„With great power comes greater predictability“ - Implementation of a machine learning algorithm to predict primary weaning failure in mechanically ventilated patients

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Introduction

Since the rise of artificial intelligence and the increasing use of machine learning models in critical care medicine, the demand for clinical decision support systems has grown exponentially.
Especially in mechanically ventilated patients, where both prolonged organ support and extubation failure pose a hazard to patient safety, identifying the “right” moment for extubation is crucial.[1]
In this project, we created a prediction model for primary weaning failure, using, among other input variables, the Mechanical Power (MP)[2] as a measure of ventilator-induced lung injury (VILI) to predict readiness for weaning from invasive mechanical ventilation.

Methods

From AmsterdamUMCdb[3], patients with one or more episodes of invasive mechanical ventilation were identified. The start of a new episode less than 24 hours after the end of the previous episode was defined as primary weaning failure.
To predict weaning failure, we identified possible input parameters for a supervised machine learning algorithm. These input parameters included ventilation parameters (e.g., PEEP, Vt, driving pressure), compound variables (e.g. Mechanical Power normalised to ideal body weight (MP/IBW), $PetCO_2/PaCO_2$, P/F-Ratio), and laboratory parameters (e.g., lowest Hb, highest Lactate, lowest Albumin) each within the last 48 hours of the ventilation episode. Feature selection was performed after removing collinear items (threshold 0.3). Using a train-test-split procedure, 30% of all instances were randomly assigned to the test cohort. K-fold cross-validation was implemented to ensure high generalization performance (k = 10). An open-source machine learning library (PyCaret) was used to identify the best-performing algorithm. The performance was visualized using the area under the receiver operator characteristics curve (AUROC) for all patients and the eight most frequent subspecialties.

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Results

We identified 15725 (32% female, median age 64.5yrs, median weight 74.5kg) patients undergoing invasive mechanical ventilation, 918 (6.2% of all patients, 30% female, median age 64.5yrs, median weight 84,5kg) of which showed weaning failure according to the above definition. Comparing different machine learning algorithms, the extra trees classifier was identified as performing best regarding accuracy, precision, AUROC, recall, and F1. Feature importance analysis identified P/F-Ratio, MP/IBW, $PetCO_2/PaCO_2$, I:E-ratio, and gender as features with the highest impact (Figure 1). Model performance for the eight most frequent subspecialties revealed an AUROC between 0.94 and 0.96, with slightly better performance in non-surgical disciplines (Figure 2).

Conclusion

We identified relevant input parameters to create a model for predicting primary weaning failure. The next steps to be performed are hyperparameter tuning for model optimization and validation with an external cohort (e.g., MIMIC IV database or prospectively as part of a multicenter study at five German university hospitals).

Fig. 1:

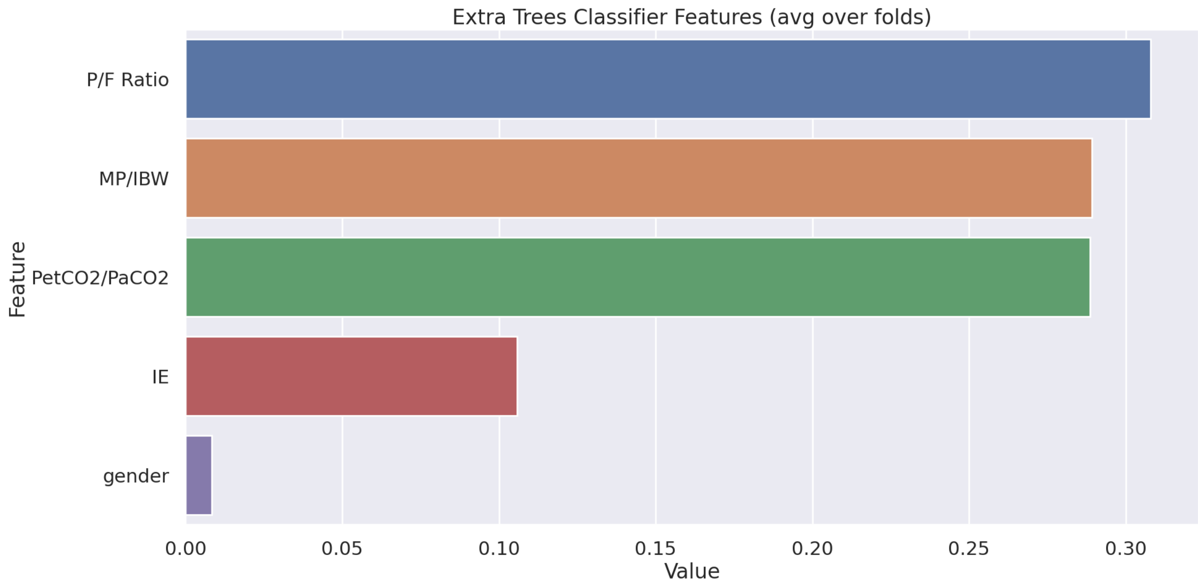

Figure 1: Feature value chart for parameters included in the extra tree classifier. After removing multicolinearities, the six most valuable parameters (P/F-Ratio, MP/IBW, $PetCO_2/PaCO_2$, I:E-ratio, and gender) were chosen for the machine learning model.

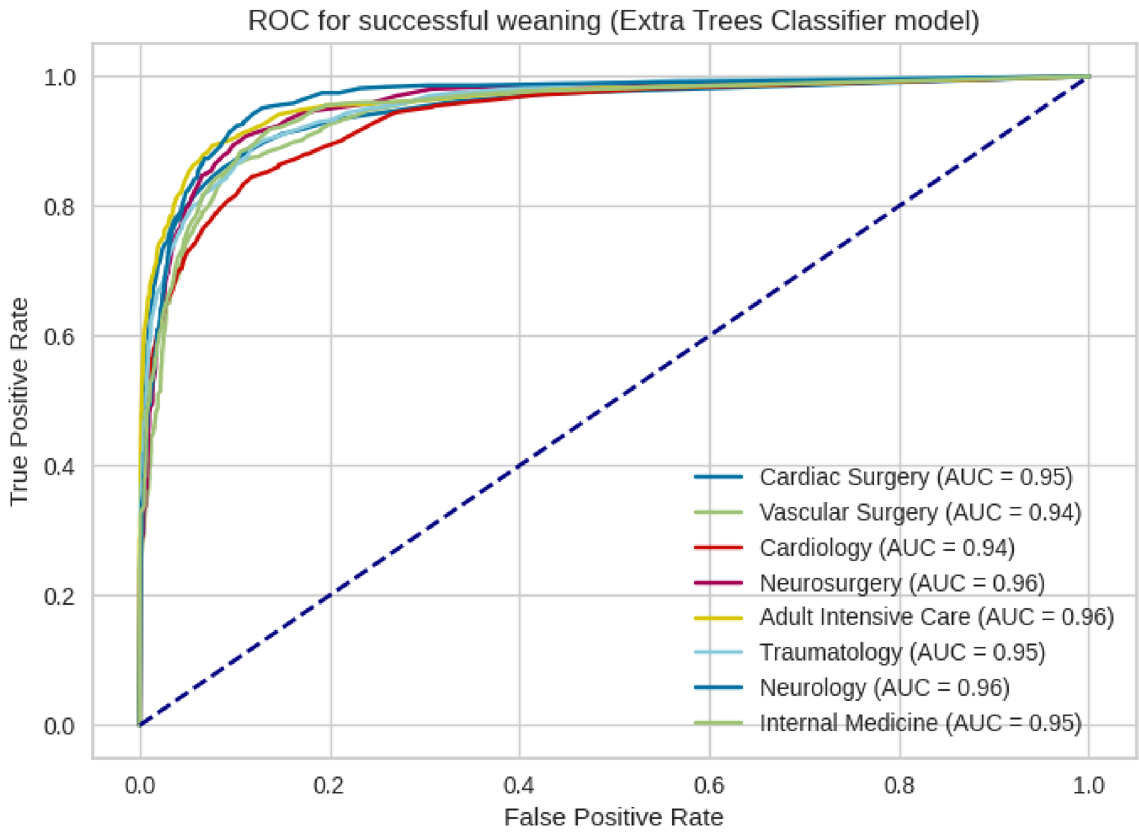

Figure 2: Area under the receiver operating characteristic curve for the extra tree classifier. The model performs significantly better when patients are separated for their respective medical disciplines.