KSN 2020
FULLY VIRTUAL MEETING

Abstract Type : Oral
Abstract Submission No. : OR-1701

Machine learning model to predict hypotension after starting continuous renal replacement therapy

Min Woo Kang, Dong Ki Kim, Kook-Hwan Oh, Kwon Wook Joo, Yon Su Kim, Seung Seok Han
Department of Internal Medicine-Nephrology, Seoul National University Hospital, Korea, Republic of

Objectives: Although hemodynamic instability after starting continuous renal replacement therapy (CRRT) due to acute kidney injury is related with worse outcomes, its prediction model has not been established. The present study addresses whether machine learning algorithms can predict the hypotension after starting CRRT.

Methods: We randomly divided a total of 1,191 adult patients who started CRRT for acute kidney injury into training (70%) and testing (30%) sets. The primary outcomes were a decrease in mean arterial blood pressure (MAP) ≥ 10 mmHg (MAP-1) or ≥ 20 mmHg (MAP-2) within 1 hour after starting CRRT. We used random forest (RF), extreme gradient boost (XGB) and artificial neural network (ANN) models for prediction. For evaluating the model performance, the area under the receiver operating characteristic curve (AUROC), accuracy, and F1 score were used. Furthermore, a multiclass classification model was applied to score the severity of hypotension, as follows: 0, no decrease; 1, < 10 mmHg; 2, 10–19 mmHg; 3, 20–29 mmHg; and 4, ≥ 30 mmHg (MAP-3).

Results: In predicting MAP-1, the RF, XGB and ANN had AUROCs of 0.73 (0.675–0.781), 0.74 (0.691–0.793), and 0.76 (0.715–0.812), respectively. In predicting MAP-2, the RF, XGB and ANN had AUROCs of 0.75 (0.697–0.811), 0.74 (0.714–0.825), and 0.76 (0.715–0.822), respectively. All of these predictive performance were not different between models. Average of AUROCs for predicting MAP-3 were 0.652, 0.654, and 0.638 in RF, XGB, and ANN, respectively. Accuracy in MAP-3-prediction RF, XGB, and ANN models were 0.590, 0.621, and 0.612, respectively. In the XGB model, MAP *itself* at the time of starting CRRT was determined as the most important variable, followed by pH, serum sodium, and body temperature.

Conclusions: Machine learning can be applied to predict the risk of hypotension after CRRT.

Figure 1. Importance of variables in developing XGB models

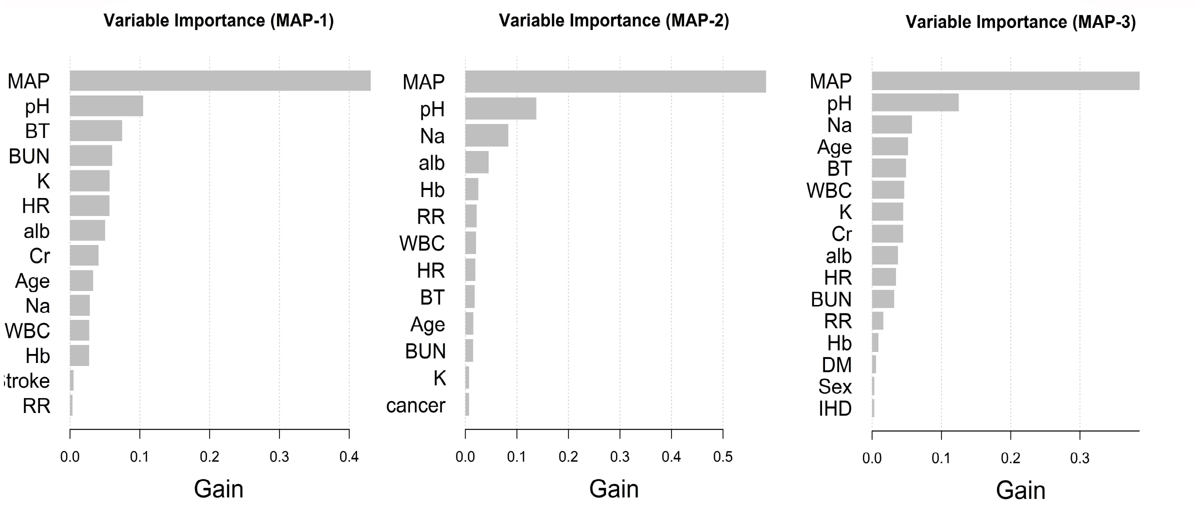

Table 1-3

Table 1. Evaluations of models predicting mean arterial blood pressure decrease >10 mmHg

Models	Metrics		
	AUROC (95% CI)	accuracy	F1 score
Logistic regression	0.762 (0.713-0.810)	0.694	0.667
Random forest	0.728 (0.675-0.781)	0.680	0.491
Extreme gradient boost	0.742 (0.691-0.793)	0.683	0.502
Artificial neural network	0.764 (0.715-0.812)	0.685	0.537

Abbreviations: *AUROC* area under the receiver operating characteristic, *CI* confidence interval

Table 2. Evaluations of models predicting mean arterial blood pressure decrease >20 mmHg

Models	Metrics		
	AUROC (95% CI)	accuracy	F1 score
Logistic regression	0.770 (0.717-0.824)	0.652	0.508
Random forest	0.754 (0.697-0.811)	0.784	0.154
Extreme gradient boost	0.770 (0.714-0.825)	0.787	0.406
Artificial neural network	0.768 (0.715-0.822)	0.784	0.319

Abbreviations: *AUROC* area under the receiver operating characteristic, *CI* confidence interval

Table 3. Evaluations of multiclass classification models predicting mean arterial blood pressure decrease ≤10, 10< ≤20, 20< ≤30 or >30 mmHg

Models	Metrics	
	Average AUROC	accuracy
Logistic regression	0.652	0.612
Random forest	0.652	0.590
Extreme gradient boost	0.654	0.621
Artificial neural network	0.638	0.612

Abbreviations: *AUROC* area under the receiver operating characteristic