Neuroréanimation (pronostic, DVE, Sedation)

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A locally optimised machine learning approach to early prognostication of long-term neurological outcomes after out-of-hospital cardiac arrest

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Position du problème et objectif(s) de l'étude:
Out-of-hospital Cardiac Arrest (OHCA) represents a major healthcare burden. Over the years, specialized care improved outcomes thanks to intensive resuscitation and invasive organ support, from mechanical ventilation to Extra-Corporeal Membrane Oxygenation. However, many survivors suffer from severe neurological damage secondary to cerebral anoxia. The purpose of this study was to build a machine learning model to predict good neurological outcomes after OHCA and identify key clinical predictors

Matériel et méthodes:
Data was collected retrospectively from 595 patients admitted between January 2014 and December 2021, to a tertiary centre in France. The primary outcome was good neurological outcome, defined as a Cerebral Performance Category (CPC) score of 1 or 2 at 6 months post OHCA. We split the dataset into training and test sets, with respectively 80 and 20% of the cohort. Next, we used a feature selection algorithm in the training dataset called Recursive Feature Elimination (RFE) to select only the relevant features for predicting good neurological outcome. Once the final set of features were selected, we trained a model to predict good neurological outcome.

We built and compared four different models: Random Forest (RF), gradient boosting model (XGBoost, XGB), Logistic Regression (LR), and multilayer perceptron. We tested each model on the test dataset (representing 20% of the cohort). We used SHapeley Additive exPlanations (SHAP), to evaluate the contribution of each variable in the model.

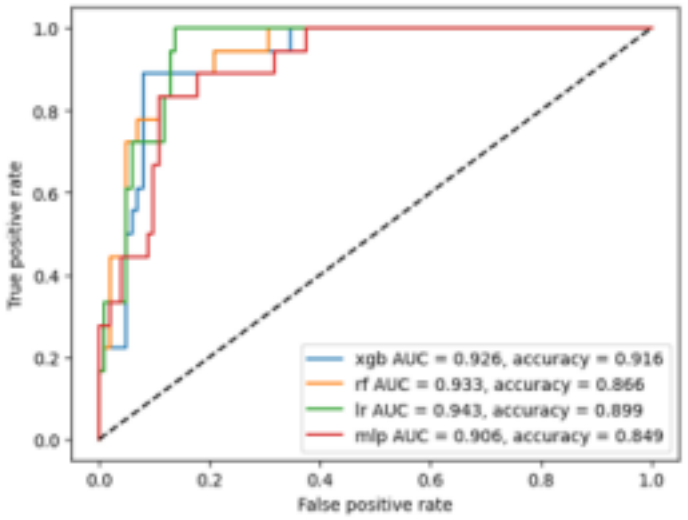
Résultats & Discussion:
Twelve features were associated with neurological outcome : blood lactate, admission temperature, emergency coronary angiography, shockable initial rhythm, low-flow duration, epinephrine administration, pH, SAPS II, age, serum troponin, no-flow duration, patient height.

In the test cohort, the best model (XGBoost) achieved model an AUC of 0.92 and an accuracy of 92% (Fig 1). The other models also achieved high discriminative power, with AUCs between 0.91 and 0.94 and accuracies between 0.85 and 0.90. Two patients among 119 in the validation cohort were misclassified (unfavourable predicted CPC and favourable actual CPC).

We created an adaptive tool allowing optimized prediction in a dataset of relatively limited number of patients and number of features. It generates a locally robust and highly accurate machine learning prognostication system. We proposed and shared a generic machine learning pipeline which allows external teams to replicate the approach locally.

Conclusion:

Model performance (Fig. 1).



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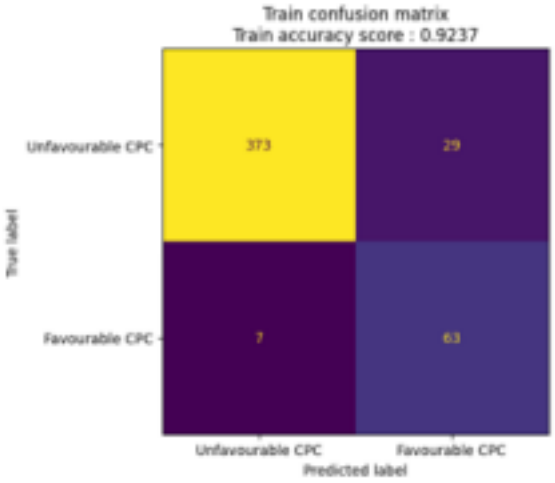

