Using machine learning to predict clinical failure in hospitalized patients with community-acquired pneumonia

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ABSTRACT

Introduction

Pneumonia is a leading cause of mortality worldwide(1). To prevent adverse health outcomes due to pneumonia, severity scores are needed to classify patients into risk groups that indicate the level and type of care the patient requires. Though most severity scores predict 30 day mortality, in-hospital clinical failure is a more relevant clinical outcome(2). Therefore, the objective of this study was to create a severity score to predict clinical failure in order to prevent negative health outcomes.

Methods

This study analyzed 3,217 adult community-acquired pneumonia (CAP) patients from the global Community-Acquired Pneumonia Organization (CAPO) database. Predictive variables were chosen using multivariate logistic regression, variable importance plots (VIPs), and principle component analysis (PCA). The weighted score was based on the risk ratio calculated by using poisson regression. ROC curves were then used to test the quality of the model.

Results

The developed Fail score model included eight variables: O_2 saturation, respiratory rate, cardiovascular event on admission, altered mental status, heart rate, creatinine, systolic blood pressure, and platelet count. Four risk groups were defined to categorize severity of clinical failure.

Conclusions

The Fail score would allow physicians to facilitate more individualized patient care to prevent adverse health outcomes and lessen health care costs.

INTRODUCTION

Pneumonia has significant impacts on health and society including increased complications, mortality, and lost productivity. Severity scores have been developed to help physicians better manage their patients and guide them towards the best clinical decisions (2).

Most severity scores focus on the outcome of mortality. However, approximately 8 percent of in-hospital CAP patients' outcomes include death. One of the more interesting and relevant outcomes from a clinical perspective is failure. Clinical failure leads to increased complications, increased length of stay, increased total direct cost of care for hospitalized patients with CAP, as well as mortality (2).

The overall goal is to develop an accurate predictive tool to make appropriate management clear to physicians so they can facilitate a more individualized and effective approach to patient care.

METHODS

The CAPO database was used for analysis. The subset of the CAPO database used consisted of 3,217 patients of which, 494 met the criteria for clinical failure. Two cohorts were made from the 3,217 patients in the study to test the internal validity of the model being created (Figure 1). PCA was used in conjunction with the VIPs to find the variables most likely to predict clinical failure. Logistic regression and a poisson regression with robust error variance model that corrected for violation of the assumptions were used to develop the predictive Fail score model. Receiver Operating Characteristic (ROC) curves were then used to test the model's quality in relation to sensitivity and specificity.

METHODS, CONTINUED

Derivation Cohort 80% of sample N=2574 391 Failure (+)	Validation Cohort 20% of sample N=643 103 Failure (+)

Figure 1: Two cohorts

RESULTS

Variable Importance Plots (VIPs) are dot charts of all variables in ranked importance as measured by a computation of decision trees using ensemble learning (Figure 2). The random forest algorithm estimates the importance of a variable by looking at how much prediction error increases when data for that variable is permuted and all other variables are left unchanged(4).

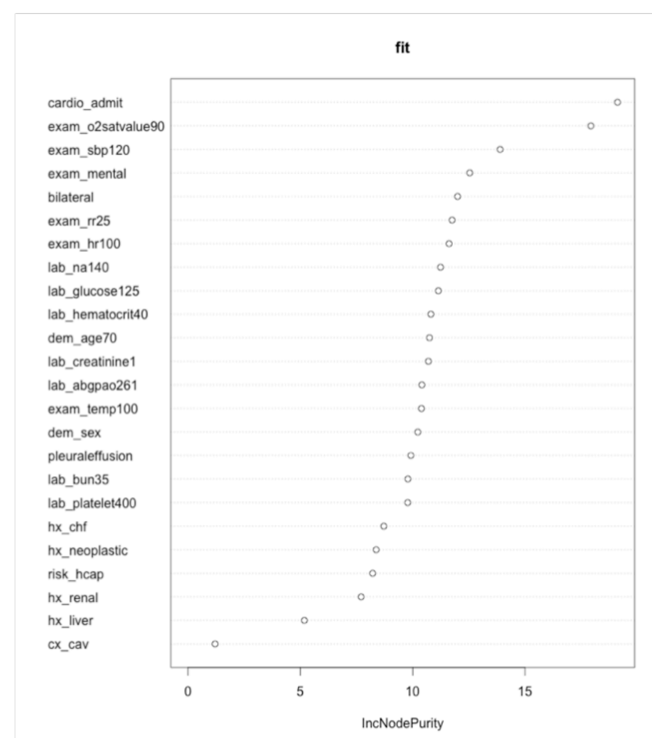


Figure 2:
Variable Importance Plot (VIP)

