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Artificial intelligence in predicting weaning from mechanical ventilation in patients with respiratory failure

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Abstract

Weaning from mechanical ventilation in patients with artificial respiration is a complex process with a high impact on the patient's prognosis. Both its delay and its anticipation, and above all the failure in the process, have significant repercussions for the patient. Some clinical variables, pulmonary mechanics, and baseline demographic or physiological conditions of the patient that influence the outcome are traditionally known, but until recent years, no computational algorithms have been developed with combined variables to determine a prediction of the outcome. Several series have recently been published, aimed at describing this predictive model with Artificial Intelligence (AI) that tells us the best moment or condition to achieve success in disconnecting from mechanical ventilation. Different tools and models have been used to propose the predictive system, but with heterogeneous results. In the article, we highlight the role of AI to achieve this purpose, we highlight some of the most important published series with their proposals, we point out the usefulness and advantages of AI to guide decision-making, also the current limitations of the models and, finally, we highlight the future directions that we think will happen in this topic.

Keywords: Weaning; Mechanical ventilation; Artificial intelligence; Failure; Machine learning.

Introduction

Mechanical ventilation is a life-saving type of life support used in Intensive Care Units (ICUs) for patients who cannot maintain adequate ventilation on their own. Weaning is the gradual process of reducing ventilatory support to transfer the work of breathing back to the patient. The decision to initiate weaning and subsequent execution involves multiple parameters, including clinical assessments, respiratory mechanics, and physiological parameters, and patient preparation.

Weaning from mechanical ventilation is a determining process in the prognosis of the patient undergoing artificial ventilation. The appearance of complications and a prolonged stay in the unit are common effects of a poor outcome of the process. Successful weaning will make it possible to return to adequate spontaneous breathing without the support of a ventilator, better elimination of deep secretions, better physiotherapy and mobilization of the patient, lower rate of nosocomial infection, among other advantages. However, premature weaning will again lead to the presence of respiratory failure, reintubation if the patient has been extubated, muscle exhaustion and most likely a new deepening of sedation analgesia to become dependent on the respirator again, among other complications [1].

On the other hand, delayed weaning may increase the risk of ventilator-associated complications, higher rates of nosocomial infection, orotracheal tube obstruction with tube exchanges with their own complication rates, a new increased need for sedation, greater muscle atrophy than It will delay more effective respiratory physiotherapy, higher rates of dysphagia due to prolonged intubations, etc. These and other factors make weaning from mechanical ventilation so important, ensuring its success is a very desirable measure.

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The rapid-shallow breathing index and the result of a spontaneous breathing test with analysis of respiratory parameters are the most used methods [2]. Until now, no single and appropriate predictor has been able to be standardized, and those described have focused solely on respiratory parameters, to accurately predict weaning outcome [3].

Artificial Intelligence (AI) has emerged as a promising tool to improve decision-making in this area, offering improvements in predicting the optimal time for weaning and thus patient outcomes.

Role of artificial intelligence, positive aspects

AI, particularly Machine Learning (ML) and Deep Learning (DL), offer a way to manage the complexity and variability of weaning prediction by analyzing large data sets to identify patterns and predictive characteristics. AI algorithms can process continuous data streams from ventilators and electronic medical records, potentially providing more accurate and individualized predictions. The current possibilities of managing an enormous amount of patient data (clinical, demographic, genetic, lifestyle habits, treatments, etc.) make possible what has been called precision medicine or also "High-performance medicine" [4]. The analysis of all these patient variables will provide a more refined management adapted to the patient's own personal reality and situation.

AI models improve the accuracy of predictions based on traditional methods due to their ability to process large and complex data sets. Currently, the most accurate method will be based on clinical observation, but combined with the prediction obtained from the AI model. Another advantageous aspect of AI is that it can continuously monitor and analyze patient data in real time, providing dynamic predictions. Also, the personalization or individualization of the machine learning model will enable personalized weaning strategies that will improve weaning success rates. In addition to the above, AI tools can reduce the cognitive load and the time taken to make sometimes difficult decisions with the uncertainty that many medical acts entail.

