Closed-loop AI systems may monitor parameters of patients, then directly treat patients and induce changes in those very parameters they may be monitoring. These systems may make direct real-time adjustments to patient care without any human input [4,5]. Examples of some of the patient care modalities they may modify are anesthetics/analgesics, antiepileptic drugs, blood pressure, glucose, fluids/electrolytes, neuromuscular blockade, and ventilator settings [6–17]. When decision making is combined with the ability to execute those decisions, it would not be unrealistic to foresee a future where AI systems are able to completely manage neurocritical care patients with little or even no supervision. Below, we discuss the different commonly measured parameters in neurocritical care and discuss the innovations that have allowed for the automation of analysis and management and for the increased role of artificial intelligence.

3. Bioinformatics, algorithms, and AI decision making in neurocritical care

Decision making and data analysis ability are absolutely essential to the function of an AI with ambient intelligence. In order to interact with patients and guide treatment an AI must have the function to parse through large amounts of physiological data gathered through various modalities and make complex neurocritical care decisions. Two overarching general approaches are usually applied when analyzing critical care data: model-based methods and machine learning (data driven) methods. Briefly, model-based methods utilize a model constructed on our understanding of a system, and parameters are fed into that model

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to generate a predicted outcome. In clinical practice, model-based methods attempt to create a physiological model of the patient where various factors are weaved together and treatment is aimed at pushing the patient towards a favorable physiological state rather than correcting a specific physiological variable [18,19]. In machine learning methods, algorithms use prior outcomes and prior data to predict future outcomes based on unseen data. With both approaches, there are several methods of generating an outcome.

One such method is referred to as dynamic systems models, which attempt to describe the many interactions in a system using classic physical mechanics. One example of this type of model has been created by Ursino et al., in which he modeled the relationship between cerebral hemodynamics, cerebral vascular reserve, cerebral perfusion pressure, and autoregulation [20]. One problem with dynamical system models is that they generally work on the assumption that in a modeled biological system each component contributes linearly to the model. Real biological systems are actually typically nonlinear, and small changes in variables in these systems could result in enormous downstream results [21].

Bayesian inference is another method that can be used with either model-based or machine learning systems. Bayesian inference functions to estimate diagnostic states of patients using Bayes rule. Using this technique different diagnostic states are generated and each diagnostic state is assigned a probability of it being the true patient's state based on empirical data [22]. Different probabilities are weighed using Bayes rule and a best estimate can be made about a patient's diagnostic state. Prediction of transition from one diagnostic state to another may be accomplished using dynamic Bayesian networks [23]. One real world example of a clinical application of Bayesian networks in the setting of neurocritical care is the Avert-IT project by BrainIT [24]. Using demographic, physiologic, and clinical data from traumatic brain injury (TBI) patients Avert-IT creates a prediction index of the occurrence of hypotension following TBI.

The two types of learning algorithms that are utilized by machine learning systems can be classified as either supervised or unsupervised. These algorithms use prior outcomes and prior data to predict future outcomes based on unseen data. In supervised learning, one loads the model with labeled data so that model can use that data to predict a certain outcome. Supervised learning models can produce outcomes either by classification (as in decision tree analyses) or by regression (predicting trends using previously labeled data). In unsupervised learning, data is unlabeled, and the system tries to cluster the unlabeled data by identifying patterns. Decision tree analysis methodology may be very familiar to physicians as many have been exposed to this methodology during their training when using flowcharts to "work up" conditions. A group of complex multivariate data begins at the highest point before it is grouped into descending trees based on a certain factor (i.e. disease type, sex, age) [25]. Each "tree" is then subdivided in a similar manner using various other factors. At the end of the trees an endpoint can be examined (i.e. percentage success of outcome from a certain procedure) and correlated with the parameters that were used to create that tree. An example could be "a 25% success rate of fluid resuscitation in hemorrhagic hypotensive men over 85" vs. "a 75% success rate of fluid resuscitation in hemorrhagic hypotensive women under 35".

A particularly sophisticated form of supervised learning is the usage of artificial neural networks. These complex AI systems are able to apply iterative learning to successfully accomplish multivariate nonlinear analysis and multifactorial classification. They may also discover patterns and represent sophisticated data relationships. Clinical examples of the usage of artificial neural networks include the work of Vath et al. which was able to predict TBI outcomes based on sequences of clinical and neuromonitoring criteria [26]. Another interesting clinical application of neural networks was developed by Cohen et al., and it utilizes hierarchical clustering (a dimension reduction technique originally used in genomics) to identify clusters of physiological data in trauma patients in specific states [27]. By correlating these patient states (such as risk of infection, multiorgan failure, and death) with physiological data the neural networks were able to identify prognostic patterns too complex for traditional techniques. Data was visualized in a dendrogram and a heat map where it was visually apparent where "clusters" of physiological data were correlated with specific states. In this case the neural network was practicing unsupervised learning as it was able to identify and correlate data where the outcome was not known with specific states and in doing so discover new associations between parameters.

