Original Research Paper

Volume - 14 | Issue - 08 | August - 2024 | PRINT ISSN No. 2249 - 555X | DOI : 10.36106/ijar

Clinical Science

ARTIFICIAL INTELLIGENCE AS A NEW PARADIGM IN CRITICAL CARE : A COMPREHENSIVE REVIEW .

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KEYWORDS :

In ICU settings, doctors are required to make life-saving decisions while dealing with high level of complexity of ICU data and individual heterogenecity,It is expected to provide early treatment strategies before decompensation under strict time constraints.

Applying the concept of AI in real life required a tremendous amount of computing time and resources. This could only be done in limited fields, including physics or astronomy. However, with recent exponential growth in computing power and portability, the power of AI became available to many fields, including critical care medicine where data are vast, abundant, and complex.

In the domain of intensive care , wherein most of the patient requires prompt and timely interventions due to the perilous nature of the condition, AI's ability to monitor, analyze, and predict unfavorable outcomes is an invaluable asset.AI is seen as a convincing and promising tool. It can significantly improve timely interventions and prevent unfavorable outcomes, which, otherwise, is not always achievable owing to the constrained human ability to multitask with optimum efficiency.

Artificial intelligence in critical illness and its impact on patient care, including its use in perceiving disease, predicting changes in pathological processes, and assisting in clinical decision-making(1) AI in the critical care setting could reduce nurses' workload to allow them to spend time on more critical tasks, and could also augment human decision-making by offering low-cost and high capacity intelligent data processing.

AI has been implicated in intensive care units over the past many years. It is essential to explore it's prospects, and the changes needed to train future critical care professionals.

AI have aided clinicians in various labor-intensive tasks such as rapid diagnosis and prediction of patient outcomes, risk stratification, optimizing resource allocation, and continuous patient monitoring.The most revolutionary application of AI would involve early disease identification, predicting disease evolution, individualized treatment, and optimizing the allocation of resources.Acute respiratory distress syndrome (ARDS) phenotyping: A study by Calfee et al. points out how the heterogeneous nature of ARDS translates to a possible lack of understanding of the biological mechanisms.Galen of Pergamon (130–210 AD) suggested the pulse has different presentation depending on the etiology (inflammation, lethargy, jaundice, etc) and described twenty-seven characteristics from a single beat of pulse based on the speed, frequency, and size that were associated with different causes and outcomes(3)

PREDICTION OF ADVERSE HAEMODYNAMIC EVENT :

A number of early warning scoring models were devised over the past 40 years using demographic, laboratory findings, and physiologic measures as their input variables. The goals of these models have been predicting long term organ insufficiency events or mortality during ICU stay by using either direct physiologic variables or biochemical markers reflecting organ dysfunction. The Acute Physiology and Chronic Health Evaluation (APACHE) and the Simplified Acute Physiologic Scores (SAPS) were two of the early scoring systems. The APACHE Score was subsequently designed to assess the severity of disease admitted to the ICU , while the SAPS as well as Mortality Probability Model (MPM) were designed to predict ICU mortality using admission and subsequent physiologic variables within the ICU (4, 5). Sequential Organ Failure Assessment (SOFA) score and Multiple Organ Dysfunction Score (MODS) have been used to determine the degree of organ dysfunction, ICU mortality, and hospital mortality (6, 7)

As elucidated, deterioration in critically-ill patients often follow courses of waxes and wanes until overt decompensation, rather than a linear progression from health to dysfunction. practically such thresholds for values calculated artificially do not acknowledge individual heterogeneity and dynamic changes, potentially leading to misinterpretation or underestimation of instability (8)

In order to overcome the caveats , newer data-driven analytic techniques using machine learning algorithms can be employed for this to address these complex and often subtle confounders, by discovering numerous untapped hidden signals and patterns once used to be thought of as noise. Recent literature suggests that a data-driven approach based on machine learning algorithms could reveal telltale signs of impending instability (9-11)

It gives computer the ability to learn without being explicitly programmed .The most fundamental characteristic of machine learning that sets itself apart from traditional statistics is that the decision process is achieved with minimal human interventions despite numerous confounders. With high-density, multi-granular physiologic data, as well as with trained and validated machine learning algorithms, prediction of hemodynamic crisis could be achieved with physiologic relevance. Machine learning algorithms can be classified into two broad categories - supervised and unsupervised learning - by the availability of 'annotations' or 'answers' to algorithms(12)

