Decision Support in Trauma Management: Predicting potential cases of Ventilator Associated Pneumonia
Ventilator Associated Pneumonia (VAP) is a complication of intubated trauma patients and a leading cause in Intensive Care Unit (ICU) mortality.
Studies have reported some 70% higher mortality rates for Ventilator Associated Pneumonia.
Diagnosis of Ventilator Associated Pneumonia 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 Ventilator Associated Pneumonia 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 are mathematical models …….
…… constructed on the basis of organic neural systems....
….. with an ability to learn and improve.
Artificial Neural Networks in Outcome Prediction

- Increasingly prevalent in physiological modeling, these systems are adept at predictions of a classification type.
- Mathematical models constructed on the basis of organic neural systems, these ANNs are flexible systems which are increasingly used in predictive modeling due to the ability of the ANN to learn and improve.
- This occurs by a methodology known as feed-forward/back propagation, in which the artificial neuron adds weights according to positive or negative deviation from a training set of data from which it 'learns'.
Materials & Methods

Patient Population

- Study data was taken from the USA National Trauma Data Bank (NTDB), version 6.2 issued in Jan 2007. The NTDB dataset contains trauma data from submitting facilities.

- The total number of records entered during this period into the Registry was 1,438,035 cases with no exclusion criteria.
Materials & Methods
Creating New Variables

- Neural Networks are good for classification problems, working best with data in a binary format.
- New variables were created for Intubation and ICU>2 days.
- Additional variables based on RTS- revised Trauma Score, and age predictors used in TRISS –Trauma Injury Severity Score.
- A new output variable was created for VAP.
Materials & Methods

New Variables

- LowSBP – Systolic Blood Pressure less than 40
- LowRR - Respiratory rate shallow (less than 10)
- NoVent - No ventilation/Intubation
- ICU2Day – in ICU Ward 2+ days
- 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
Artificial Neural Network basic structure.
Basic Neuron Design

Input → Sum → Transfer → Output

Processing
Materials & Methods

The Artificial Neural Network

- This study used Tiberius software (www.philbrierley.com),
- Operates multilayer perceptron (MLPs) methodology to create ANN model algorithms.
- The process consists of two steps; the forward pass, where predicted outputs corresponding to given inputs are evaluated, and the backward pass, where partial derivatives are propagated back through the network.
- The chain rule of differentiation gives very similar computational rules for the backward pass as the ones in 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.
Materials & Methods
The Artificial Neural Network

- The neural network was designed using seven input variables and one output variable.
- Consists of three layers, one being 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 performance of the model.
Materials & Methods

ANN design

- Use of Ventilator
- 2+ days in ICU
- Sex
- Age
- Low SBP
- Low RR
Materials & Methods

ANN Model Analysis

- Gini co-efficient (measure of equality)
- R.M.S.E. (measure of difference)
- Predictive Performance
# Results

## Table 1: VAP Predicting ANN

<table>
<thead>
<tr>
<th></th>
<th>Training: RMSE 13.67</th>
<th>Test: RMSE 14.07</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>True</td>
<td>False</td>
</tr>
<tr>
<td>Correct</td>
<td>7198</td>
<td>500625</td>
</tr>
<tr>
<td>Of</td>
<td>8426</td>
<td>573921</td>
</tr>
<tr>
<td>%</td>
<td>85.4</td>
<td>87.2</td>
</tr>
</tbody>
</table>

Gini (model average) = 0.80435
Results

- 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.
- 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).
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.
- Mortality figures should be reduced with only 1 in 10 cases being missed.
- 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.
Conclusion I

- Variable ranking table indicates physiological variables at scene may have little impact.

- Patient risk is greater due to factors such as age, injury severity, intubation and the number of days likely to be in the ICU.

- NTDB lacks information on pulse, an apparent key factor in mortality prediction, but is no indication it will improve the model in VAP prediction.
Conclusion II

- Factors suggest that since physiology plays a minimal role that other factors might be relevant to 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 to a health-care facility could reduce the number of cases requiring broad spectrum anti-biotic treatment, thereby reduce the risk of resistant strains developing in the facility.
Conclusion III

- 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.
Future Work

• Re-assess ANN with additional or alternative variables or known risk factors

• Adding more variables may produce a tighter model.

• Single-Center study to investigate bed numbers patient ratio etc.