A Neural Approach for Controlling Vital Signs in the Intensive Care Unit Patients

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Abstract — *Controlling of vital signs is crucial for patients in an intensive care unit (ICU) who need safe diagnostic and therapeutic interventions. The devices used in ICU should ensure accuracy, reliability and safety of alarms. The goal of personalized medicine in the ICU is to predict which diagnostic tests, monitoring interventions and treatments are necessary. In this study, we propose an intelligent approach based on artificial neural networks which is able to automatically learn the features of a patient and consequently send the required alarms in order to reduce the number of wrong alarms in ICU. Six of the most important risk factors are used and the importance of input variables is quantified by weighting according to expert's knowledge. The data chosen for this study have been provided in a real ICU environment in the University of Queensland in Australia. The results demonstrate that the proposed neural approach can be used as an efficient method for controlling vital signs in a real ICU environment*[1]

Keywords — artificial neural networks, vital signs, ICU, patient monitoring, intelligent systems.

I. INTRODUCTION

Much of the work in the ICU revolves around information that is recorded by electronic devices. Such devices typically incorporate simple alarm functions that trigger when a value exceeds pre-defined limits (1). The high rate of false alarms is not only a nuisance for patients and caregivers, but can also compromise patient safety and effectiveness of care. The development of alarm systems has lagged behind the technological advances of medical devices over the last years (2).

The idea is that in order for an alarming scheme to be able to be efficient, the definitions of normal, abnormal and intermediate state have to be changed many times on an hour to hour basis, since in ICU the patient state can change dramatically from day to day (3). In a study 2176 alarms events were recorded, 68% were false, 5.5% were significant, and 26.5% were induced by interventions. Concluded that 94% of alarms events were clinically insignificant (Chambrin: 2001). In another study only 5.9% of 3166 alarms needed call to a physician (4). The goal of personalized medicine in the ICU is to predict which diagnostic tests, monitoring interventions and treatments translate to improved outcomes given the variation between patients (5).The rapid accurate diagnosis of critical disorders is an essential component of intensive care. Traditional diagnostic techniques have relied on physicians' experience, which is based on a data set chosen from his or her personal preferences, rather than from scientific merit (6).

Health care, especially critical care medicine, is complex and expensive both in terms of money (10-20 % of total hospital budgets) and human terms (15-20 % mortality). Good medical decision-making depends upon knowing the patient's history as well as having accurate and current clinical information. The less complete the information the greater the potential for error and waste. This is also true of decision making within a health care system. The data should be selected based on:

A. usefulness, reliability and feasibility

B. action enabling

C. representing a mixture of outcomes, processes and cost

D. reflecting present performance (7).

Also as a component of hospital cost containment policy, the National Institutes for Health recommends that hospitals limit ICU resources to patients who have a reasonable probability of recovery. In order to provide more ethical and objective measures of the likelihood of ICU recovery, hospitals have turned increasingly to decision support software such as APACHE (acute physiology and chronic health evaluation). Rapid advancements in computer software and hardware technology have encouraged researchers to use more computationally intensive non-parametric techniques such as neural networks (NNs) whose prediction capabilities are purported to be greater than those of parametric models (8).

II. BACKGROUND

Scoring systems are very attractive due to their simplicity of use, although this may undermine their predictive capacity. Logistic regression (LR), commonly used for hospital mortality prediction, has limitations. Artificial neural networks (ANNs) have been proposed as an alternative. Bayesian models seem to be a good compromise between complexity and predictive performance, but model recalibration is generally necessary. K-nearest neighbor may be a valid non parametric technique, though computational cost and the need for large data storage are major weaknesses of this approach. ANNs have intrinsic advantages with respect to common statistical models, though the training process may be problematical. A rational choice also requires evaluation and comparison of actual performances of locally-developed competitive models in the clinical scenario to obtain satisfactory agreement between local needs and model response (9, 10).

Neural networks are a new alternative method for developing predictive instruments that offer both

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advantages and disadvantages when compared to other more widely used statistical using techniques (11). Also neural networks compared to apache II showed better classification performance as both predictive models (12). Consensus review by experts in critical care or the implementation of models such as multivariate linear and logistic regression have led to the creation of scoring systems such as the Acute Physiology And Chronic Health Evaluation (APACHE) or Sequential Organ Failure Assessment (SOFA). These scoring tools include physiological variables (such as heart or respiratory rate); the overall score follows the rule that higher scores represent more severe illness (13).

A machine learning technique is used to predict the patient's length of stay in ICU. A GP (Gaussian Processes) model that uses PDMS data of the first 4 hours after admission in the ICU of scheduled adult cardiac surgery patients was able to predict discharge from the ICU as a classification as well as a regression task. The GP model demonstrated a significantly better discriminative power than the EuroSCORE and the ICU nurses, and at least as good as predictions done by ICU physicians. The GP model was the only well calibrated model (14).