Supervised machine learning” denotes a process where the algorithm is learning the patterns if annotated (labelled) output value were given along with corresponding input data as a training set. When adequately trained, the algorithm can accurately determine the class labels for new and unseen input data. In different areas of industry, supervised machine learning algorithms are used to solve classification (categorical output: e.g. tomorrow's main news belong to stock market or fashion industry), or regression (real value output: e.g. peak wind speed at International Airport in upcoming weekend) problems. In the realm of critical care medicine, supervised algorithms can be used in various scenarios, such as classifying issues including anomaly detection (13) or regression in prediction of impending shock in step-down unit (14). Algorithms commonly used for this include; standard vector machine (SVM), random forest, logistic regression, k-nearest neighbours, and so on.

“Unsupervised machine learning” is often used where input data have no corresponding annotated output values. Since there is no labelled “answers”' the algorithm teaches itself throughout the training period, and the goal function of the unsupervised learning becomes accurate estimation of underlying geometry embedded in the output values inferred from the input data. It could be used for clustering . In medicine, unsupervised algorithms are used for clustering to describe different trajectories towards circulatory shock (15) or for solving association problems such as identifying genetic and environmental associations to form a phenotype in handling heterogeneous data (16). Algorithms commonly used for this include; clustering such as k-means, anomaly detection, neural networks and learning latent variables such as principal component analysis, etc.

Machine learning algorithms can recognize and learn from characteristic patterns by using physiologically relevant feature parameters. Understanding such differences in same type of cardiovascular instability can potentially help clinicians to provide tailored management strategies(17) In the future, collaborative real-time data acquisition platform would allow researchers to predict impending hemodynamic crisis with higher accuracy. Also, personal phenotyping of crisis, identifying and focusing of more important features (data parsimony), and incorporation to current hemodynamic monitoring system would be needed to facilitate practical implementation of the data-driven prediction model to bedside. Eventually, the prediction needs to be connected to treatment and outcome evaluation.

AS A DIAGNOSTIC MODULE :

More than anything, the underlying context should be deciphered correctly while analysing the root cause of the pathology which is often often a challenging task because of the insidious characteristic of early disease progression or the presence of co-existing conditions masking the main problem. For example, pulmonary infiltrates cannot simply be assumed to represent excessive alveolar fluid. They could indicate pulmonary edema from a cardiac cause, pleural effusion, parapneumonic fluid from inflammation or infection, or in some cases collections of blood as a result of trauma. Without clinical context and further testing, adequate and timely management could be delayed. AI could assist in such cases by obtaining a more precise diagnosis, given advanced text and image processing capability. The presence of congestive heart failure (CHF) could be differentiated from other causes of lung disease using a machine learning model (18), and amounts of pulmonary edema secondary to the CHF could be quantified with semi-supervised machine learning using a variational autoencoder (19). During the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic, imaging data from patients admitted to hospital were processed to detect coronavirus disease 2019 (COVID-19) using an AI model(20). With recent efforts in image segmentation and quantification of lesions by convolutional neural networks, a type of algorithm particularly apt at interpreting images, the presence of traumatic brain injury (TBI) on head computed tomography (CT) could be evaluated with higher accuracy than manual reading (21). Similarly, traumatic hemoperitoneum was quantitatively visualized and measured using a multiscale residual neural network(22).

EVOLUTION OF DISEASE :PROBABILTY

In a series of step-down unit patients who experienced cardiorespiratory instability (defined as hypotension, tachycardia, respiratory distress, or a desaturation event using numerical thresholds), a dynamic model using a random forest classification showed that a personalized risk trajectory predicted deterioration 90 min ahead of the crisis (23)Tachycardia, one of the most commonly observed deviations from normality prior to shock, was predicted 75 min prior to development using a normalized dynamic risk score trajectory with a random forest model (24)

Hypotension events have also been predicted in the ICU where vital sign granularities are lower and datasets contain more noise. Using electronic health record (EHR) as well as physiologic numeric vital sign data, clinically relevant hypotension events were predicted with a random forest model, achieving a sensitivity of 92.7%, with the average area under the curve (AUC) of 0.93 at 15 min before the actual event(25).

