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Editorial

Is artificial intelligence at the doorstep of Intensive Care Units and operating room?

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For data scientists, variables collected in data warehouse are defined by three main characteristics: "Volume", "Velocity" and "Variety". Usually, the amount (i.e. volume) of data collected defines big data. Big data defines massive dataset with much more variables than observations and an amount of more than 1 terabit of data. "Velocity" describes the frequency at which data are generated, captured and shared. "Variety" represents unstructured or semi-structured dataset like video, text or sound files, which will require algorithm involving machine learning (ML) in order to be analysed. Analysing big data has become possible with the technological progresses made, as they have allowed to develop evolving algorithms based on artificial intelligence (AI). Recent publications have reported potential medical applications for AI [1–3]. In ophthalmology, De Fauw et al. developed an algorithm analysing optical coherence tomography with deep learning, using a database of 877 images. The algorithm was then "trained" on nearly 15,000 tissue maps [1]. Performance of the algorithm was compared to highly trained ophthalmologists and the diagnostic performance was comparable [1]. AI performances for referral decision (urgent, semi-urgent or not urgent) were comparable or better than retinal specialists' [1]. In dermatology, Esteva et al. demonstrated that an algorithm developed with convolutional neural network, using a data set of 129,450 clinical images, was able to identify malignant skin melanoma and skin carcinoma just as well as 21 certified specialists [3]. Performance of the algorithm was confirmed by the results of skin biopsies [3]. In medical imaging, AI algorithms developed with deep learning or neural network performed just as well as radiologists to detect, screen and stage tumours [2].

In the current ACCPM issue, Pirracchio et al. depict the recent developments of Big Data analysis in the field of anaesthesia and intensive care, its possible application for the prediction of clinical events and its ability to help physicians in the decision-making process at the bedside. The authors underline the fact that modern, precision and personalised medicine needs multiparametric monitoring, which increases analysis difficulties for the bedside practitioner. The increased number of information required to assess the clinical state of a patient is well-illustrated in the field of neurocritical care [4,5]: assessing brain tissue perfusion and metabolism requires nowadays Intra-Cranial Pressure (ICP) monitoring, partial brain oxygenation measurements, microdialysis, cerebral blood flow assessment and electro-physiological measurements (EEG, SSEPs) [4]. New magnetic resonance imaging sequences (diffusor tensor imaging) has also recently been developed to diagnose white matter damage and may predict neurological recovery [6]. Analysing all this information in a decision-making process can be very challenging for a clinician. Moreover, as recent studies demonstrated metabolomics and proteomics usefulness to screen and identify particular sub-phenotype in critical illness [7–9], the implementation of "-omic" technology may help to understand the pathophysiology process, but will significantly increase the amount of information to be analysed at the bedside.

Anaesthesia and intensive care seem to be an ideal field to develop AI algorithm, as massive dataset are required to train and learn continuously the algorithm. Actually, continuous monitoring devices used in daily practice are unique opportunities for researchers to acquire large dataset and develop advanced tools to assist clinician's decision-making process. This is illustrated by the recent study reported by Hatib et al. [10], analysing 2,606,147 arterial waveforms from 1,684 patients, and using it to develop a hypotension predictive algorithm with a threshold of a mean arterial pressure < 65 mmHg [10]: the Hypotensive Prediction Index (HPI). Compared to mean arterial pressure (MAP) trends, HPI was significantly more accurate to predict arterial hypotension events 5, 10 and 15 min before they occured [10].

Another example of recent advances in analysing time series in intensive care units is illustrated by research on continuous analysis of Intra-Cranial Pressure (ICP) in TBI. Predicting and managing Intra-Cranial Hypertension (ICH) is a critical clinical challenge [11,12]. Hu et al. investigated ICP pulse morphological metrics and validated an algorithm able to extract ICP features at the bedside [13]. This algorithm detected changes in ICP waveforms during cerebral blood flow variation induced by hypercapnia [14]. It was able to predict increase of ICP and decrease of the cerebral blood flow [15,16]. These promising results need to be prospectively confirmed and validated on a larger multicentre cohort.

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AI may also assist clinicians in the decision-making process during haemodynamic optimisation. Recently, Komorowski et al. developed and evaluated the ability of an ''AI clinician'' to suggest optimal haemodynamic treatment (vasopressor and/or fluid challenge) in septic patients during the first 72 hours [17]. They used reinforcement-learning tools (AI tools used to identify the best medical decision that maximise the likelihood of 90-day survival) to develop an ''AI policy'' on a training dataset (n = 17,083). The best ''AI policy'' was selected and tested on an independent dataset (n = 79,073). Interestingly, ''AI clinician'' decision recommended lower amount of fluid administration and higher amount of vasopressor infusion than the ''Human'' clinician. Patients managed according to the ''AI policy'' had lower 90-days mortality [17]. This interesting finding needs to be confirmed by prospective real-time evaluation at the bedside.

''AI clinician'' have not yet replaced the human practitioner in our intensive care units and operating rooms , however the promising results have encouraged intensivists and anaesthesiologists to start collecting, sharing and analysing Big Data. As the authors mention it, collecting such data requires a rigorous methodology so that data set can be properly analysed. Thus, signal quality and standardised recording waveform time series are essential. This unprecedented rates and amount of data sometimes exceed software capacities [18]. Clouds storage may be a solution to overcome this pitfall [18]. In the near future, development of AI technologies will imply a close partnership between engineers, data scientists, mathematicians and clinicians. Subsequently, creating research consortia is urgently needed to develop collaboration for collecting, analysing and sharing such data set.

