

Outcome Prediction in Intensive Care Units Based on Clinical Adverse Events: A Clustering Model Approach

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ABSTRACT

During the past 20 years, Intensive Care Units (ICU) risk-prediction models have undergone significant development, validation and refinement. Among the general ICU severity scoring systems the Simplified Acute Physiology Score (SAPS II) [1] have become the most accepted and used.

Recent innovation risk adjustment includes the use of Artificial Intelligence (AI) techniques and Knowledge Discovery from Database (KDD) where the clinical data of patients are collected in large Databases (DB). These innovations have the potential of extending the uses of case severity-of-illness adjustment in areas of clinical outcome research and patient care.

The objective of this work is to demonstrate that the SAPS II score, which allows the estimation of the patient probability of death in hospital, can be complemented or even substituted by the modern AI techniques. We reach to prove that Clinical Adverse Events (CAE) based approaches are better in evaluation of risk mortality as a complement of current SAPS II. Applying clustering techniques we can trace a patient's evolutionary line (related to the process of care), by the analysis of the intermediate outcomes.

KEY WORDS: Mortality Predicting Models based on Intermediate Outcomes, Knowledge Discovery from Databases, Data Mining, Databases, Artificial Neuronal Networks, Artificial Intelligence.

1. Introduction

The SAPS II score allow us to measure the patients severity of illness at ICU admission (first 24 hours), and also to estimate his risk of death. Nonlinear, nonparametric models such as Artificial Neuronal Networks (ANN) have increasingly been used for building prognostic models.

The previous studies presented by Santos and Silva [3,5] identified the use of Data Mining techniques (DM) as a contribute in the creation of probability models using ANNs.

Another two authors that studied the same subject, Hanna and Lucas [4], identified the “importance of prognosis in medicine and the arising mutual awareness between the AI and statistical communities are promising conditions for the methodological progress and practical applications of medical prognostic models”.

This paper, exploits the applications of ANNs as clustering techniques in a KDD process to predict hospital mortality, based on CAEs.

After this introduction, the paper presents the characterisation of the source data used in the study, the definition of CAEs and to some fundamentals concepts. Later, it will be presented the overall process of models construction, the experimental results and discussion. Finally is focused the importance of the clustering approach in the prevision of hospital mortality.

2. Clinical Data

The present study is based on a data set for the database of the EURICUS II [6] project. This database contains the information about 13,160 patients registered in 42 ICUs of 9 European countries. During 10 months all records of every patient were carefully registered and standardized.

The collected data is structured as follows:

Admission data: date of admission, age, type of admission (unscheduled surgery, scheduled surgery and medicine); diagnostic (medical or pos-surgery); data from before ICU admissions; SAPS II data at the time of ICU admission.

Daily data: Elements daily acquired by monitors, that identify deviations from previously established parameters.

Transfer data: vital data registered at the ICU and at the Hospital at the time of transference.

Derived data: number of days at ICU; data registered by measuring certain parameters and registration of the patient's stay in ICU and in Hospital.

The rest of the information comes from a combination of the different Case-Mix variables that permit generate relations in a more consistent fashion related to the final result (risk or death).

3. Clinical Adverse Events (CAE)

Four physiological parameters usually monitored were studied continually and hourly registered in every ICU: Systolic blood pressure (BP), Heart Rate (HR), Oxygen Saturation (O2) and Urine Output (DIUR).

A team of experienced physicians established the accepted limits for each parameter (Table 1), which were used for this study. The ringing of these alarms signifies that the established limits for one of them have been exceeded. These alarms emitted by the measuring equipment are called Out of Range Measurements (ORM).

Table 1 - Definition of Clinical Adverse Events.

a)	Events (EV)		
	Limited suggested	Continuously out of limits	Intermittent out of the limits
BP	90-180	≥ 10 min	≥ 10 min em 30'
O2 (%)	≥ 90	≥ 10 min a)	≥ 10 min em 30'
HR (bpm)	60-120	≥ 10 min	≥ 10 min em 30'
DIUR (ml/hora)	≥ 30	≥ 1 hour	-

b) Critical Events (CrEv)

	Limited suggested	Events Continuously	Events Intermittent	Events in any time
BP (mm Hg)	90-180	≥ 1 hour	≥ 1 hour in 2 hours	BP < 60
O2 (%)	≥ 90	≥ 1 hour b)	≥ 1 hour in 2 hours	O2 < 80
HR (bpm)	60-120	≥ 1 hour	≥ 1 hour in 2 hours	HR < 30 or > 180
Diur (ml/hora)	≥ 30 ml/hr	≥ 2 hours	-	≤ 10

The events are defined by two attributes: 1) *yes* or *no*, within the established limits; and if *yes*, by how long.

