Machine learning to detect recreational drugs use in cardiac intensive care units

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Background: While recreational drugs use is known to be a strong risk factor of acute cardiovascular events, there is no available prediction tool to detect it in patients admitted to intensive cardiac care units (ICCU), and urinary testing is not routinely performed. Machine learning (ML) methods could provide an accurate model for detection of recreational drugs use.

Purpose: To assess the feasibility of recreational drugs use detection in patients admitted to ICCU using a ML model with clinical, biological, ECG, and echocardiographic data.

Methods: From 7 to 22 April 2021, a systematic screening for all traditional recreational drugs (cannabis, opioids, cocaine, amphetamines, 3,4-methylenedioxymethamphetamine [MDMA]) was performed by urinary testing prospectively in all consecutive patients admitted to ICCU in 39 French centres. We compared several ML algorithms to detect recreational drugs use from clinical, biological, ECG and echocardiographic data. The study population was divided in an internal (31 centres, 80% of the population) and an external (8 centres, 20% of the population) cohorts. The internal cohort was divided in a training (70% of the cohort) and a testing (30% of the cohort) dataset. XGBoost algorithm was used for feature selection to avoid overfitting, and gain interpretability. Final performance of the algorithms were evaluated on the external validation cohort and compared against a standard logistic regression model, using receiver operating characteristics (ROC) and precision-recall (PR) curves and area-under-the-curves (AUC).

Results: Of 1,499 consecutive included in the cohort (63±15 years, 70% male), 161 (11%) had a positive test for recreational drugs (cannabis: 9.1%, opioids: 2.1%, cocaine: 1.7%, amphetamines: 0.7%, MDMA: 0.6%, Figure 1). Of the patients with a positive test, only 57% reported using recreational drugs. Out of 165 clinical, biological, ECG, and echocardiographic features, 9 variables were selected as being the most important in detecting drugs use: age, systolic pulmonary artery pressure, body mass index, hemoglobin, NT-pro BNP, temperature, active smoker status, heart rate, and mean blood pressure. The random forest model showed the best performance compared with the other ML models (AUROC=0.82 vs. 0.80, and PR-AUC 0.62 vs. 0.46; both p<0.001) to detect recreational drugs use. The random forest model also exhibited a good performance for detecting recreational drugs use in the external validation cohort (AUROC=0.76 and PR-AUC=0.44).

Conclusions: In a large ICCU registry, our ML algorithm including clinical, biological, ECG and echocardiographic data exhibited a higher performance to detect recreational drugs use than traditional statistical methods. Knowing the high rate of underreporting in this study, it is crucial to validate the performance of this ML tool in further studies.
Figure 1: ML model using clinical, biological, and TTE data for recreational drugs use detection

- Population constituting the study cohort: N=1,499
- Recreational drugs use: 11% (N=161)

- Internal cohort: N=1,205 (31 centres)
- Validation cohort: N=294 (8 centres)

- 165 available features
- XGBoost for feature selection

- 9 variables for model building:
  - Age
  - Systolic PA pressure
  - Body mass index
  - Hemoglobin
  - NT-pro BNP
  - Temperature
  - Active smoker status
  - Heart rate
  - Mean blood pressure

Model development

Figure 2: Model Performances for recreational drugs use detection

ROC

- Sensitivity
- Specificity

Precision-Recall

- Precision
- Recall

Model performances