Development of Mechanical Ventilator Weaning Algorithm based on Common Data Model: Pilot Study

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Background

Standardized data structure and terminology such as the Common Data Model (CDM) are essential components for interoperable clinical decision support systems (CDSS).
Big data in healthcare is complex and varies from institution to institution, so data collection and standardization is a necessary process for multicenter database research. The common data model can standardize the data structure and enable the analysis of different formats of electronic health record data. Data-based machine learning algorithms have a high potential for medical decision support and are also being researched to solve problems that are cumbersome or difficult to solve in the medical field.
Ventilator weaning protocols can improve clinical outcomes and reduce ventilator-associated complications. The success of weaning off of a mechanical ventilator (MV) was higher with application of the protocol, but protocol application requires greater medical knowledge and constant education.

Objective

The aim of this study is to develop a data-driven machine learning algorithm to predict which patients will need re-intubation as well as extubation that is decided by spontaneous breathing trial (SBT) protocol.

Methods

Data were collected from the Clinical Data Warehouse (CDW) of the Samsung Medical Center from January 1, 2010, to December 31, 2017. Among the patients that were admitted to the intensive care unit during the study period, patients who were younger than 18 years, and patients whose ventilator therapy treatment was less than 24 hours were excluded. Detailed eligibility processes are described in Figure 1. We employed random forest for the algorithm, and used arterial blood gas analysis results before and after SBT and respiratory rate as input variables. In this study, we adopted an under-sampling method at a 1:2 ratio to handle unbalanced data problems. The cases with the missing value were omitted. After developing the algorithm, we mapped the input variables to match the CDM structure.

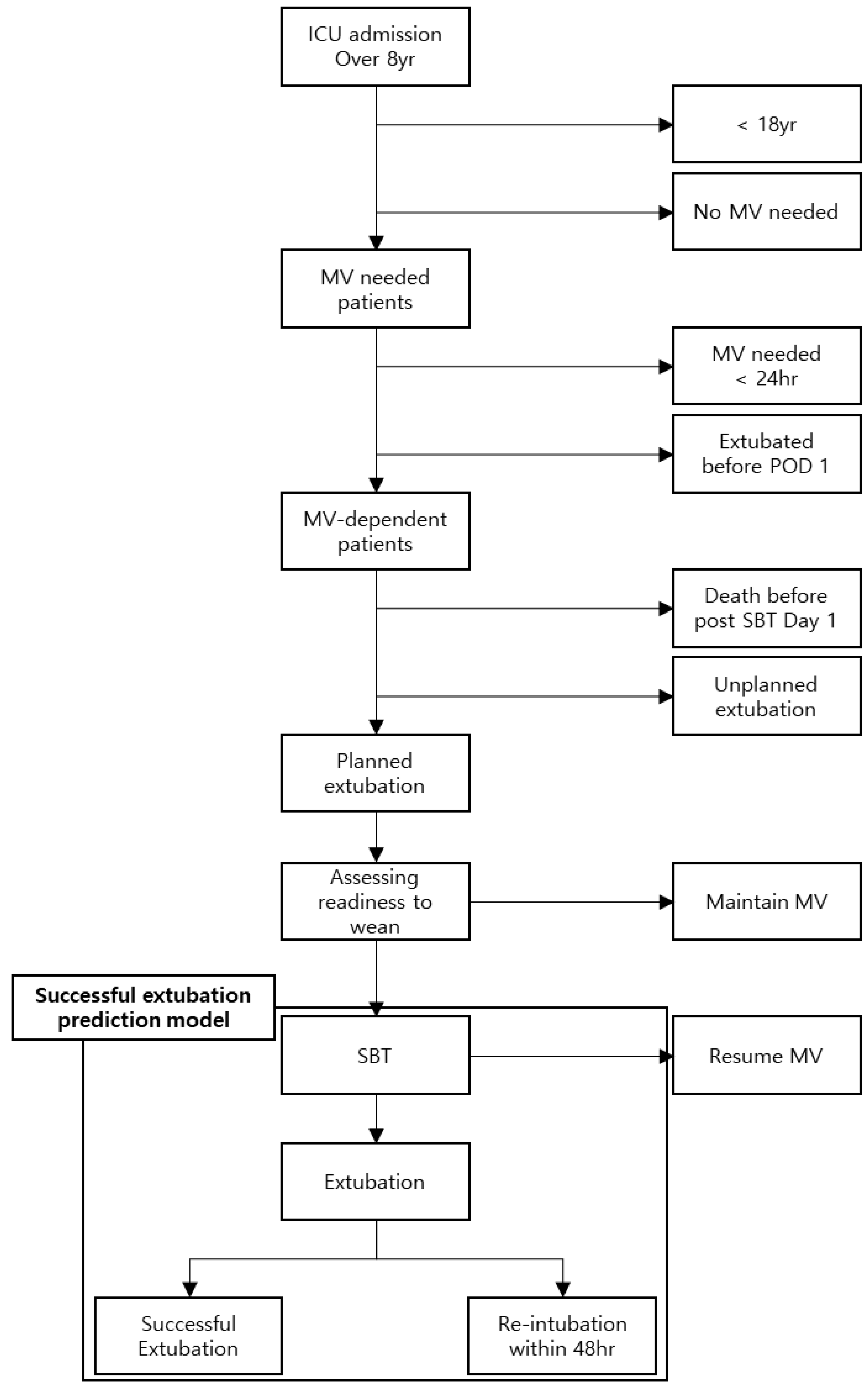

Figure 1. Patients inclusion flowchart. ICU: Intensive care units; MV: Mechanical ventilator; POD: Post operation day; SBT: spontaneous breathing trial

Results

Among 298 extubation cases, 99 cases were in the re-intubation group, and 199 cases were part of the control group. The accuracy and Area Under the Receiver Operating Curve (AUROC) of the algorithm for predicting a 48 hour reintubation after extubation was 66.7% and 0.678, respectively. (Figure 2) Detailed concept ID of input variables are described in Table 1.

