



Machine learning improves prediction of OHCA survival



Cardiac arrest, a leading cause of admission to the intensive care unit (ICU), is associated with high mortality. Current illness severity scores perform poorly in predicting survival for this patient group. New research from Australia shows machine learning (ML) techniques can significantly increase the accuracy of estimating survival for ICU patients after a cardiac arrest, without the use of pre-hospital data.

"We found that the machine learning models were more accurate at estimating the risk of death [compared with illness severity scores], and were able to use another algorithm to explain the reasoning behind the risk estimate given for a particular patient," according to study authors, who added that "explainer models" provide patient-level explanations for ML predictions, for clinician interpretation of accuracy.

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The authors note however that their findings have only been assessed in a single large group of patients, and should be validated in another separate group, with other predictors added.

Out-of-hospital cardiac arrest (OHCA) occurs annually in over 300,000 adults in the United States, with less than 11 percent of patients surviving to hospital discharge. For those patients successfully resuscitated in the field, in-hospital mortality remains high, being accounted for by irreversible neurologic injury and by a post-cardiac arrest syndrome.

An assessment of the probability of survival after OHCA is performed to aid in the discussion between the clinical team and the patient's family and to guide interventions. In this context, several prognostic tools have previously been developed, however none specifically developed for OHCA patients after admission to the ICU.

In the current study, researchers used in-hospital data available within the first 24 hours of admission in order to develop more accurate models of risk prediction using both logistic regression (LR) and ML techniques, with a combination of demographic, physiologic, and biochemical information. Patient-level data were extracted from the Australian and New Zealand Intensive Care Society (ANZICS) Adult Patient Database for patients who had experienced a cardiac arrest within 24 hours prior to admission to an ICU during the period January 2006 to December 2016. The primary outcome was in-hospital mortality.

The risk prediction models were trained and tested on a dataset (split 90:10) including age, lowest and highest physiologic variables during the first 24 hours, and key past medical history. LR and five ML approaches – gradient boosting machine (GBM), support vector classifier (SVC), random forest (RF), artificial neural network

(ANN), and an ensemble – were compared to the APACHE III and Australian and New Zealand Risk of Death (ANZROD) predictions. In all, 39,566 patients from 186 ICUs were analysed. Mean (\pm SD) age was 61 ± 17 years; 65% were male.

Overall in-hospital mortality was 45.5%. Models were evaluated in the test set. The APACHE III and ANZROD scores demonstrated good discrimination (area under the receiver operating characteristic curve [AUROC] = 0.80 [95% CI 0.79–0.82] and 0.81 [95% CI 0.8–0.82], respectively) and modest calibration (Brier score 0.19 for both), which was slightly improved by LR (AUROC = 0.82 [95% CI 0.81–0.83], DeLong test, $p < 0.001$). Discrimination was significantly improved using ML models (ensemble and GBM AUROCs = 0.87 [95% CI 0.86–0.88], DeLong test, $p < 0.001$), with an improvement in performance (Brier score reduction of 22%).

In addition, explainability models were created to assist in identifying the physiologic features that most contributed to an individual patient's survival.

"To identify potential relevant features on a per-patient basis, we assessed explainability using local interpretable model-agnostic explanation (LIME)," the researchers pointed out. "In brief, LIME generates a locally interpretable model for individual prediction from a complex model using an explainer algorithm that perturbs the inputs (in this case, the specific variables for a patient) together with an evaluation of the effects on the predictive model. This process generates a learned explanation for an individual."

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