If *yes*, we classify the events in two categories (Table 1): Events (EV) and Critical Events (CrEv). They are defined by the uninterrupted duration of the out of limit alarms for a certain period more 10' and less than 60'. In the case of intermittent alarms and for periods of less 10' Ev is defined when the total out of limits period is more 10' for a period of 30'. A new measurement is taken after 30', except for DIUR parameter, which is made after two hours.

The CrEv are defined by the continuity of the out of rang values for a period of 60' except for Diur. Measurements are made again after 60' except for Diur; for it, the interval is 2 hours.

4. Variables Studied

The data used in this work was previously filtered and subject of selection and pre-processing (e.g., blank registers and duplicated information elimination, formatting of values). For this study were excluded from the analyses:

- Patients younger than 18 years old;
- Registrations omitting information were completely erased (e.g., discharge date, critical events, final clinical results);
- Burn patients;
- Coronary care patients;
- Cardiac surgery (bypass).

The other variables result from the transformation of distinct variables (Table 2), which were created to help in understanding certain phenomenon, as well as in classifying some patients in classified homogeneous groups.

Table 2 – Selected Variables.

Field	Description
ADMTYPE	Type of admission (surgical

Field	Description
	unscheduled, scheduled or medical)
AGE	Age of patients
SAPSII	Severity illness score at admission
HOSDEAD	Hospitality Mortality (pos ICU discharge)
ADMFROM	Patients referral source of admission prior to ICU
EVBPDAY	Number of Events of Blood Pressure/day
EVHRDAY	Number of Events of Heart Rate/day
EVO2DAY	Number of Events Oxigen of Saturation (O2)/day
EVDIURDA	Number of Events Urine of Output/day
CRIVBPDA	Number of critical events in Blood Pressure per length of stay in UCI
CRIVHRDA	Number of critical events in Heart Rate per length of stay in UCI
CRIVO2DA	Number of critical events in Oxigen Saturation (O2) per length of stay in UCI
CRIVURDA	Number of critical events in urine output per length of stay in UCI
DIAGNO1	Diagnostic category (medical or post-operative admission)

The dependent variable chosen was the HOSDEAD, meaning that it will be our Output variable in the models of the work. This allowed checking the possible interaction between intermediate outcomes and final outcomes. The Table 3 presents a statistical summary of patient data.

Table 3 - Statistics Description of variables.

Field	Min.	Max.	Median	Standard Deviation	Mean
ADMTYPE	1	3	2	2,23	0,83
AGE	19	100	66	62,00	18,72
SAPSII	0	127	31	32,79	18,02
HOSDEAD	0	1	0	0,20	0,40
ADMFROM	1	7	3	2,73	1,64
EVBPDAY	0	24	0	0,72	1,39
EVHRDAY	0	21	0	0,49	1,26
EVO2DAY	0	21	0	0,27	0,93
EVDIURDA	0	22	0	0,77	1,67
CRIVBPDA	0	4	0	0,26	0,52
CRIVHRDA	0	5	0	0,17	0,42
CRIVO2DA	0	5	0	0,08	0,31
CRIVURDA	0	4	0	0,32	0,59
DIAGNO1	0	1	0	0,44	0,50

5. Process Description

We used the Clementine¹ toolkit to obtain different models as showed in the Table 4.

Table 4 – Outcome Prediction Models.

Model	Input Variables and Relative Importance	ANN Architecture	Predictive Accuracy
SAPS II + CAE	SAPS II 0,877	12-8-1	80,20%
	CRIVO2DA 0,627		
	CRIVHRDA 0,386		
	EVO2DAY 0,361		
	EVHRDAY 0,270		
CAE	CRIVO2DA 0,557	12-8-1	77,91%
	EVO2DAY 0,444		
	EVBPDAY 0,330		
	EVHRDAY 0,325		
	CRIVHRDA 0,258		
SAPS II	SAPS II 0,781	1-7-1	76,80%

Due to the high heterogeneity existing between the entries, a cluster approach was made using an ANN to make a distribution of the 13160 patients in a 3x3 matrix (nine clusters). After this, eight distinct clusters were produced (one of them was empty) as characterized in the Figures 1 and 2.