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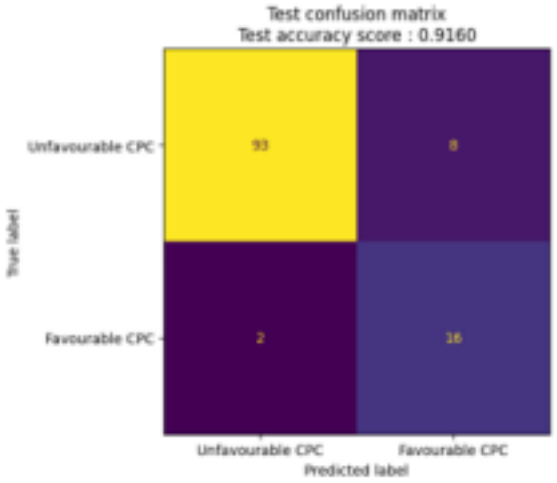

c

Fig. 1a: **Receiver operating curve for the four models** in the test cohort ; xgb : xGBoost ; rf : Random Forest ; lr : Logistic Regression ; mlp : Multilayer Perceptron.
Fig. 1b,c : **Confusion matrix for neurological outcome prediction** in (b) training cohort and (c) test cohort for the best model (xGBoost). CPC:

Top features associated with good neurological outcome (Fig. 2).

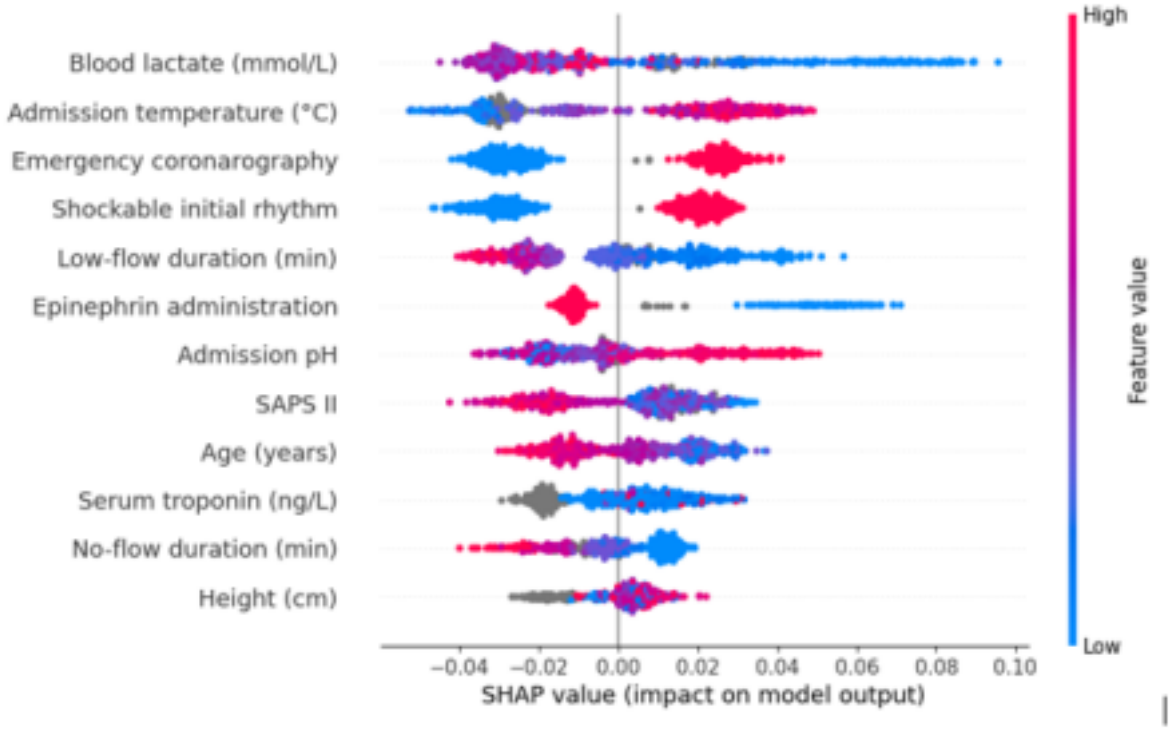

Fig.2 **Mean SHAP value for the top 12 features of the XGBoost model**. Variables are shown from top to bottom in order of importance (average absolute SHAP values). The contribution of each feature on each prediction is shown on the x axis. Each dot represents one patient in the test set, and their colour encode the value of the associated variable for each individual. Overlapping points are vertically separated for clarity. Gray points represent missing values, estimated by the model based on the values of other features. A positive SHAP value means that the variable, for this individual, contributes positively to the final outcome prediction. For example, a low lactate (blue colour) is positively associated (positive SHAP value) with good neurological outcome, whilst long low-flow duration (red colour) is negatively associated (negative SHAP value) with good neurological outcome.

Les auteurs déclarent ne pas avoir toute relation financière impliquant l'auteur ou ses proches (salaires, honoraires, soutien financier éducationnel) et susceptible d'affecter l'impartialité de la présentation.