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Detection of Ventilator-Associated Events Among Adults: Comparing a Naïve Bayes Classifier and Logistic Regression

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Abstract

A Naïve Bayes classifier was used to identify mechanically ventilated patients at risk for ventilator-associated events (VAEs). VAEs, which can lead to ventilator-associated pneumonia (VAP), are considered preventable and have therefore been extensively studied. Data were gathered from May 2013 to August 2016 from hospital surveillance records and matched 1:1 with non-VAE cases using age, sex, unit while intubated, use of vasopressors, and total ventilator days. The dataset was split 7:3 to create samples for training and testing. From the training set, the classifier calculated the conditional probabilities for each factor in the model. After the proposed model was trained, it was validated against the testing data sample. The model demonstrated an overall accuracy of 83.0% (95% CI; 74.8% – 89.5%) and was able to correctly classify 80.4% of VAEs (sensitivity) and 85.7% of non-VAEs (specificity). The PPV and NPV were 81.4% and 84.9%, respectively. The AUC was 0.831 (95% CI; 0.751 – 0.911) and the MCC was 0.662. This study indicates that a Naïve Bayes classifier can be used to classify mechanically ventilated patients at risk for VAEs with moderate accuracy. The model could be used to screen for VAEs at the time of intubation and to strengthen manual surveillance. Further research is needed to validate the model in terms of prognostic and diagnostic use for hospitals and clinical settings with different patient characteristics.

Keywords: Ventilator-associated events; machine learning; naïve Bayes classifier; logistic regression; predictive models

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1. Introduction

Patients on mechanical ventilation are at risk for ventilator-associated pneumonia (VAP). Many consider VAP to be preventable and there has been extensive effort in monitoring VAP rates. In 2013, the Centers for Disease Control and Prevention (CDC) ceased looking solely at VAP and began to develop more objective, detailed measures. As a result of that effort, the CDC established surveillance definitions known as ventilator-associated events (VAEs) (1). Under the VAE continuum, mechanically ventilated patients can develop a ventilator-associated condition (VAC), which risks progression to an infection-related ventilator-associated complication (IVAC) or a possible ventilator-associated pneumonia (PVAP).

Naïve Bayes classifiers are a popular method for disease prediction in machine learning applications, with one recent example being the classification of COVID-19 disease severity (2). This computational approach calculates the probability of an outcome based on a set of independent factors. For example, disease severity may be classified as 'mild', 'moderate', or 'severe' based on prior (or active) vital signs collected from telemetry monitoring. In contrast, Logistic Regression is a statistical method used to analyze and model the relationship between two possible categories and one or more predictor variables (3). The goal is to understand how the predictor variables contribute to the likelihood of the categorical outcome. Both statistical models were chosen for their simplicity, interpretability, and resistance toward irrelevant attributes (that are more likely to obscure k-Nearest Neighbor models, for example). In this study, they provide a probability to classify a patient as either a 'VAE' or 'non-VAE' using predefined parameters.

This study aimed to compare two machine learning methods used to classify mechanically ventilated patients at risk for VAEs.

2. Methods

VAEs were gathered from May 2013 to August 2016 from hospital surveillance records at the University of Toledo Medical Center. VAE surveillance is conducted manually at our institution by reviewing daily ventilator values and applying CDC definitions to identify cases. The cases were matched 1:1 with controls from the same period in our clinical database. Our matching variables consisted of age, sex, unit while intubated during the hospital encounter, use of vasopressors during intubation, and total ventilator days.

The machine learning model assessed potential predictors using Pearson chi-square tests and only statistically significant factors were utilized. To construct a classifier, the dataset was split 7:3 to create samples for training and testing. The nested classifications in the VAE continuum – VACs, IVACs, and PVAPs – were properly represented in each sample. From the training set, the classifier calculated the conditional probabilities for each factor in the model. After training the proposed model, it was validated against the testing data sample. To appraise the model's performance, accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), the area under the curve (AUC), and the Matthews correlation coefficient (MCC) were calculated. The aforementioned summary indices are traditionally used to evaluate prediction models (4).

All analyses were performed using R 4.3.3 (R Foundation for Statistical Computing), and an alpha level of < 0.05 was considered statistically significant.

3. Results

Between May 2013 and August 2016, a total of 186 cases of VAEs were reported, consisting of 99 VACs, 47 IVACs, and 40 PVAPs. These cases were matched 1:1 with non-VAE cases. Following dataset partitioning, the analysis included 260 patients in the training sample and 112 patients in the testing sample. The seven variables outlined in Table 1 were used in the creation of the predictive models.