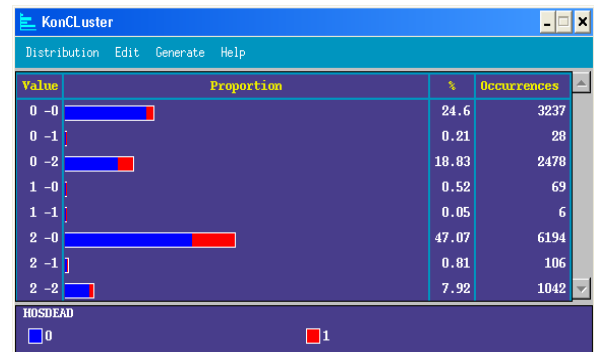


Figure 1 – Clusters with SAPS II+CAE.

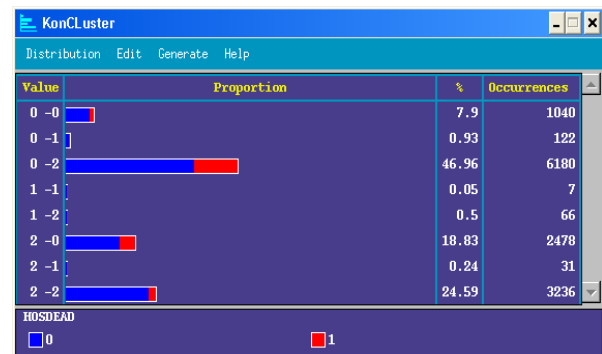


Figure 2 – Clusters without SAPS II.

¹ Clementine Data Mining System, Copyright SPSS Inc.

The previous phase had, as main goal, the analyses and classification of the clusters obtained. For further studies two new databases were created differencing between data with SAPS and CAE. This procedure allows us a quicker identification of the elements being analysed.

Tables 5 and 6 show the results obtained for the different clusters.

Table 5 – Accuracy with SAPS II+CAE.

Cluster	Accuracy	Standard Error	N.º Patients
00	91,90%	0,3	3237
01	63,30%	11,6	28
02	81,40%	0,5	2478
10	72,60%	4,9	69
11	83,30%	16,7	6
20	81,40%	0,5	6194
21	75,60%	4,2	106
22	87,80%	1	1042
Global	85%	0,3	13 160

Table 6 – Accuracy without SAPS II.

Cluster	Accuracy	Standard Error	N.º Patients
00	85,20%	0,9	1040
01	77,80%	0,3	122
02	79,40%	0,6	6180
11	85,70%	14,3	7
12	71,90%	4,7	66
20	82,00%	0,5	2478
21	97,50%	2,5	31
22	91,70%	0,2	3236
Global	83,6 %	0,2	13 160

6. Experimental Results and Discussion

As we can see in the Table 8, the experiments proved the advantage of the clustering approach permitting:

- a slightly higher global accuracy relatively to the unique model;
- a fine grained analysis of the clusters enabling the medical understanding of each cluster separately.

In the same way (Figures 3 and 4) using the DM algorithm C5 it is possible to demonstrate that, in some cases, the substitution of the SAPS II variable by CAE becomes meaningless.

Table 8 – Accuracy among different DM techniques.

SAPS II + CAEs	ANN	77,03%
	C5 (cross-validation)	85,00%
CAEs	ANN	77,03%
	C5 (cross-validation)	83,60%
Clustering		
SAPS II + CAEs	ANN	78,31%
	C5 (cross-validation)	84,36%
CAEs	ANN	78,16%
	C5 (cross-validation)	83,37%

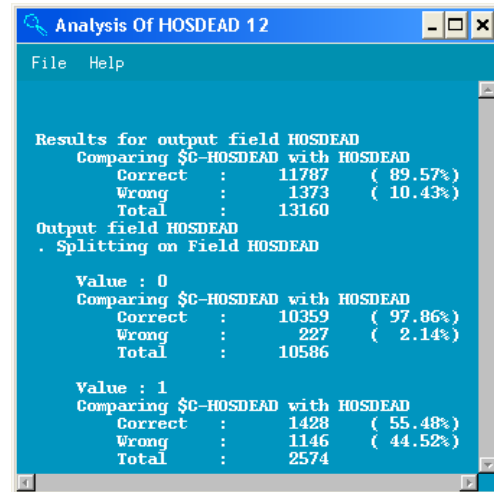


Figure 3 – Analysis of C5 Model with SAPS+CAE.

