"Predictive Modeling of Critical Care Patient Mortality Rates Using Neural Networks: A Study on US Healthcare Data"

Yuta Tsukumo MD, MPH,

February 16, 2024

Abstract

This study aims to develop predictive models for mortality rates among critical care patients using neural networks, utilizing large-scale healthcare data from the United States. While acknowledging the limitations of generalizing findings to other healthcare systems, we emphasize the significance of accurately predicting mortality rates for informed resource allocation and quality assessment in intensive care settings.

Introduction

Predicting mortality rates for critically ill patients requiring intensive care is essential for making informed decisions regarding allocation of limited medical staff, medical equipment prioritization, assessing quality of treatment facilities, and appropriately classifying severity of illness for clinical research. However, traditional severity assessment standards in critical care, such as Apache scores, are widely used but have been reported to have low calibration for predicting mortality rates. Therefore, creating a model with higher discrimination and calibration using neural network techniques, based on large-scale patient data from the United States, holds significant importance. In Japan, healthcare database research lags behind, making studies utilizing large-scale patient data like this challenging. Personally, I aspire to contribute to the integration of patient data and the establishment of large-scale databases as a physician working for the Ministry of Health, Labor and Welfare in Japan after graduation, aiming to advance data science in Japanese healthcare. Through this project, I aim to reaffirm the significance and considerations of data sharing and database development in Japan's healthcare system.

Related Work

In 2022, a study by Jesse et al. at MIT proposed a novel scoring system using The Global Open Source Severity of Illness Score (GOSSIS) data to predict mortality rates for patients requiring intensive care. While the specific code details were not provided in the paper, the study utilized a logistic regression model based on generalized additive mixed models (GAM) to ensure interpretability and explanatory power. In our project, there's potential to achieve higher discrimination and calibration in predicting mortality rates by leveraging neural networks.

Proposed Work

First, data cleaning will be performed, and missing values will be imputed using either multiple imputation or model-based imputation. Additionally, the dataset comprises 85 columns, and feature engineering will be conducted, utilizing exploratory data analysis (EDA) and medical knowledge, to select or discard variables suspected of multicollinearity. Afterward, model fitting will proceed, comparing the results of discrimination and calibration between the generalized additive mixed model-based logistic regression chosen by Jesse et al. and other models, including neural networks.

Datasets

The dataset consists of 91,714 rows (patients) and 85 columns, with a data size of 31.4 MB. The columns in the dataset include Hospital ID, patient-specific information such as Patient ID, age, gender, race, as well as ICU type. Additionally, various Apache scores, blood pressure, heart rate, underlying medical conditions such as diabetes or immunodeficiency, and information regarding in-hospital mortality status are included. After data cleaning, the dataset will be divided into 70% training data and 30% test data. For hyperparameter tuning, the training data will be further divided into five subsets for cross-validation.

Evaluation

The multiple models will be evaluated using the test dataset, employing the Area Under the Receiver Operating Characteristic Curve (AUROC) for differentiation evaluation, a calibration plot for assessing calibration, and considering AIC, BIC, and the confusion matrix for additional performance metrics.

Timeline

2/16: Project Proposal Due
2/19 - 3/3: Data Cleaning
3/4 - 3/10: Exploratory Data Analysis (EDA)
3/11 - 3/17: Spring Break
3/18 - 3/24: Variable Selection
3/25 - 4/7: Model Fitting
4/8 - 4/20: Summary
4/25, 27: Presentation

Conclusion

In this study, we will divide the large-scale dataset of patients receiving critical care in the United States (GOSSIS) into training and testing sets. Subsequently, we will create models using neural network methods and other traditional machine learning techniques to predict mortality rates among patients receiving critical care. Developing a model capable of accurately predicting mortality rates in critical care is considered significant as it contributes to the allocation strategies of limited medical resources in intensive care settings. Furthermore, it aids in the quality assessment of healthcare institutions and facilitates appropriate categorization of patients in research related to intensive care. On the other hand, it's important to note that the data used in this study are from the United States, and there are certain limitations to generalizing findings to other countries with different intensive care systems and healthcare resources.

References

[1] Raffa, J. D., Johnson, A. E. W., O'Brien, Z., Pollard, T. J., Mark, R. G., Celi, L. A., Pilcher, D., & Badawi, O. (2022). The Global Open Source Severity of Illness Score (GOSSIS). Critical care medicine, 50(7), 1040–1050. https://doi.org/10.1097/CCM.0000000000005518

[2] Nassar, A. P., Jr, Mocelin, A. O., Nunes, A. L., Giannini, F. P., Brauer, L., Andrade, F. M., & Dias, C. A. (2012). Caution when using prognostic models: a prospective comparison of 3 recent prognostic models. Journal of critical care, 27(4), 423.e1–423.e4237. https://doi.org/10.1016/j.jcrc.2011.08.016