The naïve Bayes classifier achieved an accuracy of 66.2% (95% CI; 60.1% – 71.9%) on the training data. The model demonstrated a sensitivity of 61.5% (95% CI; 56.3% – 72.6%) for identifying VAEs and a specificity of 70.8% (95% CI; 56.0% – 84.1%) for correctly classifying non-VAEs. The PPV and NPV were 67.8% (95% CI; 58.6% – 76.1%) and 64.8% (95% CI; 52.6% – 69.9%), respectively. The AUC was 0.662 (95% CI; 0.604 – 0.719), with a MCC of 0.324. In the testing dataset, the naïve Bayes classifier correctly classified 83.0% (95% CI; 74.9% – 88.9%) of the cases. It identified 80.4% (95% CI; 67.9% – 88.8%) of VAEs (sensitivity) and 85.7% (95% CI; 73.9% - 92.7%) of non-VAEs (specificity). The PPV and NPV were 81.4% (95% CI; 69.4% - 89.4%) and 84.9% (95% CI; 72.6% - 92.7%),

respectively, with an AUC of 0.831 (95% CI; 0.749 – 0.889) and a MCC of 0.662.

The logistic regression model demonstrated a training accuracy of 70.0% (95% CI; 64.0% – 75.5%), identifying 73.1% (95% CI; 60.4% – 76.4%) of VAEs (sensitivity) and 66.9% (95% CI; 62.4% – 79.1%) of non-VAEs (specificity). The PPV and NPV were 68.8% (95% CI; 64.6% – 80.5%) and 71.3% (95% CI; 58.1% – 74.9%), respectively, with an AUC of 0.770 (95% CI; 0.714 – 0.826) and a MCC of 0.401. On the testing dataset, the logistic regression model achieved an accuracy of 80.4% (95% CI; 71.8% – 87.3%), identifying 78.6% (95% CI; 65.9% - 87.4%) of VAEs (sensitivity) and 82.1% (95% CI; 69.9% - 90.1%) of non-VAEs (specificity). The PPV and NPV were 81.5% (95% CI; 68.9% – 89.7%) and 79.3% (95% CI; 67.0% - 86.7%), respectively, with an AUC of 0.804 (95% CI; 0.720 – 0.867) and a MCC of 0.608.

4. Discussion

Machine learning has been used to predict VAP with an AUC of 0.854 and 0.744 in two studies (5,6). Yet, naïve Bayes classifiers and logistic regressions are not frequently used to address VAE prediction. We believe this is the first study using machine learning models to predict VAE risk among mechanically ventilated patients. Given the summary indices in both models, the performance is acceptable, with moderately high accuracy and the ability to classify outcomes correctly. Likewise, the AUC suggests that someone using this model has at least an 80% chance to correctly distinguish a VAE from a non-VAE. In addition, the MCC in both models can be interpreted as a strong positive relationship denoting predictions that matched the true classification. Based on the results, there are no strong indications of overfitting in either model. Both the naïve Bayes and logistic regression models appear to generalize well to unseen data, showing improvements in performance metrics on the testing dataset. Ultimately, the naïve Bayes model would be preferred for implementation given its superior performance on the testing dataset for all metrics apart from PPV.

This was a single-center retrospective study, so the results may be difficult to generalize to other hospitals. One critical limitation of the paper is that the reported PPV is based on a test population with a very high prevalence of VAEs (50%). One must realize that PPV will decrease if the same models are implemented within an unselected ICU population where the prevalence of VAEs would be closer to 30% (7). We would anticipate variables implicated in previous studies, such as congestive heart failure (CHF), to be ubiquitous factors (8). Additionally, there may be institution-specific factors that contribute to the classification of at-risk patients. For instance, we chose to include a time-dependent variable with our median time-to-event of 5 ± 3 ventilator days. This is consistent with most VAEs occurring early after intubation (9,10). Likewise, we found chronic kidney disease covaried with CHF, while positive smoking history covaried with chronic obstructive pulmonary disease (COPD). The addition of both predictors did not enhance the quality of the model, so both were subsequently removed. While not implicated as a risk factor for VAEs, other variables used in the model, such as diabetes, have been associated with clinical VAP development in adult patients (11,12).

5. Conclusion

This study demonstrated that logistic regressions and naïve Bayes classifiers can categorize mechanically ventilated patients at risk for VAEs with an overall accuracy of 80.4% and 83.0%, respectively. These models could screen patients at risk for VAEs during intubation and as a reassessment tool as time progresses on the ventilator. Further research is needed to validate the model with different patient characteristics in other hospitals and clinical settings.

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