A REVIEW ON ASSESSING THE USE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING ALGORITHMS TO ANALYZE ICU DATA FOR EARLY PREDICTION OF PATIENT

ABSTRACT

The intensive care unit, also known as the intensive therapy unit is one of the most sensitive areas in a healthcare organization, as the decisions made here may make a difference between life and death of a patient. The amount and detail of information that are collected about the patient in the ICU ranging from simple parameters such as temperature and blood pressure to investigations like X-rays and laboratory results can be overwhelming to the healthcare provider. Recently, the emergence of the AI and ML technologies introduced the ways to use this data to amplify the patients' outcomes. There are several benefits of AI and ML technologies for the analysis of a significant amount of data collected in ICUs to compare patients' conditions and identify their changes, as well as to personalize the treatment and supply chain to match patients' needs with the available resources efficiently. These technologies have the potential to transform ICU practices due the capability of the algorithms involved in analyzing and interpreting large volumes of data much faster and accurately than is humanly possible. Such model can also detect the symptoms which suggest that the patient is getting worse so that appropriate action can be taken to prevent adverse effects. The use of AI can help improve the accuracy of patient care because, unlike mass-produced medicine, the treatment plan will be developed based on the client's specific traits and situation. Furthermore, the optimization of the ICU utilization, in compliance with the data analysis, contributes to the overall health care provision and cost-effectiveness. This literature review presents an overview of the current state of the art in the application of AI and ML to the

ICU context, and assess the strengths and weaknesses of the proposed solutions in order to establish the challenges that must be addressed.

Keywords: Artificial intelligence, intensive care unit, patient care, critical care, ICU data evaluation.

INTRODUCTION

Artificial intelligence (AI) is a set of procedures whereby machines can mimic the intelligence possessed by human beings in perceiving, comprehending, and solving problems, making decisions, developing new knowledge, and learning from past experiences in order to achieve set objectives without prior programming for the tasks in question. (1) This technology, which is based on machines' ability to learn from experience and show enhanced performance, is quite different from the intelligence found in humans or any other living organisms. (2)

AI in healthcare is one of the most discussed and progressive fields incorporating this technology. Healthcare AI deals with the utilization of software, artificial neural network, and other forms of artificial intelligence to imitate biological neural functions for interpreting, evaluating, and understanding healthcare information. (3) For example, in the diagnosis of breast cancer, algorithms using AI assist the radiologist by offering an opinion and second opinion as well. (4)

These include the general improvement in the standards of care so that critically ill patients are now receiving better quality medical care. (5) However, the methods of critical care for traditional models remain insufficient in addressing patient complications, early identification of the patient's decline, and timely intervention. Thus, the introduction of devices for monitoring, as well as noninvasive and invasive interventions at the patient's bedside has improved the quality of care. (6) But, whether these developments signify the next step in critical care is debatable. AI's purpose is to help computers learn and discern patterns in diverse and large data - a task that was previously only feasible in sciences like physics or astronomy because of the limited computational capacity. The current glut in computational power now allows the use of AI in areas such as critical care medicine, where a profusion of data is present. (7) (8)

A scoping review aimed at investigating the trend, productivity, and quality of AI research in CCM showed that the number of papers published from 2018 to 2020 was significantly higher than in previous years, and many of them were of high quality, being published in the best-ranked journals. These studies indicate that AI has great potential in modeling disease prognosis and improving client management in intensive care environments. (9)

THE APPLICATIONS OF ARTIFICIAL INELLIGENCE IN THE INTENSIVE CARE UNITS OF HOSPITALS

Although the application of AI in the ICU is mainly centered on the predictive type, there is an emerging trend in the development of prescriptive AI. For instance, Shahn et al. conducted a 'target trial emulation', in which they constructed a marginal structural model that indicates that sepsis outcomes may be enhanced by lesser fluid management. (10) Likewise, Komorowski and colleagues have proposed a reinforcement learning model that can forecast the ideal fluid and vasopressor dosing regimen in sepsis. (11)

While Shahn's method relies on statistical analysis, Komorowski approaches the problem using machine learning (ML) to perform the causal inference tasks. (12) However, both of them use observational data, which means that, despite the use of statistics or ML, no one can be sure of obtaining a causal effect. When it comes to estimating causal effects using observational data, it is always a complex task and requires some prior knowledge in the clinical domain. (13) The use of casual diagrams may aid in identifying the possible sources of bias, though it is important to understand that bias cannot be eliminated when using observational data. However, there is a crucial issue of the small 'effective sample size', which is the number of patient histories for which both the modeled and actual treatment regimes are the same. Overcoming these challenges is imperative for the realization of practical AI in clinical environments. (12)

AI in the hospital setting is highly feasible and presents many opportunities, including supervised and unsupervised machine learning. There are various categories of learning methods and among them, unsupervised learning methods have been used to search through the electronic medical records data base in order to extract important information from patients' charts and to find out high cost patients. (14)

Supervised machine learning algorithms have been proved to be very useful in many areas of medicine because they are capable of identifying patterns without any directions. Such applications include radiology, histopathology, surgical robotics, early diagnosis and monitoring of heart failure in cardiology, and the classification of tumors in cancer research. (15)