4. Future directions

4.1. Intracranial pressure

Intracranial pressure (ICP) is the most widely monitored parameter in neurocritical care, as it has been shown to be highly predictive of mortality [28,29]. Increased ICP is dangerous because it can lead to impaired cerebral perfusion, brain tissue hypoxia, and subsequent infarction, which can lead to secondary neurological injury. MMM allows for the continuous recording of ICP, which allows the physician to be more responsive to adverse changes. AI can take advantage of the continuous monitoring provided by MMM to optimize treatment regimens.

Some applications of artificial intelligence for monitoring ICP already exist, albeit still in experimental phases. One example is the ability to predict future mean ICP. Given the dangers of increased ICP, it would be of tremendous benefit to a clinician to have access to AI that could make predictions about a patient's ICP. Zhang et al. developed a forecast algorithm that has demonstrated an ability to predict future mean ICP, which enables clinicians to identify dangerous trends in ICP early [30]. Within the intensive care unit (ICU), this kind of technology would obviously be beneficial for patients. Clinicians and other caretakers would be able to anticipate harmful increases in ICP and prepare treatments accordingly.

In addition to novel modalities of predicting future mean ICP, other new approaches for analyzing ICP involves the analysis of data in real-time as opposed to just displaying the most recent ICP reading. The pressure reactivity index is one such parameter, and it represents the correlation between ICP and mean arterial pressure. Instead of keeping track of ICP and mean arterial pressure separately, following the pressure reactivity index allows the clinician to determine if the patient is adequately maintaining cerebral pressure autoregulation. Following the pressure reactivity index has already been successfully used in patients with intracerebral hemorrhage and in TBI patients [31,32]. Another parameter used to analyze elevated ICP is its variability. While monitors typically display the latest ICP measurement, instruments that are able to compute the variability of ICP over a given time may be more useful clinically since reduced ICP variability is associated with a poorer outcome [33,34].

While AI has already made headway in predicting future mean ICP and assessing ICP variability, the next exciting step in implementing AI would be automating treatments in direct response to elevated ICP. With continuous monitoring of ICP, AI could be implemented to automatically administer mannitol once it detects persistent elevation of ICP greater than 20 mmHg for a pre-specified period of time assigned by the intensivist [35]. Another advantage to automating this step would be that once the mannitol is administered, data from repeat blood work could be synced to the AI to ensure that as mannitol exerts its diuretic effect, serum osmolality does not rise above 320 mmol [35]. If elevated ICP remains refractory to initial mannitol treatment, AI could switch to treatment with hypertonic saline [35]. All urinary losses in this time could be recorded and replaced with automated fluid management. The management of elevated ICP as it exists today requires frequent checks on the patient by the medical team. While AI cannot replace the vigilance of the medical team, automating these steps would increase the likelihood that sudden changes in ICP are addressed more quickly.

4.2. Seizures

Other potential applications of AI in neurocritical care include the detection of seizures and the adjustment of antiepileptic drugs.

Computer-assisted real-time analysis of electroencephalograms (EEGs) have already been shown to be able to classify seizure by type. Cloostermaans et al. demonstrate that their EEG classification system has been able to categorize EEG activity into one of eight types: isoelectric, low voltage, artifact, burst suppression, generalized periodic discharge, seizure activity, slowed activity, and normal [36]. Artificial neural networks have also been used to detect seizure activity [37,38]. These systems of automatically detecting seizure activity can assist those who do not specialize in reading EEGs to assist clinicians to manage patients with seizures, expediting treatment.

In addition to classifying EEG activity, AI can also automate the preparation and/or the administration of anti-epileptic drugs (AEDs). The current recommendations for treating status epilepticus require constant EEG monitoring and adjusting treatments depending on the monitored epileptiform activity. Like with monitoring blood pressure, respiratory status, and intracranial pressure, the role of AI in treating seizure activity would be to reduce the amount of time between the adverse event and administration of treatment. AI could directly sync the administration of AEDs with data collected from the EEG. For example, current recommendations suggest that AED infusion should be titrated to the cessation of epileptiform activity. As the AI system would constantly be collecting and analyzing data from the EEG, the titration would be much more precise than is currently possible [39].

