A PREDICTIVE MODEL OF MORTALITY IN ACUTE RENAL FAILURE IN THE CRITICAL PATIENT: USEFULNESS OF ARTIFICIAL INTELLIGENCE

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Background and Aims: Patients with Acute Renal Failure (ARF) have a high risk of mortality, especially those who enter the Intensive Care Unit (ICU). In this population, predictive models of mortality on prognostic scales, such as SAPS-II (Simplified Acute Physiology Score II), linearly relate risk factors without taking into account the com- plex relationship's variables can have. There are models where Machine Learning (ML) techniques have been used, but there is still room for improvement. The implementa- tion of deep artificial neural networks (DANN) can be challenging.
The literature models, using SAPS-II report an accuracy, f1 and ROC area (receiver operating curve) in ranges of 0.538-0.621, 0.333-0.377 and 0.781-0.809 respectively. The best results with ML are improved in neural networks of a hidden layer or random forest, being the best performance in the latter: accuracy 0.715-0.741, F1 0.449-0.470 and ROC between 0.862-0.870.
The aim is to evaluate and improve the predictive capacity of ML techniques for the prediction of mortality in patients with ARF admitted to the ICU, through the use of the open database MIMIC-III (Medical Information Martfor Intensive Care III). Method: Design: Retrospective analysis of historical cooperation of 20,928 patients with ARF from Beth Israel Deaconess (Boston), from 2001 to 2012.

Method: ML algorithm based on DANN. Creation of a model to predict in-hospital mortality after discharge from the ICU with the variables of the first 24 hours after admission to the ICU. To evaluate the robustness of the model has been performed cross-validation by sepa- rating the samples into different combinations of training and test data (k-folds). The unavailable variables haematological with means extracted from the training set of the respective fold. The DANN trained with the complex relationship's variables folds, two hidden layers of 75 and 40 neurons respectively.
Inclusion criteria: > 16 years, AKI according to KDIGO criteria and predictive variables based on SAPS-II.
Variables: Age, sex, type of admission, number of admissions in ICU, heart rate, blood pressure, temperature, PaO2, FiO2, sodium, potassium, bilirubin, bicarbonate, urea, leukocytes, diuresis and diagnosis of ICD-9 (metastatic cancer, haematological malignancies).

Results: Accuracy: 76.7% 0 6 1.7%, f1: 86.6% 6 1.9%, RO area: 0.859 6 0.006, sensi- tivity: 75.7% 6 2.8%, specificity: 80.5% 6 2.9%.

Conclusion: The use of Machine Learning techniques based on deep artificial neural networks can improve the predictive ability of mortality in acute renal failure of the critically ill patient of traditional clinical risk scales and even current Machine Learning models.