Current AI models in weaning prediction

Machine learning models: They are usually based on supervised learning, since they have the intervention of the professional in their training and design, they are trained with historical data, learning to associate specific characteristics with successful weaning results. Once all data is collected, the variables will be subjected to statistical regression analysis that will be used to estimate the probability of successful weaning based on various predictors.

Deep learning models: To use this type of learning, we need more complex neural networks, such as convolutional and recurrent neural networks, which will enable the processing of image data [5], natural language, unstructured data from clinical summaries and notes, with time series data capture and analysis of ventilators and other monitoring devices to predict weaning readiness.

Materials and methods

We carried out a bibliographic review to analyze the current use of AI to create predictive models in weaning from mechanical ventilation in patients with artificial respiration. The articles had to have been published in the last 5 years, with free access on the Internet. The search engines used were PubMed, Scopus, and Google Scholar. The search strategy was carried out using keywords, MeSH terms (Medical Subject Headings), and Boolean operators (AND, OR, NOT) to combine terms effectively, combining "mechanical ventilation weaning, artificial intelligence, weaning failure, machine learning." With "weaning mechanical ventilation AND machine learning" we obtained 23 references, with "weaning mechanical ventilation AND artificial intelligence" 18 references. After analysis and preliminary reading, we selected 23. We performed a narrative synthesis of the main findings of the selected articles.

Results

Several studies in recent years have demonstrated the potential of AI in weaning prediction, we highlight some of them:

Chen et al. (2019) [6] developed a machine learning model and used the MIMIC III database to develop their ML predictive model, to predict weaning failure from Mechanical Ventilation (MV). 3,636 records were analyzed based on 68 characteristics in the initial stage and reduced to 36 characteristics by applying the "Light Gradient Boosting Machine (LightGBM)" algorithm, demonstrating that this model is feasible for the prediction of Extubation Failure (EF) and outperformed other learning methods such as "XGboost, logistic regression, Support Vector Machine and Neural Network". They pointed out as influential variables: ventilation time prior to the start of weaning, PaO_2, $PaCO_2$, and sedation time showed a high positive correlation with EF. Arterial pH and BUN, heart rate, age, and weight were also important.

Zhao QY et al. (2021) [7] designed their model to predict EF. It was a "CatBoost" model based on MIMIC IV data with 19 functions. This model is an open source algorithm used by "machine learning", it is capable of processing heterogeneous data from different sources, making it complementary to deep learning. They obtained an area under the ROC curve (AUROC) of 0.835. Among 89 variables, they selected 19 key characteristics. Age and Body Mass Index (BMI) are two important factors associated with an increased risk of EF [8], stroke patients suffer an increased risk of EF which also have the added difficulty of managing the respiratory tract [9]. An altered heart rate, respiratory rate, Mean Arterial Pressure (MAP), peripheral oxygen saturation (SpO_2) and temperature were related to an increased risk of EF [10]. A lower than normal pH indicates hypoventilation or severe lung disease and was a notable predictor of EF. Central Venous Pressure (CVP) was also a main characteristic; their study demonstrated that its monitoring may be associated with better outcomes after extubation. The time to success of the spontaneous breathing test and parameters such as tidal volume, PEEP and mean airway pressure contributed to the predictive value of the model. The duration of MV and the level of Pressure Support (PS) were the most important characteristics for prediction. Other parameters such as fluid balance and a higher number of antibiotics administered were related to a higher risk of EF.

Liu CF et al. [11] developed predictive models in two phases: the weaning test phase and the actual weaning phase of mechanical ventilation, in order to determine the optimal moment to withdraw Mechanical Ventilation (MV) in patients intubated in the ICU, with the aim of integrating it into clinical practice to support medical decision-making. Twenty-five features were used for the first stage models, while twenty features were used for the second stage models. Seven machine learning algorithms, including Logistic Regression (LR), Random Forest (RF), Support Vector Machines (SVM), K Nearest Neighbor (KNN), lightGBM, XGBoost, and Multilayer Perceptron (MLP), were used. Electronic medical records of patients intubated in the ICU of Chi Mei Medical Center from 2016 to 2019 were included for modeling. A total of 5,873 cases were included in the machine learning modeling for Stage 1, with the AUROCs of the optimal models ranging between 0.843 and 0.953. Additionally, 4,172 cases were included for Stage 2, with the AUROCs of the optimal models ranging from 0.889 to 0.944. They concluded that two-stage AI prediction models could effectively and accurately predict the optimal time to wean intubated ICU patients from ventilator use. It was also concluded that this AI-assisted prediction system is beneficial for doctors to cope with a high demand for ventilators during the COVID-19 pandemic.

