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Using Artificial Neural Networks to Predict Potential Complications during Trauma Patients' Hospitalization Period

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Abstract. Complications during treatment of seriously injured trauma patients cause an increase in mortality rates, and increased treatment costs, including bed occupancy. Current methods treat those at risk, and include numbers of false positives. By finding a method to predict those at risk of the three most common recorded Trauma Registry complications, considerable savings in mortality and treatment costs could arise. Artificial Neural Networks (ANN) work well with 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 Root Mean Squared Error (RMSE) scores. The model ensemble for the three major complications recorded in the registry were determined, variables ranked and model accuracy recorded. The basic ANN is fairly accurate for those likely to contract Acute Respiratory Disease Syndrome (ARDS) though with a high rate of false positives. The ANN ability to predict Ventilator Associated Pneumonia (VAP) is less effective, though better at producing fewer false positives. Predicting Urinary Tract Infections (UTI) cases is not good enough using these input variables. Both VAP and UTI relate to those aged over 55 years, while ARDS related more to those under 16 years. The models need improving.

Keywords. artificial neural networks, outcome prediction, traumatic injury

1. 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 major complications recorded were Acute Respiratory Disease Syndrome (ARDS), Ventilator Associated Pneumonia (VAP), and Urinary Tract Infections (UTI). These complications cause an increase in mortality rates, with studies reporting 70% higher for VAP, and 30–45% for those contracting ARDS and UTI [1, 2]. Current methods include treating potential cases who may not suffer from these complications [3], therefore prescribing un-necessary treatments. If predictive models could be developed to indicate those most likely to contract these complications, then substantive savings in terms of mortality and treatment costs can be made.

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Artificial Neural Networks (ANN) in outcome prediction is increasingly prevalent in physiological modeling [4, 5], due to the ability of the ANN to learn and improve. Mathematical models constructed on the basis of organic neural systems, these ANNs 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. Most recently we have concentrated on mortality [4]. In this piece of work we are now looking at how effective an ANN could perform with infectious classification events.

2. Materials and Methods

Patient Population. Study data was taken from the National Trauma Data Bank (NTDB) dataset (version 6.2) issued in January 2007. This version covers the years 2001–2005. The NTDB dataset contains large volumes of trauma data from submitting hospital 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.

Creating New Variables for Analysis. Neural Networks are good for classification problems, working best with data in a binary format. New binary variables were created for intubation and for being in an Intensive Care Unit (ICU) for more than two days. Additional variables were coded based upon the categories of the Revised Trauma Score, and the age predictors used in TRISS (Trauma Injury Severity Score) [6, 7]. Output variables were created for each of the three complications being investigated; ARDS, VAP and UTI.

The following variables were created as defined below:

Novent – No ventilation/intubation

Icu2day – in ICU ward for 2+ days

LowSBP – Systolic Blood Pressure less than 40

LowRR – 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

Development of the Artificial Neural Network. This study used Tiberius software (www. philbrierley.com) which operates by use of multilayer perceptron (MLPs) methodology, a feed-forward neural network trained with the standard back-propagation algorithms. 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 [8]. The neural network was designed using seven 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.

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 lowSBP and lowRR. The model used 3 neurons in the hidden layer. The output for each model was one of the complication causes under investigation.

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 [9]. 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 [10]. 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. 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.

3. 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. Cases were excluded due to missing requisite variables. 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* for each of the three major complications recorded in the registry were determined, variables ranked and model accuracy recorded. Tables 1, 3 and 5 present the percentage of cases predicted for each complication investigated for both training and test data sets. Tables 2, 4 and 6 present the relative importance of each variable used in the ANN for each complication investigated.