Hypoxia and respiratory distress have also been major targets for prediction, the roles of which have expanded during the recent coronavirus pandemic. In the first few months of the pandemic, AI-driven models were used to predict the progression of COVID-19, using imaging, biological, and clinical variables(26). Cardiac arrest has also been predicted using an electronic Cardiac Arrest Risk Triage (eCART) score from EHR data, showing non-inferior scores compared to conventional early warning scoring systems(27). Sepsis has also been predicted, with an AUC of 0.85 using Weibull-Cox proportional hazards model on high-resolution vital sign time series data and clinical data(28). Other clinical outcomes may be predicted using AI models, including mortality after TBI (29) or mortality of COVID-19 patients with different risk profiles.(30)AI could delineate distinctive phenotypes or endotypes that could reflect influences from the critical state and hence open up avenues to personalize management, integrated into existing guidelines.

Sepsis, one of the most common ICU conditions, is a highly heterogenous syndrome, and has been a favourite target of AI algorithms. Recently, using different clinical trial cohorts, sepsis was clustered into four phenotypes (α, 3, γ, and 6) by consensus K-means clustering, a type of unsupervised machine learning model. The phenotypes had distinctive demographic characteristics, different biochemical presentations, correlated to host-response patterns, and were eventually associated with different clinical outcomes(31)

Dynamic phenotyping for prediction of clinical deterioration can be performed on time series data. Using analysis of 1/20 Hz granular physiologic vital sign data, several unique phenotypes, including persistently high, early onset, and late onset deterioration, were identified prior to overt cardiorespiratory deterioration, using K-means clustering . Time-series of images can be clustered for dynamic phenotyping, as performed using transesophageal echocardiographic monitoring images in patients with septic shock: using a hierarchical clustering method, septic shock was clustered into three cardiac deterioration patterns and two responses to interventions, which were linked with clinical outcome with different day 7 and ICU mortality rates (32).

Concerns And Potential Solutions: (33)

Concern	Rebuttal	Potential Solution
Patient factors		
Lack of awareness by patients and families	Newer technology in healthcare without significant lay exposure	Public education and media explanation of AI in healthcare
Reluctance to have AI in care	Noninvasive and meant to augment clinical care, not replace physicians	Explanation of use of algorithm and potential benefits during clinical care
Privacy concerns	Newer systems use HIPAA-compliant cloud computing resources	Emphasis on HIPAA compliance approaches in clinical use
Clinician factors		
Lack of awareness by clinicians	Minimal teaching in this area during medical education	Improved medical education in this area, engagement of clinicians in implementation
Mistrust of AI approaches	Older algorithms lack sophistication, abilities and performance of newer deep learning algorithms	More research and education demonstrating benefit in clinical care.
Concerns about medicolegal aspects using AI	Field is young without clear precedent	U.S. Food and Drug Administration and other regulatory approval; clear “intended use” for AI algorithms
Lack of definitive multicenter randomized trials	Data are evolving; field is young and dynamic	Federal funding agencies should support grant funding on mature algorithms
Technology factors		
Suboptimal predictive abilities of AI algorithms	Powered by big data and multimodal data, these systems are rapidly improving	Newer deep learning algorithms, advances to augment data availability (e.g., biopatches, data by smart laboratories)
Lack of infrastructure for real-time predictive scores	Newer cloud computing and interoperability technologies are lowering the infrastructure barriers	Incorporating cloud computing, healthcare interoperability standards, software engineering, and hospital information technology education into clinical AI curriculum
Systems factors		
Poor implementation approaches	Historically, this has been overlooked in favor of algorithm development	Implementation science and multidisciplinary teams improve use of algorithms

Lack of administrative support to properly implement AI algorithms into clinical use	Although there are upfront costs, potential benefits likely outweigh this	Studies demonstrating improved outcomes and cost-effectiveness; emphasis on interoperability standards
Misalignment of patient care, quality improvement, and financial incentives	Value-based care and the changing landscape of digital health reimbursement	Closer collaboration of AI experts, hospital quality improvement, value-based care, and finance teams

CONCLUSION:

AI can facilitate the understanding of medical processes by presenting recommendations for patient care in an interpretable and hierarchical manner through techniques. The technology has the potential to improve understanding of the diverse clinical needs of critically ill patients, risk assessment for treatments, and the analysis of patient outcome.The technology is promising and will revolutionize the the therapeutic module in future.

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