Belief networks provide a causal probabilistic framework for the representation of medical knowledge. Evaluation of complex belief-network models is difficult due to the lack of a gold standard for comparison, and because there is a large number of possible sets of input states (15). Evaluating the system aims to demonstrate that human-machine cooperation in information overload situations can improve the work environment of clinicians, improve health care delivery, and ultimately reduce health-care costs (16). However, these newer methods have yet to demonstrate their practicality and usefulness within the context of predicting outcomes in the critically ill (17).

Our major motivation for this study is to reduce the number of the wrong alarms and save doctors' time and reduce number of the errors occur. In order to achieve accurate identification, the researchers used ANNs technique. It is a sophisticated modeling technique capable of modeling extremely complex functions that has a natural propensity for storing experiential knowledge and making it available for use (Jayalskshmi and Snathakumaran, 2010) (7).

Traditionally, NN refers to a network or circuit of biological neurons and modern usage of artificial neurons or nodes. Biological neuron is a unique piece of equipment that carries information or a bit of knowledge and transfers to other neuron in the chain of networks. It receives signals through synapses that control the effects of the signal on the neuron, which is similar to the connecting weights (7). It is well known that a network which has been trained as a classifier will closely approximate a Bayes classifier when the network architecture is sufficiently complex, the training set is sufficiently rich, and the training algorithm succeeds in minimizing the mean squared error (18). Intelligent decision support systems for mechanical ventilation can be quite helpful to clinicians in today's ICU settings. To be useful, such systems should be designed to be safe and easy to use at patient's bedside. In particular, these systems must be of noise removal, artifact detection and effective validation of data (19). There are several factors that should be monitored in ICU. Some of them are: HR (Heart rate) derived from the ECG sensor, ST segment index derived from the ECG sensor, Pulse Rate (heart rate) derived from pulse oximetry, Blood oxygen saturation derived from pulse oximetry, Perfusion index derived from pulse oximetry, End-tidal CO2 measured using sidestream capnography, Inspired minimum CO2 measured using sidestream capnography, and etc.

III. METHOD

Neural Network Toolbox of MATLAB 7.10.0 (R2010a) was used to design the neural network. The toolbox is a set of functions and structures that handle neural networks such that writing complex code for all activation functions, configuring network, initializing weights (20).
The dataset used for this study is taken from 32 ICU patients' vital signs that were recorded during 32 surgical cases where patients underwent anesthesia (21). Five cases have been chosen for this study and the data of these patients are recorded in about an hour and 30 minutes. Other cases that are excluded had the recording time either less or more than this time. Six risk factors used in this study are:

- HR (Heart Rate)
- BP (Blood Pressure (Diastolic))
- SpO2 (Blood oxygen saturation)
- Tidal Volume
- RR (Respiratory Rate)
- Number of patient alarms.

First five factors are used as the inputs of the network (HR, BP (Diastolic), SpO2, Tidal Volume, and RR) and the sixth one is as the target. A multilayer feedforward backpropagation architecture is designed using Neural Network Toolbox of Matlab. 2 hidden layers of 4 and 1 neurons, an output layer of 1 neuron have been used. Tansig transfer function is at the hidden layer and a linear transfer function is at the output layer. The best validation performance and the relative gradient for each person are shown in table 1. Number of neurons at the hidden layer was varied, as well as the number of epochs. These parameters were varied to improve performance of the neural network. At the end, the best number of neurons was chosen.

IV. RESULTS

The best findings of the neural networks for five cases are listed in table 1.

Table I. 5 best findings of trained networks for 5 selected cases

	No of epochs	Time	Performance	Gradient	BVP	R
Case 1	268	00.24.29	0.0351	6.70e-06	0.035252	0.87065
Case 2	97	00.07.22	0.0454	7.73e-05	0.045287	0.77911
Case 3	174	00.14.08	0.0102	0.000375	0.010025	0.96417
Case 4	46	00.03.08	0.00125	2.59e-11	0.001037	0.96831
Case 5	375	00.27.37	0.0148	8.51e-07	0.014223	0.90791

For case one for example, a two layer feedforward neural network of 4 and 1 neurons at hidden layers with correlation coefficient (R) of 0.87065 and best validation performance (BVP) of 0.035252 which occurred within 24 minutes and 29 seconds at 268th epoch was selected. The network used TRAINLM training function, LEARNGDM adaption learning function, MSE performance function, Tansig transfer function for hidden layers and PURELIN transfer function for the output layer. Fig. 1 represents ANN architecture selected during the training.

Correlation coefficient, best validation performance, time taken to reach the performance goal, gradient, and number of epochs were all considered in the selection process. Best validation performance for case four was 0.001037 which occurred at 46th epoch as shown in Fig. 2.

A regression plot between outputs of the network and targets is shown in Fig. 3. The dashed line in each axis represents perfect result – outputs = targets and the solid line represents the best fit linear regression line between outputs and targets. The correlation coefficient, R, between outputs and targets in all the axes show more than 90% of coincidence means that the network is well trained and could detect the right alarms.

