Journal of Palliative Care & Medicine
ISSN: 2165-7386

Editorial Open Access

Artificial Intelligence in the Emergency and Critical Care Environment

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Clinical application of artificial intelligence

Artificial intelligence (AI) based analytics has made significant progress in a number of scientific domains, including natural language processing, image classification, and signal processing [1]. Artificial intelligence is revolutionizing clinical research, and the traditional research paradigm is being augmented by the new technology [2]. The average treatment impact in a population is often used to govern medical decision making in a traditional treatment plan based on evidence-based medicine [3]. However, it is generally understood that patient populations are often varied, and that one size does not fit all. In other words, while a treatment technique may be useful to the general population, it may be detrimental to a subset of individuals. To address the problem of differential treatment effects in a diverse population, the concept of customized therapy is offered. Patients in emergency and critical care settings are often diverse, and their clinical conditions change frequently [4, 5], emphasizing the significance of early risk classification and tailored therapy.

In the emergency and critical care context, artificial intelligence may be used in three ways. To begin, numerous research built risk stratification prediction models in the critical care context. Various clinical hazards, such as mortality prediction in surgical ICU patients, risk of blood transfusion in liver transplantation, and risk of coagulopathy in sepsis, are characterized in a range of research populations. The supervised learning approach was used in all of these researches to train a prediction model [6]. The clinical events/labels of interest must be clearly stated. Misclassification in the database will result in model instability or inaccuracy for future samples prediction [7]. The second kind of research involves utilizing unsupervised machine learning techniques to divide a diverse population into more homogeneous subgroups. The algorithms vary from supervised learning approaches in that they do not require pre-labeling of data. Rather, they use the traits to divide samples into distinct subgroups/subtypes [8]. Prognostic and predictive enrichment can be seen in patient subgroups. Predictive enrichment implies that distinct subgroups might have varying responses to a single intervention, whereas prognostic enrichment suggests that different subgroups have different risks of clinical outcome events. This collection of papers looked at the numerous sub phenotypes of acute respiratory distress syndrome and discovered that Rosuvastatin had a varied therapy impact on each of them. The researchers created a new clinical categorization system for SARS-CoV-2 Pneumonia that demonstrated predictive enrichment in terms of mortality outcome. They went on to construct a clinically useful parsimonious class membership prediction model. The reinforcement learning algorithm is used in the third kind of clinical scenario to prescribe treatment regimens in a sequential way. The present collection of articles does not follow this process. The key principle behind this application is that the treatment plan should be modified in stages in response to changes in the patient's condition. In order to optimize the end outcome reward, the relationships between therapeutic activity, patient condition, and reward are codified in a dynamic process. The dynamic treatment regime (DTR) model, on the other hand, uses reinforcement learning to estimate a set of decision rules, one for each step of intervention, that specify how to tailor treatments to patients based on their treatment and covariate histories. DTR reduces model complexity and is hence more suitable for medical epidemiology. This model has been used to modify fluid resuscitation in sepsis and ventilation strategy in acute respiratory failure in critical care settings.

Machine learning algorithms have altered the business, and the technology will undoubtedly affect how we treat patients in emergency and critical care settings. However, AI's use in clinical practice is still in its early stages, necessitating additional research. The quality of training datasets, institutional idiosyncrasy, and model over fitting are only a few of the factors that restrict the value of AI models in clinical practice [9, 10]. As a result, some models perform well in the training dataset but not so well with new samples. The model may learn anything special to a hospital or institution, but not the real pathophysiological processes. The model interpretability is the second difficulty. Although AI models can enhance prediction accuracy in some instances, one of their most well-known drawbacks is that they are black boxes, making it difficult to comprehend the anticipated outcome. When the underlying pathophysiology is unclear or un-interpretable, physicians are less inclined to follow the machine's advice. More research is needed to solve the above-mentioned issues with using machine learning in clinical practice. If these challenges can be resolved, more research models will hopefully be translated into clinical practice.

Acknowledgement: Not applicable.

Conflict of Interests: The author declares no conflict of interests.

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Received: 07-Feb-2022, Manuscript No. jpcm-22-54954; **Editor assigned:** 09-Feb-2022, PreQC No. jpcm-22-54954 (PQ); **Reviewed:** 15-Feb-2022, QC No. jpcm-22-54954; **Revised:** 21-Feb-2022, Manuscript No. jpcm-22-54954(R); **Published:** 26-Feb-2022, DOI: 10.4172/ 2165-7386.1000445

Citation: Jones B (2022) Artificial Intelligence in the Emergency and Critical Care Environment. J Palliat Care Med 12: 445.

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