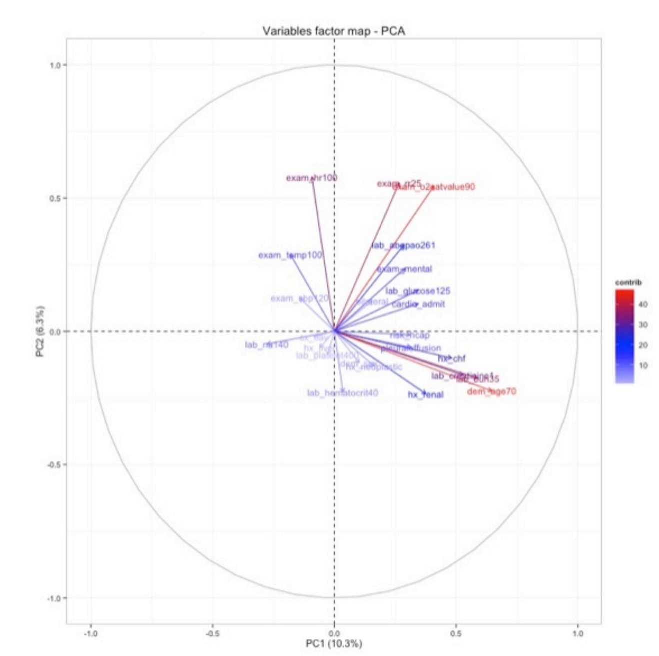


Figure 3:
Principle Component Analysis (PCA)

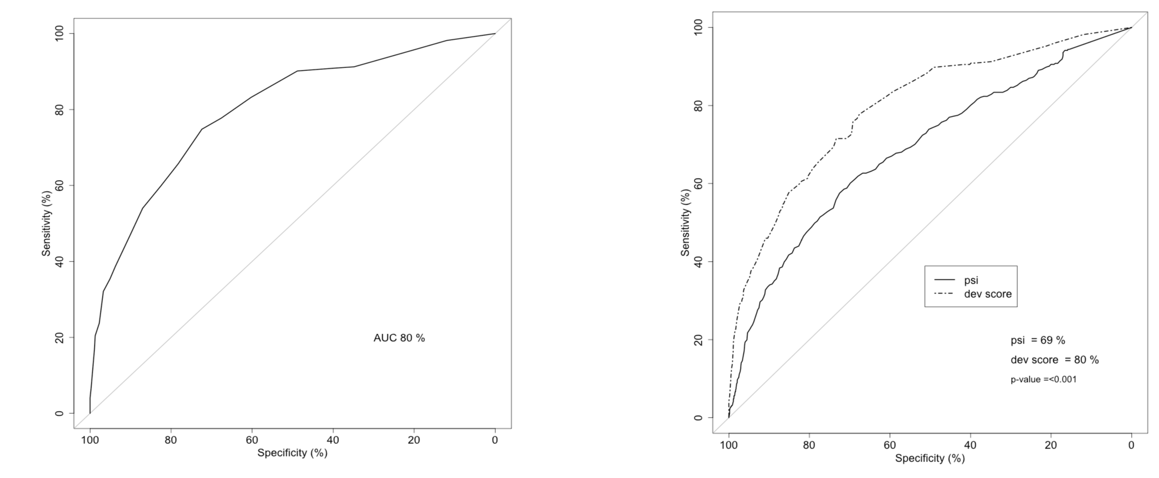
Principle component analysis (PCA) was employed as it is a common method used for exploration and reduction of high-dimensional data (Figure 3)(5). These techniques determined what predictor variables were to be included in the model. The variables were then entered into a poisson regression with robust error variance model that corrected for violation of the assumptions producing risk ratios for which the weighted values for each variable in the model were obtained. The predictors with their weighted value are shown in Table 1.