On the other hand, collecting and building large dataset will also raise ethical concerns. The increased number of big data projects in healthcare is therefore a challenge for Ethical Review Committees (ERCs), as risks and benefits appear hard to assess. In 2017, a scoping review identified a large increase of literature about big data and ethic consideration [19]. Four moral principles have been identified as the main ethical constraints for ERCs: privacy and confidentiality of data, informed consent, fairness and trust [19]. Therefore, ERCs and/or other research regulation agency will have define recommendations to promote patient's protection without depriving scientists of new opportunities in big-data-driven healthcare research.

The AI challenge is now available for researchers and clinicians in order to translate these new technologies at the patient's bedside. Machine learning is a great opportunity to improve the decision-making process in complex clinical situations in order to improve patient's outcome. This may relieve clinicians from a part of the burden they are currently carrying, allowing them to be more involved in fields still out of reach of machines, such as patient's well-being and human relations.

Disclosure of interest

The authors declare that they have no competing interest.

References

[1] Fauw JD, Ledsam JR, Romera-Paredes B, Nikolov S, Tomasev N, Blackwell S, et al. Clinically applicable deep learning for diagnosis and referral in retinal disease. Nat Med 2018;24:1342.
[2] Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer 2018;18:500.
[3] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017;542:115–8.
[4] Stocchetti N, Roux PL, Vespa P, Oddo M, Citerio G, Andrews PJ, et al. Clinical review: neuromonitoring – an update. Crit Care 2013;17:201.
[5] Taccone FS, Citerio G. Participants in the International Multi-disciplinary Consensus Conference on Multimodality Monitoring. Advanced monitoring of systemic hemodynamics in critically ill patients with acute brain injury. Neurocrit Care 2014;21(2):S38–63.
[6] Velly L, Perlbarg V, Boulier T, Adam N, Delphine S, Luyt C-E, et al. Use of brain diffusion tensor imaging for the prediction of long-term neurological outcomes in patients after cardiac arrest: a multicentre, international, prospective, observational, cohort study. Lancet Neurol 2018;17:317–26.
[7] Johansson PI, Nakahira K, Rogers AJ, McGeachie MJ, Baron RM, Fredenburgh LE, et al. Plasma mitochondrial DNA and metabolomic alterations in severe critical illness. Critical Care 2018;22:360.
[8] Langley RJ, Tsalik EL, van Velkinburgh JC, Glickman SW, Rice BJ, Wang C, et al. An integrated clinico-metabolomic model improves prediction of death in sepsis. Sci Transl Med 2013;5 [195ra95].
[9] Lasky-Su J, Dahlin A, Litonjua AA, Rogers AJ, McGeachie MJ, Baron RM, et al. Metabolome alterations in severe critical illness and vitamin D status. Critical Care 2017;21:193.
[10] Hatib F, Jian Z, Buddi S, Lee C, Settels J, Sibert K, et al. Machine-learning algorithm to predict hypotension based on high-fidelity arterial pressure waveform analysis. Anesthesiology 2018;129:663–74.
[11] Stocchetti N, Maas AIR. Traumatic intracranial hypertension. New Engl J Med 2014;370:2121–30.
[12] Stein DM, Hu PF, Brenner M, Sheth KN, Liu K-H, Xiong W, et al. Brief episodes of intracranial hypertension and cerebral hypoperfusion are associated with poor functional outcome after severe traumatic brain injury. J Trauma 2011;71:364–73 [Discussion 373–374].
[13] Hu X, Xu P, Scalzo F, Vespa P, Bergsneider M. Morphological clustering and analysis of continuous intracranial pressure. IEEE Trans Biomed Eng 2009;56:696–705.
[14] Asgari S, Bergsneider M, Hamilton R, Vespa P, Hu X. Consistent changes in intracranial pressure waveform morphology induced by acute hypercapnic cerebral vasodilatation. Neurocrit Care 2011;15:55–62.
[15] Hamilton R, Xu P, Asgari S, Kasprowicz M, Vespa P, Bergsneider M, et al. Forecasting intracranial pressure elevation using pulse waveform morphology. Conf Proc IEEE Eng Med Biol Soc 2009;2009:4331–4.
[16] Hu X, Glenn T, Scalzo F, Bergsneider M, Sarkiss C, Martin N, et al. Intracranial pressure pulse morphological features improved detection of decreased cerebral blood flow. Physiol Meas 2010;31:679–95.
[17] Komorowski M, Celi LA, Badawi O, Gordon AC, Faisal AA. The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care. Nat Med 2018;24:1716.
[18] Biology: The big challenges of big data, Vivien Marx. Nature 2013;498:255–60. http://dx.doi.org/10.1038/498255a [Available from: https://www.nature.com/articles/498255a].
[19] Ienca M, Ferretti A, Hurst S, Puhan M, Lovis C, Vayena E. Considerations for ethics review of big data health research: a scoping review. PLoS One 2018;13:e0204937. http://dx.doi.org/10.1371/journal.pone.0204937. eCollection 2018 [Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6181558/].

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