The retrospective study of [12], carried out using the "Medical Information Mart for Intensive Care IV (MIMIC-IV, 1.0)" database, analyzed 23,242 patients, of whom 81.9% were weaned from mechanical ventilation. Various algorithms were used for predictive models, such as the regularized logistic regression classifier [13], the random forest classifier [14], which uses the non-parametric "Random Forest" method through supervised learning, the "CatBoost" classifier, and finally, sets of voting classifiers known as "Stacking" [15] which builds a set of models using different learning algorithms. They studied the model for successful weaning within the 14 days following intubation, collecting variables either prior to intubation or within the first 24 hours after intubation, aiming to facilitate decisions when there are doubts as to whether invasive ventilation should be started or avoided with the initiation of end-of-life care. Using the ensemble voting classifier that combined the previous three models, the final model revealed a receiver operating characteristic AUROC of 0.861 (95% CI: 0.853-0.869). The data were relatively homogeneous, as they were obtained from the "MetaVision (iMDSoft)" clinical information system. They identified influential factors such as lactate concentration, anion gap, age, presence of cerebrovascular disease, and urea nitrogen.

The study by Menguy J (2023) [16] was a prospective monocentric analysis. One hundred and eight patients were included in this monocentric and prospective study. Their predictive model included body mass index (BMI) at inclusion, occlusion pressure at 0.1 seconds (P0.1), and heart rate analysis parameters (Low frequency/high frequency, LF/HF). This allowed for the detection of independent predictive factors for extubation success and the development of a dynamic predictive model using artificial intelligence.

Sheikhalishahi S et al. (2024) [17] used a supervised machine learning model and conducted a retrospective study that included 12,153 patients with mechanical ventilation, focusing on Positive End-Expiratory Pressure (PEEP). The objective of this study was to determine if successful weaning from mechanical ventilation could be predicted based on changes in PEEP levels using data from the "Medical Information Mart for Intensive Care" (MIMIC-IV) and the eICU "collaborative research database" (eICU-CRD). They found an AUROC of 0.84 (95% CI 0.83-0.85) and an "Accuracy Recall Curve" (AUPRC) of 0.69 (95% CI 0.67-0.70) in predicting successful weaning, based on PEEP reduction. The Positive Predictive Value (PPV) was 0.87 (95% CI 0.86-0.88), and the Negative Predictive Value (NPV) was 0.64 (95% CI 0.63-0.66). This study demonstrated that the potential application of machine learning in predicting successful weaning from MV based on continuous PEEP reduction could be a useful tool in aiding decision-making.

In the study by [18], the authors developed an Artificial Intelligence (AI) model to predict success in the weaning process from mechanical ventilation in patients with respiratory failure, including those with Acute Respiratory Distress Syndrome (ARDS). They conducted an interesting review that explores the evolution of weaning methods to include AI and ML as weaning aids, introducing into the discussion different and novel modalities of mechanical ventilation with partial support. The AI model showed high accuracy in predicting weaning outcomes, improving clinical decision-making, and reducing unnecessary duration of mechanical ventilation, potentially reducing medical errors and optimizing human resource utilization [19]. The study also highlighted the importance of integrating multiple clinical parameters and biomarkers to optimize predictions. It was emphasized that the use of AI can potentially reduce complications associated with prolonged ventilation and improve long-term outcomes in critically ill patients. Additionally, the research highlights the need for further studies to validate these findings in different populations and clinical settings.

