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Decision Support in Trauma Management: Predicting Potential Cases of Ventilator Associated Pneumonia

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Abstract: Ventilator Associated Pneumonia (VAP) is a complication of intubated trauma patients and a leading cause in Intensive Care Unit (ICU) mortality. Since early diagnosis, by specimen culture takes days to complete, an overuse of broad spectrum antibiotics is the usual treatment. As a result there is the risk of developing antibiotic resistant strains. Using an Artificial Neural Network (ANN) derived model to predict those at risk would result in reduced risk of resistant strains, a lowering of mortality rates and considerable savings in treatment costs. Artificial Neural Networks work well on classification problems, using feed-forward/back propagation methodology. Using the National Trauma Data Bank (V6.2) data files, Tiberius Software created the ANN models. Best models were identified by their Gini co-efficient, ability to predict the complication outcome selected, and their RMSE scores. The model *ensemble* for the complications recorded in the registry were determined, variables ranked and model accuracy recorded. Results show an effective model, able to predict to 85% of those likely to contract VAP and similar figures for those unlikely to contract VAP. This equates to 1 in 10 patients being missed, and 1 in 10 falsely being flagged for treatment. Important variables in model development are not related to physiological factors, but injury status and the treatment received (intubation and expected ICU stay more than 2 days). Application of a predictive model could reduce the number of false positives being treated in an ICU and identify those most at risk, thereby lowering treatment costs and potentially helping improve mortality rates.

Keywords: Artificial Neural Networks, Complication prediction, trauma

Introduction

During hospitalization, trauma patients with severe injuries are liable to experience further complications. On analysis of the National Trauma Data Bank (version 6.2) the most common complications recorded were Acute Respiratory Disease Syndrome (ARDS) followed by Ventilator Associated Pneumonia (VAP). These complications cause an increase in the mortality rate associated with an Intensive Care Unit; studies have reported some 70% higher for VAP [1].

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Diagnosis of VAP is currently performed via specimen culture, and can take a few days to complete. Consequently an overuse of broad spectrum antibiotics is the current treatment, resulting in the potential risk of antibiotic-resistant strains developing. If predictive models could be developed to indicate those most likely to contract VAP in the ICU, then a reduced risk of resistant strains would result, in addition to substantive savings in terms of mortality and treatment costs.

Artificial Neural Networks (ANN) in outcome prediction is increasingly prevalent in physiological modeling [2,3], due to the ability of the ANN to learn and improve. ANNs are mathematical models constructed on the basis of organic neural systems. These are flexible systems which are increasingly used in predictive modeling. Using a methodology known as feed-forward/back propagation, these systems are adept at predictions of classification events; our recent studies have concentrated on mortality prediction[2]. In this piece of work we are now pursuing making an effective ANN to predict an infectious classification event.

1. Materials & Methods

1.1. Patient Population

Study data was taken from the National Trauma Data Bank (NTDB) dataset (version 6.2) issued in Jan 2007. This version covers the years 2001-2005. The NTDB dataset contains trauma data from submitting facilities. The files in DBF format were extracted and combined using SPSS for Windows (V10). The total number of records entered during this period into the Registry was 1,438,035 cases. Variables extracted from the Registry included patient demographics and physiological variables taken from both Scene and ED, with no exclusion criteria.

1.2. Creating New Variables for analysis

Neural Networks are good for classification problems, working best with data in a binary format. Binary variables were created for intubation and for being in an Intensive Care Unit (ICU) for more than two days. Additional binary variables, for low blood pressure and abnormal and low respiratory rates and age predictors, were coded based upon categories of the Revised Trauma Score or used in TRISS[4,5]. A new output variable was created for VAP.

1.3. Development of the Artificial Neural Network

This study used Tiberius software (www. philbrierley.com), an inexpensive and highly user-friendly Artificial Neural Network generator which operates by use of multilayer perceptron (MLPs) methodology. The algorithm consists of two steps. In the *forward pass*, the predicted outputs corresponding to the given inputs are evaluated. In the *backward pass*, partial derivatives are propagated back through the network. The chain rule of differentiation gives similar computational rules for the backward pass as for the forward pass. The network weights can then be adapted using any gradient-based optimization algorithm. The whole process is iterated until the weights have converged[6]. The neural network was designed using nine input variables and one output variable. It consists of three layers, one a hidden layer of neurons. The numbers of neurons within the hidden layer affect the number of degrees of freedom in the optimization process, and therefore the model performance.

1.3.1. ANN design

Model design was based on the use of ventilators, being more than 2 days in ICU, sex and age category of the patient, plus the factors for low systolic blood pressure and abnormal respiratory rates. The model used 3 neurons in the hidden layer. The output was the VAP complication. Additional variables were added to improve model accuracy.

1.3.2. ANN Model Analysis

Analysis of model design was by performing best model analysis as identified by the Gini co-efficient, and the predictive performance of the model. One of the features of Tiberius is its ability to build a *model ensemble*, a method that improves the accuracy of the model other than by tailoring the algorithm[7]. This allows rapid analysis of a neural network, generating Gini values (in this instance) for 10 models, with a model average value, and a rank of importance for the input variables for the model. The Gini coefficient is a measure of equality, and can be employed as a means of comparison between ANN models[8]. Having created the *ensemble* the base model is then allowed to operate for approximately 2000-3000 epochs to rank the performance and effectiveness of the model to predict cases that match the outcome variable (true) and those that fail (false). The model is then compared with the test set.