Although research on the application of machine learning in ICUs is still limited, some works have been done to examine its utility in handling critically ill patients. (16) These studies employ big data of population to estimate factors such as the length of stay, readmission rate in the ICU, mortality rate, and the probability of contracting complications including sepsis and ARDS. Other research is centered on the analysis of clinical and physiological data of much smaller size to assist in the clinical management of patients who require ventilatory support. (17)

Length of Stay

For instance, Houthooft et al. (2018) used a support vector machine model on data compiled from 14,480 patients to predict patient survival and the length of stay, with an AUC of 0. 82 for the model to predict the PPS prolonged length of stay. This is relatively low compared to the physicians whose accuracy was determined to be 53%. (18)

Also, a study used data of physiological variables of the first 48 hours of ICU admission with a hidden Markov model to predict length of stay with moderate accuracy. The algorithm based on the artificial neural network model trained on the MIMIC-III dataset predicted the risk of ICU readmission with the sensitivity of 0. 74 and AUC of 0. 79. (19)

ICU Mortality

Awad et al. (2017) utilized, decision trees, random forest, naïve Bayes algorithms to predict ICU mortality from 11,722 MIMIC-II first admission data that included demographic data, physiological data, and laboratory data. (20) These models performed better than conventional scores such as the APACHE-II, SOFA, and SAPS scores which was supported by a time series analysis done later on. One other study carried out with artificial neural networks on data of more than 200,000 first admissions to ICU in Sweden was also reported to have better accuracy than SAPS-3 in estimating the risk of mortality. (21) Other areas that have also incorporated machine learning into mortality prediction include in trauma patients and pediatric ICU patients. (18)

Complications and Risk Stratification

Yoon et al. (2016) designed a method based on the logistic regression and random forest models of EKG measures of tachycardia to assess the instability in ICU with an accuracy of 0. 81 and an AUC of 0. 87. A recent work by Vistisen et al. (2016) presents a systematic review of the most important strengths and limitations of machine learning techniques for predicting ICU complications. (22)

Another recent study used random forest classifier with over 200,000 EHR to predict sepsis and septic shock, while the specificity was high (98%), the sensitivity was low (26%), which may not be very useful in practice. Other works have investigated the application of machine learning in constructing patient individualized risk prediction models for pulmonary emboli, risk evaluation of ARDS, risk assessment of acute kidney injury in burn patients and in general ICU patients, estimation of volume sensitivity after fluid administration, and in identifying patients who may likely develop complicated Clostridium difficile infections. (23)

However, there are limitations in applying these models in the clinical practice due to the problems like the requirement of the huge and diverse data set, prospective validation, and incorporating the clinician input to get the more reliable and actionable results. These challenges strongly suggest that AI has the potential to revolutionize ICU care, assuming further development occurs to overcome these barriers. (22)

CHALLENGES DUE TO THE IMPLEMENTATION OF AI-BASED AI TECHNIQUES

In determining the effectiveness of a given machine learning algorithm, the accuracy is determined by how well the algorithm performs on the unseen test data set. Models are developed and validated using samples from the same population, and it is not a rarity to come across reports of algorithms that boast near perfect accuracy levels in the machine learning literature. (24)

When we are careful enough in choosing the features, when we have a large enough number of instances, and when we choose the right algorithm, we are likely to end up with a model that is as accurate as possible. (25) If the data are true and verifiable, the model's predictions are also true and verifiable or accurate and credible. In contrast, when a model trained with such untested or faulty data is challenged with data sampled from the same population, the resulting predictions may be quite accurate but very much worthless. As someone else has eloquently stated, garbage in, garbage out. (26)

This leaves us with the obvious question: what are the bounds of model reliability? While AI is capable of working with a number of factors, and reduce the influence of prejudice in data categorization, it cannot guarantee the stability of models. (27)

Thus, the most complex when designing a clinical machine learning model is to determine the gold standard to be used for classification. Much of the interventions and observations made in practice are in fact quite subjective, and it is very rare to find a consensus among the intensivists. For instance, a study on the interobserver reliability of clinicians to diagnose ARDS based on the Berlin definition revealed that there was only a moderate level of reliability (kappa = 0. 50). (5)

CONCLUSION

If applied cautiously, AI technology can help in addressing information overload in the ICU. Machine learning approaches for using e-records have been used to demonstrate the ability to predict intensive care unit mortality and length of stay, as well as to better understand populations at risk for disease worsening or medical complications. Despite these retrospective studies being useful for early patient identification and stratification, they are the simplest, more accessible applications of AI.

A more difficult but a more revolutionary task is the creation of smart monitoring systems based on the machine learning approach that would be able to monitor and accurately estimate human responses to severe diseases constantly. Such advancement may lead to the establishment of partially intelligent and self-sustaining ICUs in which the smart machines take most of the responsibilities that are carried out by the human health workers.

The highest level of AI integration is when it will be used as an accurate and helpful tool for clinicians in the context of critical care. In essence, AI can free up the attention of those in the health care sector to allow them to undertake more creative, thoughtful, and empathetic approaches to patient care. In conclusion, this research provides a preview of the future of AI in the ICU, which is filled with potential and threats.

Like any other innovation, the application of AI will have its shares of fans and critics, positive and negative experiences and of course the emerging ethical dilemmas. However, as has been pointed out, AI is on its way to becoming a standard tool in critical care; thus, nurses need to get acquainted with this technology to improve patient care.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc have been used during writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

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