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Using artificial intelligence to predict prolonged mechanical ventilation and tracheostomy placement

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ABSTRACT

Background: Early identification of critically ill patients who will require prolonged mechanical ventilation (PMV) has proven to be difficult. The purpose of this study was to use machine learning to identify patients at risk for PMV and tracheostomy placement.
Materials and methods: The Multiparameter Intelligent Monitoring in Intensive Care III database was queried for all intensive care unit (ICU) stays with mechanical ventilation. PMV was defined as ventilation >7 d. Classifiers with a gradient-boosted decision trees algorithm were created for the outcomes of PMV and tracheostomy placement. The variables used were six different severity-of-illness scores calculated on the first day of ICU admission including their components and 30 comorbidities. Mean receiver operating characteristic curves were calculated for the outcomes, and variable importance was quantified.
Results: There were 20,262 ICU stays identified. PMV was required in 13.6%, and tracheostomy was performed in 6.6% of patients. The classifier for predicting PMV was able to achieve a mean area under the curve (AUC) of 0.820 ± 0.016, and tracheostomy was predicted with an AUC of 0.830 ± 0.011. There were 60.7% patients admitted to a surgical ICU, and the classifiers for these patients predicted PMV with an AUC of 0.852 ± 0.017 and tracheostomy with an AUC of 0.869 ± 0.015. The variable with the highest importance for predicting PMV was the logistic organ dysfunction score pulmonary component (13%), and the most important comorbidity in predicting tracheostomy was cardiac arrhythmia (12%).
Conclusions: This study demonstrates the use of artificial intelligence through machine-learning classifiers for the early identification of patients at risk for PMV and tracheostomy. Application of these identification techniques could lead to improved outcomes by allowing for early intervention.

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Introduction

Prolonged mechanical ventilation (PMV) is required in approximately 30% of critically ill patients.[1] While nearly 24% of intensive care unit (ICU) patients require tracheostomy placement, making the procedure the most common elective surgical procedure performed on ICU patients.[2] Timing of tracheostomy placement has been controversial, but a recent large Cochrane review found improved outcomes in patients with early (<10 d) tracheostomy placement.[3,4]

Most severity-of-illness scores for predicting mortality were developed using logistic regression techniques with a fixed number of variables. Comparisons of these conventional scores to techniques using artificial intelligence through machine learning for predicting mortality have shown that machine-learning classifiers are able to achieve similar or improved performance with fewer variables.[5-8] Applications of machine learning have shown to be highly accurate for various predictions including outcomes in surgery and burn wound healing.[9-11] Applying machine learning concepts to the ICU has also proven useful for discerning clinically relevant vital sign alarms and predicting clinical deterioration.[12,13] However, predicting which ICU patients will require PMV has proven to be difficult. Recent attempts have resulted in only modest success with accuracies of 60%-69% and areas under the curve (AUC) of 0.52-0.67.[14,15]

The purpose of this study was to use supervised machine learning to predict PMV and tracheostomy placement in patients admitted to the ICU. We hypothesized that useful predictive models could be developed for these outcomes using conventional severity-of-illness scores, their individual components, and patient comorbidities.

Material and methods

The Multiparameter Intelligent Monitoring in Intensive Care III (MIMIC-III) database contains the medical records of 46,520 admissions at Beth Israel Deaconess Medical Center from 2001 to 2012. The database contains detailed information on patient hospitalizations including International Classification of Diseases, 9th Revision, clinical modification (ICD-9-CM) codes, laboratory data, vital signs, medication administrations, and mortality data from the Social Security Death Index.[16] The database also provides several severity-of-illness scores calculated from physiologic variables on the first day of each ICU admission.

For this study, the MIMIC-III database was queried for each patient undergoing mechanical ventilation determined by the presence of data for ventilator settings. PMV was defined as mechanical ventilation for more than 7 d. Patients requiring tracheostomy placement were identified by the presence of

Table 1 – Severity-of-illness scores with components presented as mean with standard deviation.

Variable	All ventilated patients	PMV	P	Tracheostomy	P
Total	20,262	2761 (13.6)	-	1342 (6.6)	-
OASIS	35.36 ± 7.15	38.44 ± 7.15	<0.01	38.12 ± 7.38	<0.01
Age	5.15 ± 2.58	4.71 ± 2.76	<0.01	5.40 ± 2.26	<0.01
Pre ICU LOS	3.07 ± 1.99	3.77 ± 1.80	<0.01	3.66 ± 1.95	<0.01
GCS	1.59 ± 2.84	1.47 ± 3.03	0.03	1.59 ± 3.08	0.97
Heart rate	2.41 ± 2.11	3.22 ± 2.29	<0.01	2.57 ± 2.09	<0.01
Mean BP	1.65 ± 1.20	1.85 ± 1.25	<0.01	1.73 ± 1.27	0.02
Respiratory rate	2.68 ± 2.86	3.18 ± 3.01	<0.01	2.94 ± 2.99	<0.01
Temperature	2.82 ± 1.04	2.74 ± 1.08	<0.01	2.70 ± 1.02	<0.01
Urine output	3.18 ± 3.56	4.30 ± 3.90	<0.01	3.10 ± 3.29	0.37
Elective surgery	4.72 ± 2.46	5.57 ± 1.54	<0.01	5.52 ± 1.63	<0.01
SOFA	5.06 ± 2.97	6.61 ± 3.61	<0.01	5.41 ± 3.41	<0.01
Respiration	1.63 ± 1.38	2.06 ± 1.55	<0.01	1.78 ± 1.54	<0.01
Coagulation	0.52 ± 0.78	0.56 ± 0.89	<0.01	0.53 ± 0.86	0.75
Liver	0.76 ± 1.06	0.85 ± 1.06	<0.01	0.40 ± 0.82	<0.01
Cardiovascular	1.43 ± 1.14	1.90 ± 1.41	<0.01	1.59 ± 1.33	<0.01
CNS	0.63 ± 1.13	0.60 ± 1.20	0.14	0.65 ± 1.21	0.57
Renal	0.91 ± 1.36	1.34 ± 1.53	<0.01	0.77 ± 1.14	<0.01
SAPS	19.53 ± 4.68	20.54 ± 5.24	<0.01	20.97 ± 4.41	<0.01
Age	2.13 ± 1.47	1.90 ± 1.53	<0.01	2.21 ± 1.45	0.04
HR	1.79 ± 1.07	2.04 ± 1.04	<0.01	1.84 ± 0.99	0.05
Systolic BP	1.45 ± 1.21	1.71 ± 1.23	<0.01	1.74 ± 1.23	<0.01
Respiratory	1.46 ± 1.06	1.49 ± 1.14	0.22	1.44 ± 1.12	0.42

(continued)