Mortality Risk Assessment for ICU patients using Logistic Regression

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Abstract

Prediction of outcome for patients in Intensive Care Unit (ICU) is of great interest since early 1980s. Various techniques had been proposed to evade this issue. Using Physionet/CinC Challenge 2012 data set we have identified maximum, mean and minimum as potential features extracted from the parameters measured during patients stay of 48hrs at ICU to accurately predict in-hospital mortality risk. The study was done with adult patients who were admitted for a wide variety of reasons to Coronary Care Unit, Cardiac Surgery Recovery Unit, Medical ICU, Surgical ICU. The proposed risk prediction model used a logistic regression technique for assessing the probability of mortality based on the selected features. The technique shows significant accuracy on test data set-c with final event 1 score: 0.45128, event 2 score: 45.0101 and ranked within top 10 for both the events.

1. Introduction

The intensive care unit (ICU) is a speculated area where medical devices and practitioners are focused for treating severely ill patients in an hospital. The major goal of intensive care is to recover the life of patients with reversible medical conditions or offer peaceful and dignified death for unsalvageable patients with adverse condition. Presently health care groups are focused to research on techniques for improving effectiveness of the treatment for the critically ill patients in ICU. The concept of providing costeffective intensive care has now generalized to all developed countries, becoming a major interest of clinicians, hospital administrations, health care managers, medical economists and governmental policy makers [1, 2]. Therefore, to address the needs of medical practitioners and medical care givers, several ICU mortality scoring systems have been developed over the past few decades by applying different techniques [3–5]. These scores help in estimation of treatment effectiveness, the risk of hospital death, and the performance of various ICUs. Among these scoring systems, Acute Physiology and Chronic Health Evaluation System II (APACHE II) [3] and Simplified Acute Physiology Score II (SAPS II) [4] have been widely used because they are reliable, inexpensive and relatively easy to calculate.

In present study the aim was to provide a solution of predicting ICU mortality which not only shows improvement of risk estimation over SAPS-I [6] score, but also yields an acceptable accuracy which can be used in effective decision making scenario.

2. Methods

This section describes the data source along with the technique used in this study.

2.1. Data source

Data were provided by the PhysioNet/CinC Challenge 2012. Data comprised of 42 different parameters including demographic information, vital signs, pathological readings of 48 hrs from 12000 ICU patients. ICU stays of less than 48 hours have been excluded. Patients with DNR (do not resuscitate) or CMO (comfort measures only) directives were not excluded. The focus of the PhysioNet/CinC Challenge 2012 is to develop methods for patient-specific prediction of in-hospital mortality using these information collected during the first two days of an ICU stay to predict which patients survive their hospitalizations and which patients do not. The experiment was done using training set of 4000 ICU patients (set-a) and 4000 test set (set-b). The other test set of 4000 patients (set-c) were used for final evaluation. Outcomes for records in set-a were provided and undisclosed for rest of the test set data (set-b and set-c). All the 42 parameters were not present for each of the records. However, among all the parameters six variables were general descriptors (collected during admission) and rest were time series, for which multiple observations may be available. Individual observations were associated with time-stamp indicating the elapsed time of the observation since ICU admission for each record.

Table 1. Selected candidate variables

Demographic	Vital Signs	Pathological
Age	HR	Urine
	(SysABP,NISysABP)	BUN,HCT,WBC,Glucose,K,Na,Mg,
	(DiasABP,NIDiasABP)	HCO3,GCS,Creatinine,Albumin,
	Temp	ALP,ALT,AST,Cholesterol,FiO2,
	(RespRate,MechVent)	Lactate,PaO2,PaCO2,pH,
	(NIMAP,MAP)	Platelets,SaO2

2.2. Statistical analysis

2.2.1. Filtering

To come up with a statistical model for prediction of ICU mortality of the patients, we have used logistic regression (LR) method. However, before doing that the first step followed was to filter the data. Among 42 different variables which were recorded for 48hrs, some parameters were missing for most of the records. Therefore, these parameters will not be able to contribute for the expected model. During filtering process we have filtered such parameters which were absent in most of the records. After this filtering process we figured out 30 different risk variables to use, for building up our model. These candidate variables (as shown in Table 1) included demographic characteristics (age), vital signs (Blood pressure, Respiratory Rate, temperature etc.), pathological tests (Na, K etc.).

2.2.2. Feature extraction

In our study the candidate variables except the demographic parameters, all were time series, as they have been recorded multiple times with in 48hrs window. Therefore, instead of using the time series data we need to extract features from these time series variables such that they characterize the same property of the original time series. Best representation of windowed time series can be Maximum, mean and Minimum. The idea behind choosing such features was because of the fact, that there were certain parameters for which high value is favourable for the patients in a particular medical condition and low value is severe or vice versa. By extracting maximum and minimum we have include both the effects in our model. Mean represents the most important characteristics of a time series. Therefore, except the age parameter for 29 candidate variables we got 87 features. So in the next step LR was used on 88 features including age.

2.2.3. Prediction

After feature extraction we have developed a LR model to assess the relationship between these attributes and the probability of individual's mortality. We have used the outcome of the training set-a as given in the challenge. Therefore, each patient was coded by "0" for survival and "1" for death. Using LR we get the probability of ICU mortality for individual patients. However, the end goal is to classify the records in survival or death class. Therefore, a threshold on probability was determined for this classification. Though we have started with all the features extracted from the earlier step in this step again a feature selection was done in this multivariable modelling based on statistical significance. Therefore, we have tried to use the subset of features containing 70 features and a suitable threshold on the mortality probability, which gives the maximum accuracy in terms of Sensitivity (Se) and Positive predictivity (PPV) on training set-a. Also we have tested the calibration using the Hosmer and Lemeshow (H) χ^2 statistics.