Discussion

Main findings of the review

In recent years, AI has emerged as a tool to develop predictive models that serve to make clinical decisions, especially in complex processes that have important repercussions, not only for the patient but also for the institution itself, since the cost of indecision is commonly generated in the form of prolonged stays, prolonged use of limited resources, and complications that may arise as a result of their unnecessary use. The different studies are heterogeneous in the AI tools used; in some studies, such as that of Kim et al., up to five different types of models are used, which requires complexity in data management, statistical analysis, and subsequent argumentation that is very complex and not achievable for most health centers. There are series that mainly use post-surgical patients, and others, such as the review by Stivi T et al. that introduce the patient with ARDS, who is the one with the longest periods of mechanical ventilation and therefore especially interesting that its analysis be contemplated. The majority are retrospective studies against databases with a large number of patients such as MIMIC III and IV.

We can observe that the variables most commonly related to the outcome of weaning from mechanical ventilation contain a mixture of them; demographic data such as age, anthropometric data such as body mass index, related pathology such as cerebral stroke, previous mechanical ventilation and sedation-analgesia times, clinical parameters such as heart rate, respiratory rate, Mean Arterial Pressure (MAP), peripheral oxygen saturation (SpO_2) and body temperature, pH, gas exchange data such as PaO_2 and $PaCO_2$, Central Venous Pressure (CVP), and others that are related to respiratory mechanics and level of support necessary such as the success time of the spontaneous breathing test, tidal volume, Positive End-Expiratory Pressure (PEEP) and mean airway pressure, Pressure Support (PS) level, other management and need for treatments such as fluid balance and increased amount of antibiotics. It seems, therefore, that there are multiple influential variables; some of them have nothing to do directly with the respiratory state. It is very convenient to continue advancing to elucidate the best predictive model for decision support in weaning from mechanical ventilation.

Limitations and challenges

The use of Artificial Intelligence (AI) to predict weaning failure from Mechanical Ventilation (MV) in intensive care units presents several limitations and challenges.

First, data quality and availability are critical. Inconsistency in clinical data, due to differences in measurement techniques and equipment, represents a significant problem. Furthermore, the presence of incomplete records can affect both the development and accuracy of predictive models. Also, the small size of the data samples may not capture all the variability of patient conditions, which affects the generalization ability of the model. Missing or erroneous data can significantly impact the performance of the model, causing bias when designing the predictive model, which can be based on different issues such as: the effectiveness of AI models depends on the quality and integrity of the data.

Other common problems are related to interpretability: many AI models, particularly deep learning ones, are often considered "black boxes" [20], making it difficult to understand the reason behind their predictions. As users, we can understand the prediction, but not how it was made, and it is very important to have an understanding of how algorithmic models work, at least by programmers and data engineers.

There are also ethical and legal concerns. AI models can inherit biases present in the training data, which could lead to unfair or discriminatory results. Additionally, ensuring the privacy and security of patient data is a constant concern. The use of AI in clinical settings raises ethical issues related to patient privacy, consent, and potential algorithmic bias. Responsibility is another aspect to take into account, since decisions made based on predictions or recommendations from artificial intelligence will have to be assumed today by the professional.

Integrating AI tools into clinical workflow presents technical and usability challenges. Incorporating these tools into existing hospital systems and ensuring compatibility can be complicated. For AI tools to be effectively used in practice, they must be user-friendly and must integrate seamlessly into the workflow of clinicians, otherwise the digital divide will be present for a portion of professionals. Training and ongoing support for healthcare professionals are essential. Clinicians need adequate training to effectively use AI tools, and ongoing support and updates are required to maintain the performance and relevance of the AI system. We believe that it is very convenient that, in clinical teams, or at least in the hospital, there are data engineers who share spaces and objectives.

Validation and generalizability of models are crucial. Models need to be validated in diverse patient populations and at different hospitals to ensure they are generalizable [21]. Since ICU environments are highly dynamic, AI models must be robust enough to adapt to changes in patient conditions and clinical practices.

Real-time performance of these models is also a challenge. Real-time predictions require significant computational resources, which may not be available in all ICU settings. Additionally, delays in processing and providing predictions may impact clinical decision-making.

Obtaining regulatory approval for AI-based medical devices and software is a complex and time-consuming process, which represents another hurdle.