Acute Respiratory Distress Syndrome: Gini (model average) = 0.78000

Table 1. ARDS predicting ANN

	Training:RMSE 13.41			**Test:RMSE 13.84**		
	True	**False**	**Total**	**True**	**False**	**Total**
Correct	1630	423351	424981	444	105766	106210
Of	1737	533599	535336	478	133145	133623
%	93.8	79.3	79.4	92.9	79.4	79.5

Table 2. Rank of variable importance (ARDS)

Rank	**Variable**	**Scrambled Gini**	**Relative Importance**
1	Novent	0.46709	1.00
2	Icu2day	0.61532	0.558
3	Lowrr	0.79157	0.032
4	Pedage	0.79250	0.029
5	Sex	0.80028	0.006
6	Lowsbp	0.80168	0.002
7	Full Model	0.80228	0.000
8	Thirdage	0.80657	-0.013

Ventilator Associated Pneumonia: Gini (model average) = 0.77418

Table 3. VAP predicting ANN

	Training:RMSE 14.19			Test:RMSE 14.42		
	True	**False**	**Total**	**True**	**False**	**Total**
Correct	6739	459704	466443	1652	114609	116261
Of	7979	527476	535456	1966	131538	133504
%	84.5	87.2	87.1	84.0	87.1	87.1

Table 4. Rank of variable importance (VAP)

Rank	Variable	Scrambled Gini	Relative Importance
1	Icu2day	0.57827	1.00
2	Novent	0.72651	0.335
3	Thirdage	0.77681	0.109
4	Sex	0.78780	0.059
5	Pedage	0.78811	0.058
6	Lowsbp	0.79145	0.043
7	Lowrr	0.79592	0.023
8	Full Model	0.80104	0.00

Urinary Tract Infection: Gini (model average) = 0.64126

Table 5. UTI predicting ANN

	Training:RMSE 26.55			Test:RMSE 26.39		
	True	**False**	**Total**	**True**	**False**	**Total**
Correct	3811	419135	422946	649	73911	74560
Of	5254	563654	568908	893	99158	100051
%	72.5	74.4	74.3	72.7	74.5	74.5

Table 6. Rank of variable importance (UTI)

Rank	Variable	Scrambled Gini	Relative Importance
1	Icu2day	0.31008	1.00
2	Sex	0.48752	0.374
3	Thirdage	0.48862	0.370
4	Novent	0.53549	0.204
5	Lowsbp	0.58392	0.034
6	Lowrr	0.58570	0.027
7	Pedage	0.58946	0.014
	Full Model	0.59341	0.00

4. Discussion

The ability of the ANN to predict those likely to contract ARDS is fairly accurate on the basic settings given, as seen in Table 1, though it does have a high rate of false positives. This could be improved with other factors. However the ANN ability to predict VAP is less effective, as seen in Table 3, though better at producing less false positives, and clearly needs more or different input variables to tighten up the predictive nature of the ANN. Predicting UTI cases is clearly not good enough using these input variables – see Table 5.

It is evident from the tables of variable ranking (Tables 2, 4 and 6) that the most important factor in the three complication conditions is being in an ICU bed for more than 2 days, and that both ARDS and VAP were dependent on intubation. This is to be expected since both ARDS and VAP are associated with respiratory systems. However the physiological variables of low respiration rate and low systolic blood pressure bear little importance to the models predictive power. Both VAP and UTI seem more related to those aged over 55, while ARDS is more related to the younger ages (under 16 years), and appears to have a negative association to those over 55 years. UTI places a much higher importance to the sex of the patient, while it has little importance in the models generated for ARDS or VAP predictions.

5. Conclusion

In this study we continued, as in our early ANN designs, to use as few variables as possible, and those used in mortality prediction, and to rely on large volumes of data to enable the ANN to accurately train and produce a working model. As a consequence this risks creating ineffectual models. However, while both ARDS and VAP complications appear likely to work on a model using lower numbers of inputs, UTI appears to require a different set of inputs, or a greater number, to create an effective working model.

The variable ranking table indicates that the physiological variables from the scene may have little impact and that the patient risk of these complications has a greater relationship to factors such as age and sex. This implies that other variables might have greater effect in creating a predictive model, and should be addressed in future studies. Further investigations into each of the complications, including variables not held in the NTDB registry, may help derive an improved ANN model able to more accurately predict those likely to suffer these complications, while reducing the false positives.

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