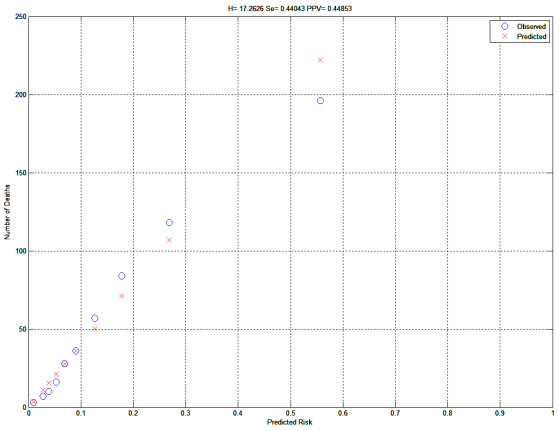

Figure 1. H-statistics, Se and PPV for training data set using LR

3. Results

The LR model used in this study yields significant accuracy for in-hospital mortality prediction on the test dataset. Accuracy was computed in terms of Se and PPV along with the calibration using χ^2 statistics. Figure 1 shows the matlab screen shot of the χ^2 plot of observed versus predicted mortality in each decile ranges of the training

data. For the proposed technique H statistic shows value 17.2626, the Se = 0.4404 and PPV = 0.4485 for set-a. The threshold probability of mortality is determined as 0.28 which gives the maximum Se and PPV for training set-a. Patients with mortality probability lower than 0.28 were classified as survival (0) and probability greater than 0.28 was classified as death (1). Physionet challenge event 1 score was determined by taking the minimum among Se and PPV (i.e. whichever is lower) for a particular technique. Event 2 score was determined by the value of H-statistic. Table 2 shows the Physionet challenge scores in both the events for different data set and using the proposed technique. Proposed algorithm showed significant accuracy in mortality prediction. We got 10th rank in event 1 and 8th in event 2. The list of features and their odds ratios in sorted order are shown in Table 3 and Table 4. As per the table most of the features used in the study, had significant contribution in the model.

Table 2. Event 1 and Event 2 scores for set-a, set-b and set-c

Dataset	Event 1 score min(Se, PPV)	Event 2 score (H-Statistic)
set-a (training)	0.4404	17.2626
set-b (test)	0.4436	45.4347
set-c (test)	0.4512	45.0101

4. Conclusions

Logistic regression can be used in prediction of in-hospital mortality of ICU patients. However, proper selection of featurs is very important in such context. We have not tried with feature selection techniques like step wise greedy algorithm, which may also have potential to give better accuracy. Sex based model for mortality prediction may perform better than the proposed method. The odds ratios could also be used as a criteria for selecting the features. As lot of data are missing for most of the patients a robust data imputation technique can improve the accuracy of the system. The proposed approach can significantly impact the Clinical Decision therefore, can be used in ICU clinical decision support system.

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Table 3. Final Feature List I with Odds Ratio

Final Features	Odds Ratio
(NIMAP,MAP)max	5.947
pHmean	2.615
pHmin	1.222
HRmin	1.194
PaO2max	1.170
(DiasABP,NIDiasABP)min	1.169
Urinemin	1.157
GCSmean	1.132
(DiasABP,NIDiasABP)mean	1.078
HCO3max	1.075
Mgmin	1.074
(DiasABP,NIDiasABP)max	1.062
Urinemax	1.054
FiO2max	1.053
(RespRate,MechVent)mean	1.027
(NIMAP,MAP)mean	1.023
Cholesterolmax	1.022
Namin	1.018
(SysABP, NISysABP)min	1.014
Namax	1.013
Kmin	1.013
HRmax	1.008
Age	1.005
(RespRate,MechVent)max	1.005
FiO2mean	1.004
Lactatemax	1.004
(NIMAP,MAP)min	1.002
PaCO2min	1.002
ASTmin	1.002
BUNmax	1.002
Plateletsmean	1.001
Tempmin	1.001
HCTmin	1.001
Lactatemean	1.001
GCSmax	1.001

Table 4. Final Feature List II with Odds Ratio

Final Features	Odds Ratio
pHmax	1.001
SaO2min	1.000
(SysABP, NISysABP)mean	1.000
SaO2mean	0.999
HCO3mean	0.999
HCTmax	0.999
Mgmax	0.999
PaO2mean	0.998
PaCO2mean	0.998
Albuminmax	0.998
Cholesterolmin	0.998
HRmean	0.997
Plateletsmin	0.997
ASTmean	0.994
Plateletsmax	0.993
PaCO2max	0.991
BUNmin	0.989
SaO2max	0.988
(SysABP, NISysABP)max	0.984
Creatininemin	0.982
Cholesterolmean	0.979
FiO2min	0.977
Lactatemin	0.969
Tempmean	0.966
Urinemean	0.961
Mgmean	0.961
Tempmax	0.941
HCO3min	0.913
(RespRate,MechVent)min	0.891
GCSmin	0.874
Namean	0.847
Creatininemax	0.771
Creatininemean	0.676
BUNmean	0.426
PaO2min	0.375