Addressing these limitations and challenges is crucial for the successful implementation of AI in predicting weaning failure from mechanical ventilation and for improving patient outcomes in ICUs.

Future directions

The future of using Artificial Intelligence (AI) to predict weaning failure from Mechanical Ventilation (MV) in Intensive Care Units (ICUs) presents several promising areas of research and development.

To achieve the set objectives, it can be very convenient for medical centers and teams to have data engineers who share their projects with institutions and clinicians.

First, it is crucial to improve data collection and quality. Developing standardized protocols for data collection will ensure consistency and reliability across different units and hospitals. Furthermore, the integration of multimodal data, including physiological signals, images, and clinical notes, can improve prediction accuracy. In terms of advanced AI techniques, great emphasis is being placed on the development of explainable models, known as explainable AI, that provide clear and understandable explanations of their predictions, thereby increasing confidence and acceptance by clinicians. Shared learning techniques are also being explored, allowing models to be trained on data from multiple institutions without compromising patient privacy.

Personalized medicine is another key area. Creating AI models tailored to individual patient profiles, considering their personal health history, genetics, and specific clinical conditions, can significantly improve the effectiveness of predictions. Furthermore, the development of adaptive algorithms, which can continuously learn and adjust based on new data and clinical results, promises significant progress in this area.

Integration into clinical workflow is essential to the success of these tools. Designing AI tools that integrate seamlessly into existing Electronic Health Record (EHR) systems and clinical workflows will make them easier to use [22]. Improving AI systems to provide real-time actionable insights during the clinical decision-making process is an important goal.

The promotion of collaborative platforms also plays a crucial role. Promoting collaboration between AI researchers, clinicians, and data scientists can lead to more relevant and practical AI solutions. Additionally, the creation of shared databases and open-source platforms will encourage innovation and transparency in the development of AI models.

Regarding regulatory and ethical frameworks, it is essential to develop AI in an ethical manner, ensuring fairness, transparency, and mitigation of bias. Establishing clear regulatory guidelines and pathways for the approval and oversight of AI tools in clinical settings is critical for their safe and effective implementation.

Continuing education and training are also vital. Providing ongoing education and training to healthcare professionals will improve their understanding and use of AI technologies [23]. Involving patients in decision-making and educating them about the role of AI in their healthcare is also important.

Validation and large-scale clinical trials are crucial to ensure the effectiveness and generalization of AI models in diverse patient populations. Implementing robust post-deployment monitoring systems will allow tracking the performance and impact of AI tools in real clinical settings.

Finally, optimizing resources is another key aspect. Developing AI models that are cost-effective and accessible, especially for resource-limited settings, and using AI to optimize resource allocation in the ICU can improve overall patient management and outcomes.

By focusing on these future directions, the use of AI to predict weaning failure from mechanical ventilation can be significantly advanced, ultimately improving patient care and outcomes in intensive care units.

Conclusion

Artificial Intelligence has great potential to improve the prediction of weaning from mechanical ventilation in patients with respiratory failure. Until now, different models have been reported focusing on multiple variables: demographics, clinical parameters, laboratory data, ventilatory mechanics, etc. Different AI tools have been used to describe predictive models. Like all emerging tools, advantages and disadvantages can be highlighted that will be defined and solved.

There are numerous studies carried out, being heterogeneous in the methodology, in the AI model used, the variables used, and the populations analyzed, so it is currently difficult to find a generalizable predictive model, so it is necessary to continue with the analysis in order to obtain a use of AI in this field with optimal validation and security.

By leveraging advanced machine and deep learning techniques, AI can provide more accurate, real-time, and personalized predictions, potentially improving patient outcomes and optimizing clinical workflows. However, successful implementation of AI in this field requires addressing several challenges, including data quality, model interpretability, and ethical considerations. Continued research and collaboration between clinicians, data scientists, and policymakers will be crucial to realizing the full potential of AI in this critical aspect of patient care.

The integration of these tools into the workflows of clinicians, promoting collaborative platforms, and regulating the use of AI, incorporating data engineers into healthcare institutions, seem key to making a leap in the importance of the data and analyses carried out.

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