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EDITORIAL

Spanish influenza score: Predictive power without giving up the classic☆

Spanish influenza score: poder predictivo sin renunciar a lo clásico

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The present number of Medicina Intensiva publishes a study on a Spanish severe influenza registry that develops a predictive score of mortality in the Intensive Care Unit (ICU).[1]

In the 1980s, intensive care became immersed in the understanding of reality and in the adoption of aids for decision making based on severity scores. Despite its particularities, the APACHE II remains valid for the assessment of severity in the critically ill. These scores were based on the accumulation of a large body of representative data and made use of logistic regression (LR) and multivariate analytical techniques to generate predictive models, with the use of beta-estimators to produce the individual scores. In relation to investigators and clinicians, the level of familiarity with the mathematical details needed to obtain the beta-estimators is sufficient, and there is a reasonable correlation between understanding and the odds ratios (ORs) and their corresponding confidence intervals—forming a methodological construct that is both comprehensible and interpretable.[2]

On the other hand, there has been an exponential growth in the use of big data analytical techniques through machine learning (ML), as can be seen from the number of literature references found in Medline.[3] However, one of the problems of ML is the difficulty of transferring the analyses to the clinical practice setting.[4] In contrast to the conventional statistical analytical techniques, the results of the published studies possess good mathematical indicators, but clinicians see only limited practical applicability in them.[5] This is due in part to the difficulty of understanding the mechanisms through which the results or outcomes are generated, and of using a large number of variables simultaneously. Such analyses are probably more concordant to the complex biological reality, but reduce the possibilities for adequate handling on the part of the healthcare professionals within the clinical practice setting.

In this regard, the article presented in this number of Medicina Intensiva pursues a double aim: to incorporate ML techniques to a large database on severe influenza in the ICU, and to generate a mortality risk score combining this approach with other classical techniques more amenable to incorporation to clinical practice.

Each year, during the winter months, severe influenza poses a challenge for ICUs all over the world. While the influenza A (H1N1) outbreak in 2009 was one of the most important episodes, there have been a number of seasons in

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which severe influenza has generated care problems in ICUs, affecting also young individuals, causing severe respiratory distress, with prolonged admissions, and a high mortality rate.[6]

Comparison of the results obtained with conventional techniques and those obtained through advanced random forest analysis (ML) reinforces the findings, and appears to indicate that the new techniques will be able to add information to the classical analytical methods – though much of the substantial information can be gained from the latter.[7] Nevertheless, in order for the LR techniques to offer consistency, we need quality registries of sufficient size, as has been guaranteed in this study—in contrast to other recent publications in which an insufficient sample size strengthened the predictive capacity of ML over LR.[8]

The development of a mortality predictive score in critical patients with severe influenza may help in decision making referred to patient admission, treatment (prone decubitus, extracorporeal oxygenation, nitric oxide) or even patient transfer for the application of advanced techniques in other centers. Another utility of this score is the possibility of stratifying risk groups for guiding or orientating therapeutic trials, as well as for the benchmarking of units. The use of variables present at the time of admission in this study also must be viewed as an advantage, since it would facilitate early counseling in decision making. Some models that use clinical outcome variables may be valid for comparing the results or outcomes of different units, but not for establishing early prognoses in the first hours of patient admission or for defining groups amenable to therapeutic trials.

The study does have some limitations, however. The database is large and multicentric, but covers a broad period of time (10 years) in which the therapeutic strategies and outcomes have experienced changes. Although internal validation is made, segmenting the database, it is essential to assess the usefulness of the score on a prospective basis in order to corroborate the accuracy of the predictions. On the other hand, the score analyses mortality in the ICU, and the APACHE II score is designed for application to in-hospital mortality, while the SOFA score was not even designed with this purpose in mind. Likewise, we cannot rule out the possibility that the use of ML with a larger number of registered variables could have had greater predictive power.

The future of the analytical techniques based on ML will almost surely lie in the real-time counseling of clinical activity, with immediate feedback and enrichment of the analytical processes.[9] Although we will witness this scenario, it will be necessary to assess the power which such information will have in decision making, from an ethical, legal and deontological perspective.[10] In addition, it will be necessary to clarify the role of the clinician in the application and withdrawal of treatments when the ML system becomes fed by the decisions it induces. These will be problems for the new generations, and the near impossibility of understanding how the mathematics work will generate complex sensations among the professionals. In the meantime, we will have to continue relying on the development of accessible and valid techniques such as that presented in this number of the journal.

Intensive care medicine works locally with few patients, and when attention must focus on concrete disease conditions, the limitations are even greater. Hence the importance of having potent multicentric registries to facilitate complex analyses and allow us to add knowledge in areas characterized by difficult management and with an impact upon the health of the population. Given the current importance of the COVID-19 pandemic, this represents a call for the development of collaborative data registries.

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