4.3. Blood pressure

In the ICU setting, management of blood pressure is especially important as sudden changes in blood pressure can lead to lasting damage of several organs [40]. Optimal management of blood pressure requires careful monitoring of blood pressure trends. Important considerations in blood pressure management include the degree of hypertension (moderate vs. severe) and the time frame in which the hypertension develops (urgency vs. emergency). As MMM already has the ability to gather this data, an automated response to administer an antihypertensive to achieve a goal blood pressure might be feasible. Furthermore, depending on the specific context of a patient's hypertensive event, such an automated system might make suggestions as to which antihypertensive to administer. For example, if a patient develops increased heart rate and/or arrhythmias, MMM might suggest betablockers because it algorithmically deduces an increased adrenergic tone in the patient. Or if the MMM detects a concurrence of increased ICP and elevated blood pressure, it may once again suggest betablockers and warn against using vasodilators for it would be programmed to calculate cerebral perfusion pressure at all times to protect against lowering blood pressure at the expense of decreasing cerebral perfusion. Whichever option the physician chooses based on the system's suggestions, the ability to continually monitor blood pressure response after treatment is another advantage of AI. For example, reduction in blood pressure should not drop more than 20% within the first hour. AI could continually adjust drip rates to ensure blood pressure does not fall below this threshold [41].

4.4. Ventilation

The monitoring of a patient's respiratory status is important in neurocritical care. Many patients with severe head trauma have impaired respiratory drive [42]. Furthermore, inducing hyperventilation in a patient is one way to manage elevated ICP [43]. To improve the oxygenation status of neurocritical care patients, it may be necessary to place them on positive end-expiratory pressure (PEEP). However, PEEP, while important for maintaining oxygenation, may induce intracranial hypertension [44]. It is therefore critical that the data collected from a patient's respiratory status communicate with data regarding the patient's ICP. In the event of an acute elevation of a patient's ICP, hyperventilation can be induced to cause a drop in PaCO2, resulting in cerebral vasoconstriction. While hyperventilation can reduce ICP, this is generally not recommended for prolonged management. It has previously been shown that the vasoconstrictive effect of hyperventilation lasts less than 24 h, after which the cerebral vasculature equilibrates with the new PaCO2, causing vessels to re-dilate and to cause a rebound elevation in ICP [45]. Once again, it is possible to fathom that these interventions can be monitored by AI systems. MMM already allows for the concurrent collection of the patient's respiratory status and ICP status. As many patients in neurocritical care require respiratory support and mechanical ventilation, AI could allow for adjustments in respiratory settings to respond directly to acute changes in ICP. However, given the limitations of manipulating ventilation settings to achieve an ICP goal, these automated responses would have to be carefully overseen by the medical team.

Another drawback of utilizing hyperventilation as a means of controlling ICP is that it could induce cerebral ischemia [43]. Therefore, an ideal AI system would also incorporate data accumulated from continuous brain tissue oxygenation monitoring. The two main invasive methods by which brain tissue oxygenation can be continuously monitored are jugular bulb oximetry and intraparenchymal oxygen monitoring [46,47]. In states of cerebral ischemia, the brain via a compensatory mechanism increases oxygen extraction, reducing the jugular bulb venous oxygen saturation ($SjvO_2$). Jugular bulb oximetry is useful because this increase in cerebral oxygen extraction occurs more than 24 h before the advancement to symptomatic cerebral vasospasm [48]. Incorporating this information into an AI system would allow for the automatic adjustment of ventilation settings in states of cerebral ischemia. Ventilatory control in neurocritical care patients requires a balance between maintaining ICP and oxygenation. Allowing AI to manage this balance would certainly reduce the amount of time needed to make the necessary adjustments for the patient.

5. Limitations

While there is great potential for artificial intelligence technologies to assist future generations of neurocritical care physicians, there remain significant hurdles before these technologies can be used. Perhaps the most significant challenge is to identify adequate regulatory mechanisms to ensure that patients under the care of these artificial intelligence systems remain safe and protected. For instance, when an AI system independently makes a decision to intervene on a patient's care and causes an adverse event, who should be held accountable? Patient autonomy might also be challenged. In the traditional patient-doctor relationship, dialogue between the two parties ensures that the patient always understands and consents to care. With the advent of AI systems in the hospital setting, it is a reasonable concern to think that the patient-doctor relationship might become more “distant” the more AI systems make their own decision. These challenges need to be carefully considered before AI systems can play any role in patient care.

6. Conclusion

The advancement of neurocritical care will involve the increasingly greater integration of multiple parameters and management of patients with closed-loop systems, giving the clinician more tools with which to guide patients back to recovery. Already, MMM provides data on a patient's ventilation status, intracranial pressure, hemodynamics, body temperature, fluid intake-output, and neurological status. The next goal in advancing neurocritical care is to develop systems in which all of this data can be monitored and processed by AI. While the clinician must be ultimately responsible for a patient's care, these technologies will greatly optimize the clinician's time, allowing him/her to focus more broadly on the patient's recovery.

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