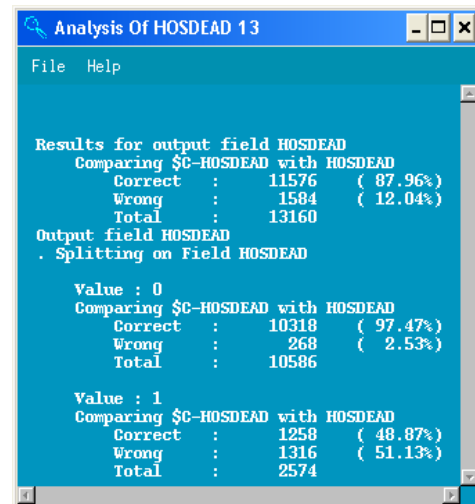


Figure 4 – Analysis of C5 Model without SAPS.

Regarding the clustering techniques, they allow us to identify homogenous groups of patients. This is a very important factor, because it allows us to classify certain clusters of patients rapidly. The segmentation of the database in clusters can be visualized under the form of rules:

Rule #1 for 02:
if DIAGNO1 <= 0

then -> 02 (7342, 0.842)

Rules for 11:

Rule #1 for 11:

if ADMTYPE > 1
and ADMTYPE <= 2
and ADMFROM > 6
and DIAGNO1 > 0
then -> 11 (6, 0.875)

Rules for 12:

Rule #1 for 12:

if ADMTYPE > 2
and ADMFROM > 4
and DIAGNO1 > 0
then -> 12 (69, 0.944)

Rules for 20:

Rule #1 for 20:

if ADMTYPE <= 1
and DIAGNO1 > 0
then -> 20 (2478, 1.0)

Rules for 21:

Rule #1 for 21:

if ADMTYPE > 1
and ADMTYPE <= 2
and AGE <= 44
and ADMFROM > 2
and EVDIURDA > 0
and DIAGNO1 > 0
then -> 21 (5, 0.857)

Rule #2 for 21:

if ADMTYPE > 1
and ADMTYPE <= 2
and AGE <= 44
and ADMFROM > 3
and ADMFROM <= 4
and DIAGNO1 > 0
then -> 21 (12, 0.857)

Rule #3 for 21:

if ADMTYPE > 1
and ADMTYPE <= 2
and AGE <= 57
and ADMFROM > 4
and ADMFROM <= 6
and DIAGNO1 > 0
then -> 21 (12, 0.857)

Rule #4 for 21:

if ADMTYPE > 1
and ADMTYPE <= 2
and AGE > 57
and ADMFROM > 5
and CRIVHRDA > 0
then -> 21 (3, 0.8)

Rules for 22:

Rule #1 for 22:

if DIAGNO1 > 0
then -> 22 (5818, 0.556)

Default : -> 02

The values presented between parentheses stands for the number of cases in which the rule applies (support level)

and the proportion of those cases in which the rule is true (confidence level). Instances are reported both as number of records and percentage of total data, separated by a colon.

7. Conclusion

The increasing use of AI techniques in medicine helps to explain, more clearly, certain aspects that still lack consensual explanation.

The developed study intended to demonstrate the utility of CAE (Clinical Adverse Elements) in the forecast of the patients' final outcome, submitting the data being studied to clustering techniques in a DM process.

From the results, we can come to some conclusions, namely the importance that must be attributed to the CAEs and clustering techniques, as support indicators in the decisions to be taken by doctors about their patients.

It is equally demonstrated that the model of hospital probability (SAPS II), when analyzed separately, presents a degree of accuracy lower than when compared with other elements (e.g., CAE). This situation demonstrates, on one hand, that SAPSII has a relatively important place as evaluation model, however, when complemented with CAEs and the patients' physiological defining factors they point to a sufficiently significant relevance in the final accuracy of the model.

This also means that the patients' state can be analysed with better accuracy in certain cases, if we can use the cluster approaches, submitting the CAEs to AI techniques. The evolution of the present study will be able to demonstrate, as well, if the CAE are directly or indirectly influenced by the physiological elements of the patients.

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