Root Mean Squared Error (RMSE) is a measure of the differences between values predicted by a model or an estimator and the values actually observed and acts as a good measure of accuracy. RMSE is used to compare differences between two things, neither of which is accepted as the *standard*, and so helps in model comparisons.

2. Results

Tiberius Data Mining Software is capable of performing random selection to divide data into training and test datasets. For this project 85% of the data were randomly selected as a training set and 15% as the test set. Records were excluded due to missing outcomes. The best models were identified by their Gini co-efficient, ability to correctly predict the complication outcome selected, and their RMSE scores. The model *ensemble* was determined, the variables ranked and model accuracy recorded.

Table 1. VAP Predicting ANN

	Training:RMSE 13.67			**Test:RMSE 14.07**		
	True	**False**	**Total**	**True**	**False**	**Total**
Correct	7198	500625	507823	1268	88975	90243
Of	8426	573921	582347	1499	101947	103446
%	85.4	87.2	87.2	84.6	87.3	87.2

Gini (model average) = 0.80435

In Table 1 we see the predictive results of the best model when applied to its training and test sets, with Table 2 showing the ranked level of importance for the variables used in the model.

Table 2. Rank of Variable importance (VAP)

Rank	Variable	Scrambled Gini	Relative Importance
1	Icu2day	0.59646	1.00
2	Injury Severity Score	0.72328	0.372
3	Noventilation	0.74614	0.259
4	Sex	0.79731	0.005
5	Low Systolic B.P.	0.79744	0.005
6	Pedage	0.79759	0.004
7	Abn. Resp.Rate	0.79773	0.003
8	Full Model	0.79835	0.0
9	Low Resp. Rate	0.80124	-0.014
10	Thirdage	0.80179	-0.017

Key:
Abnormal Respiratory Rate - <10 and >29 breaths per minute
Low Respiratory Rate - Respiratory rate shallow (less than 10)
PedAge – Age of patient class for under 16 years: 0 = >16; 1= ≤ 16
ThirdAge – Age of Patient greater than 55 years: 0 = ≤ 54; 1= >54
Low Systolic B.P. – Systolic Blood Pressure less than 40

3. Discussion

The predictive model appears to be well balanced between identifying those at risk from contracting VAP from those who are unlikely to contract VAP. Applying the model to an ICU could reduce the amount of false positives given treatment, since at this level only 1 in 10 is falsely flagged. Furthermore mortality figures should be reduced with only 1 in 10 cases being missed.

Looking at variable importance, we see a key component is whether the patient has been in an ICU for more than two days. As a predictive model, this will need to be an assessed value rather than a measured one. Of lesser importance is the respiratory rate, either classed as abnormal (higher than 29 less than 10) or flagged as low, which seems to have a detrimental effect on the model.

4. Conclusion

In this study we rely on large volumes of data to enable the ANN to accurately train and produce a working model. Using smaller number with additional variables may produce a tighter model, and single-centre studies with sufficient data could be investigated.

The variable ranking table indicates that the physiological variables from the scene may have little impact and that the patient risk is greater due to factors such as age the injury severity, intubation and the number of days likely to be in the ICU. Both age and sex have some effect on risk, more so with the younger patients. While the NTDB dataset lacks information on pulse, an apparent key factor in mortality prediction, there is no indication it will improve the model in VAP prediction.

Factors showing importance in potential VAP complications suggest that since physiology plays a minimal role that other factors might be relevant to more successful prediction e.g. nos. ICU beds, staff per patient ratios etc. Further studies centered on a single facility where these conditions can be included could clarify this.

Application of the model to a health-care facility could reduce the number of cases requiring broad spectrum anti-biotic treatment, and thereby reduce the risk of resistant strains developing in the facility. Mortality rates could be reduced by identifying those at greater risk. Cost of care could have beneficial consequences by lowering treatment costs by lowering the false positive rates.

Further study into how this and other models for additional complications could best be applied in a busy ICU facility is required.

References

[1] Erbay RH, Yacin AN, Zencir M, Serin S and Atalay H. Costs and risk factors for ventilator associated pneumonia in a Turkish University Hospital's intensive care unit: A case control study. BMC Pulmonary Medicine 2004;4:3

[2] Pearl, Caspi & Bar-On. Artificial Neural Network Versus Subjective Scoring in Predicting Mortality in Trauma Patients. Stud Health Technol Inform. 2006;124:1019-1024

[3] Nimgaonkar A, Karnad DR, Sudarshan S, Ohno-Machado L, Kohane I., Prediction of mortality in an Indian Intensive Care unit. Intensive Care Med. 2004 Feb;30(2):248-253

[4] Champion HR, Sacco WJ, Copes WS, Gann DS, Gennarelli TA, Flanagan ME**.** A revision of the Trauma Score. J Trauma 1989;29(5):623-629

[5] Boyd CR, Tolson MA, Copes WS. Evaluating Trauma Care: J.Trauma 1987;27:370-378

[6] Haykin, S. (1994), Neural Networks: A Comprehensive Foundation, NY: Macmillan

[7] Elder JF.The Generalization Paradox of Ensembles, Journal of Computational and Graphical Statistics 2003, 12(4):853–864

[8] Brown M. Using Gini-style indices to evaluate the spatial patterns of health practitioners: theoretical considerations and an application based on Alberta data. Soc. Sci. Med. 38(9):1243-1256. 1994