We trained the neural network for 5 people individually and results are reported in table1. As the table represents, the best correlation coefficient for each person is written and all the data show that the neural network is well trained and can detect the right alarms. If the neural network ignores the wrong alarms, the staff don’t have to visit a patient in each alarm and waste the time. So they can investigate the time on all patients effectively. With the results obtained through this study, these networks can be applied in an ICU ward as an intelligent system to prevent wrong alarms.

V. DISCUSSION

Because of the critical aspects of the ICU ward, all the processes in this section should be exact and accurate. So with the help of computer and some methods, we can approach this goal. Another reason for choosing computers and artificial methods in hospitals is the high cost of treatment that can be reduced by the use of computers. The method chosen for this study is artificial neural networks. The study has presented a multilayer feedforward backpropagation network with two hidden layers of 4 and 1 neurons and an output layer of 1 neuron. The dataset used for this study is taken from 32 ICU patients’ vital signs that were recorded during 32 surgical cases where patients underwent anesthesia. 5 of them have been chosen that the recording time was about 90 minutes for each one. The network is trained for each person and the results are acceptable which have been reported in table 1.

Six risk factors that are assumed to be the most important factors according to expert knowledge for 5 people and their strength of association to critical states of the patients are used as relative weight of input variables. Because we wanted to compare our findings, we chose these people according to the time that the data have been recorded. And the time of data recording for these people was about one hour and half. The time for other cases was either less or more than this time. One limitation of this study is that we have just used the data of 5 people, also the networks trained have not been implemented in a real ICU environment. Another limitation is that we didn’t find a scientific reason for how to divide the data for train and test during the training process. We divided them to 65% for training and 35% for testing.

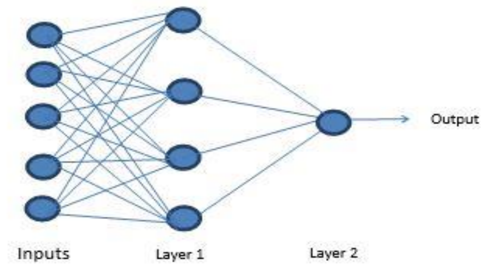

Fig. 1. Architecture of the neural network of this study; five inputs; two hidden layers of four and one neurons

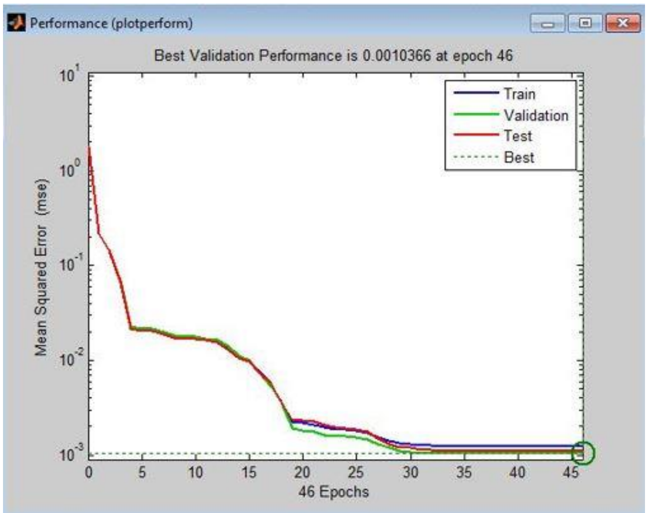

Fig. 2. Best validation performance and number of epochs for case 4

VI. CONCLUSION

In conclusion, we have found results that are acceptable and can be applied to a real ICU environment. In this study, we proposed an intelligent approach based on artificial neural networks which is able to automatically learn the features of a patient and consequently send the required alarms in order to reduce the number of wrong alarms in ICU**.** In comparison with the previous studies, the results show more accurate alarms that could be used for more effective care. We consider that the method of artificial neural networks would be the most effective for this study because number of the factors that should be considered are a lot, it would be extremely hard to make rules for all cases (22). Future work should consider implementing the found networks in live workflows of ICU that may help improve patient care.

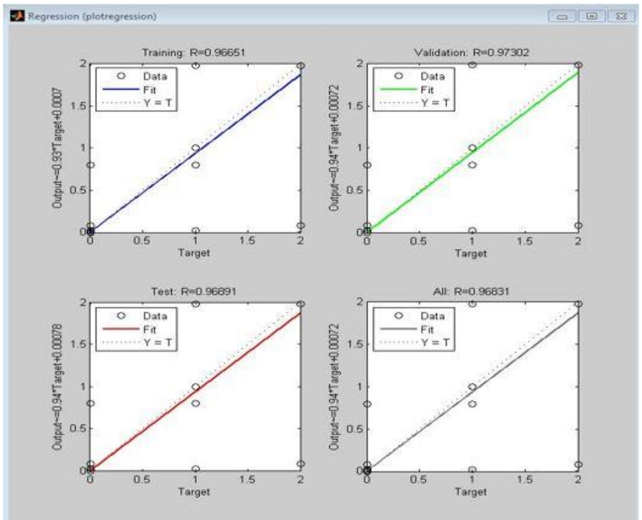

Fig. 3. Regression plot for case 4

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