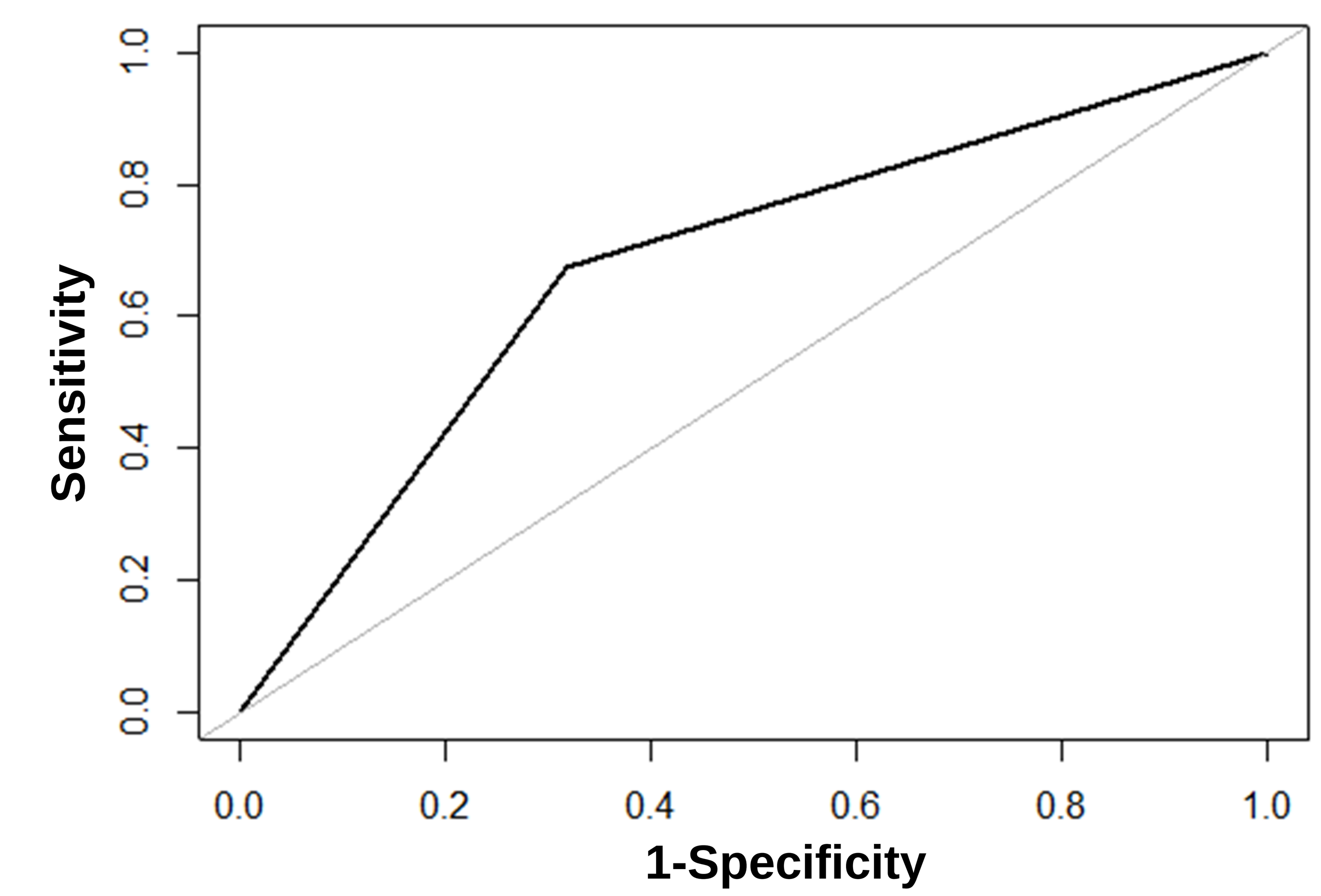

Figure 2. Receiver operating characteristics (ROC) curves for 48hr reintubation prediction after extubation based on spontaneous breathing trial protocol.

Table 1. Mapping table for input variables between CDW and CDM structure.

Concept Name	RR	SBT	PaO2	PaCO2	pH	SaO2
CDW code	1004	115	BL318503	BL318502	BL318501	BL318507
CDM code	1175625	36305294	3027801	3027946	3019977	3016502

CDW: Clinical data warehouse; CDM: Common data model; RR: Respiratory rate; SBT: Spontaneous breathing trial; PaO2: partial pressure of oxygen in arterial blood; PaCO2: partial pressure of carbon dioxide in arterial blood; pH: hydrogen ion concentration; SaO2: oxygen saturation in arterial blood

Conclusions

We have developed an algorithm to suggest re-intubation risk when physicians are determining extubation. By mapping the input feature in the CDM structure, the algorithm can be easily distributed in hospitals where CDM conversion has been completed.

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