Variable	Weight
02 saturation <90	2
Respiratory Rate >25	2
Cardiovascular Event on Admission	3
Altered Mental Status	2
Heart rate >100	1
Creatinine>1	1.5
Systolic Blood Pressure <120	1.5
Platelet <100 or >400	1.5

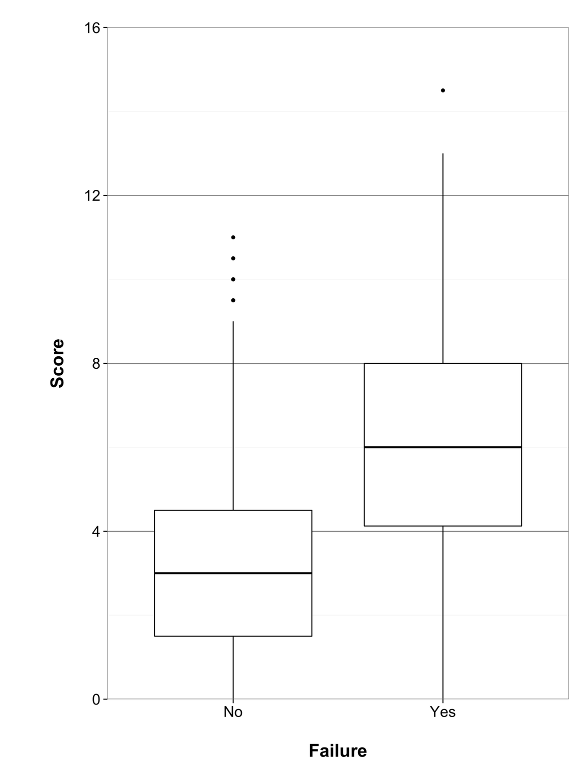
Table 1: Weighted variables selected for final model

RESULTS, CONTINUED

ROC curves were used to measure how well the model classifies those with and without clinical failure. Figure 4A is an ROC showing the diagnostic accuracy of the Fail score for the prediction of failure for CAP patients. Figure 4B is an ROC curve showing the commonly used Pneumonia Severity Index (PSI) compared to the Fail model in predicting clinical failure. Figure 5 shows a boxplot that was the basis for formulating the risk groups, and Table 2 shows the categories of risk groups. All data were analyzed in R v. 3.2.1. R packages used included "OptimalCutpoints" to dichotomize the variables, "randomForest" for the variable importance plot, "FactoMiner" for principle components analysis (PCA), and several other internally developed R functions.



A B
Figure 4: ROC curves



Risk Groups:
Group 1: 0.00-3.00
Group 2: 3.01-5.00
Group 3: 5.01-10.00
Group 4: 10.01-14.00

Table 2: Risk group categories

Figure 5: Boxplots of risk categories

CONCLUSIONS

The Fail score allows clinicians to make better assessments by classifying patients in terms of their risk. The identification of a patient's risk class allows all patients more efficient and appropriate treatment. With preventive tools like this Fail score, we can lessen both the burden of disease, and adverse health outcomes due to CAP.

REFERENCES

1. Prevention CfDCa. Mortality in the United States, 2012. Available from: http://www.cdc.gov/nchs/data/databriefs/db168.htm.
2. Wiemken T, Kelley R, Ramirez J. Clinical scoring tools: which is best to predict clinical response and long-term outcomes? Infectious disease clinics of North America. 2013;27(1):33-48.
3. Charles PG, Wolfe R, Whitby M, Fine MJ, Fuller AJ, Stirling R, et al. SMART-COP: a tool for predicting the need for intensive respiratory or vasopressor support in community-acquired pneumonia. Clinical infectious diseases : an official publication of the Infectious Diseases Society of America. 2008;47(3):375-84
4. A. Liaw and M. Wiener (2002). Classification and Regression by randomForest. R News 2(3), 18--22.
5. Francois Husson, Julie Josse, Sebastien Le and Jeremy Mazet (2015). FactoMineR: Multivariate Exploratory Data Analysis and Data Mining. R package version 1.31.3. http://CRAN.R-project.org/package=FactoMineR.