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Prediction on Lengths of Stay in the Postanesthesia Care Unit Following General Anesthesia: Preliminary Study of the Neural Network and Logistic Regression Modelling

The length of stay in the postanesthesia care unit (PACU) following general anesthesia in adults is an important issue. A model, which can predict the results of PACU stays, could improve the utilization of PACU and operating room resources through a more efficient arrangement. The purpose of study was to compare the performance of neural network to logistic regression analysis using clinical sets of data from adult patients undergoing general anesthesia. An artificial neural network was trained with 409 clinical sets using backward error propagation and validated through independent testing of 183 records. Twenty-two inputs were used to find determinants and to predict categorical values. Logistic regression analysis was performed to provide a comparison. The neural network correctly predicted in 81.4% of situations and identified discriminating variables (intubated state, sex, neuromuscular blocker and intraoperative use of opioid), whereas the figure was 65.0% in logistic regression analysis. We concluded that the neural network could provide a useful predictive model for the optimization of limited resources. The neural network is a new alternative classifying method for developing a predictive paradigm, and it has a higher classifying performance compared to the logistic regression model.

Key Words: *Recovery Room; Postoperative Care; Neural Network (Computer)*

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INTRODUCTION

In recent years, increased use of high technology and higher standards of care have turned the postanesthesia care unit (PACU) into a costly environment and thereby, have escalated the need for the most efficient use of resources. Balancing between patient's safety and cutting costs has become an important issue in the management of the PACU (1). To maintain patient's safety and simultaneously to cut costs, analysis of many factors that determine the lengths of stay has been considered in the area of cost-effectiveness (2-4). Complicated determinants attributed to perioperative periods which affect the duration of stay. Among them, the use of newly-developed anesthetics, pain control regimens, sedatives and relaxants were seen to help decrease the length of stay, while intraoperative hypothermia and postoperative complications such as pain, nausea and vomiting were reported to delay discharge from the PACU (4, 5). However, the interaction of these determinants hindered the process of pinpointing the major contributors which make it difficult to predict the duration of stay. Studies have confirmed that the neural network is adept at recognizing the sets of clinical data (6, 7).

The neural network is a network of many simple processor (the unit analogous to the biological neuron is referred to as a "processor" or "processing element"), each possibly having a small amount of local memory. The units are connected by communication channels ("connection") which usually carry numeric data. The units operate only on their local data and on the inputs or "connections" they receive via the connections. The weights of connections are adjusted based on the data by a "training rule". The neural network learn from examples (as children learn to recognize dogs from examples of dogs) and exhibit some capability for generation beyond training data. Depending on the type of network, the favored applications are prediction, classification, data association, data conceptualization, data filtering and optimization. The applications require many observations which are used to determine the underlying relationship. There are many ways to train the neural network. Most of them are related to back-propagation.

The aims of this study were to evaluate the performance of the trained neural network and to compare it to logistic regression analysis using clinical sets of data from adult patients undergoing general anesthesia.

MATERIALS AND METHODS

All data were collected retrospectively from March 1998 to June 1998 and selected randomly from patients over 16 years of age undergoing general anesthesia performed in our hospital for 4 months (total 4, 200 cases). We chose anaesthetic records by random number seeded by the computer. However, the patients with physical status above 4 according to the American Society of Anesthesiologists (ASA), the patients transferred to ICU without staying at PACU, and those undergoing regional and cardiothoracic anesthesia were excluded. Discharge from PACU was determined by post-anesthetic recovery scale (PARS) score. The PARS score took into account activity, respiration, circulation awareness and color. An arbitrary number (0, 1 or 2) was assigned to each patients depending on characteristics. The PARS score was similar to the Apgar. More intense nursing care was needed to patients with the lesser PARS scores than those with greater scores. Twenty-three variables were investigated in each patient's record and every item was coded depending on its attributes (Table 1). Schematic process of the neural network and logistic regression modelling were shown in Fig. 1.

We used the backpropagation network type containing various basic elements applicable in a wide range of problem solving, and trained the neural network with the clinical sets of 409 patients, inputting 22 variables for each. The neural network was developed using Neural Ware's Professional II/Plus (Neural Ware, Pittsburgh, PA, U.S.A.). Three layers were built for the applied neu-

Table 1. Investigated items in each clinical set

Items	Code
1. Sex	female (0), male (1)
2. Age (yr)	
3. ASA class	1 (1), 2 (2), 3 (3), 1E (4), 2E (5), 3E (6)
4. Premedication	none (0), done (1)
5. Past history	cardiovascular (1), pulmonary (2), hepatorenal (3), others (4)
6. Operation site	head and neck (1), upper abdomen (2), lower abdomen (3), extremities (4), others (5)
7. Intraop hypertension	none (0), yes (1)
8. Intraop hypotension	none (0), yes (1)
9. Intraop arrhythmia	none (0), yes (1)
10. Intraop transfusion	none (0), yes (1)
11. Intraop use of opioid	none (0), yes (1)
12. Neuromuscular blocker	scc + pan (0), vec/atra (1), vec/atra + pan (2), none (3), pan (4), scc + vec/atra (5), others (6)
13. Electrolyte imbalance	none (0), yes (1)
14. Abnormal ABG	none (0), yes (1)
15. Other abnormalities	none (0), yes (1)
16. Abnormal temperature	none (0), yes (1)
17. Intubated state	none (0), yes (1)
18. Used major agents	IV only (0), enflurane (1), isoflurane (2), others (3)
19. PCA	none (0), yes (1)
20. Duration of anesthesia (mins)	
21. Complications in the PACU	none (0), yes (1)
22. Other problems in the PACU	none (0), yes (1)
23. Lengths of stay (mins)	more than 30 but less than 60 (1), more than 60 (0)

ASA, American Society of Anesthesiologists; Intraop, intraoperative; scc, succinylcholine; pan, pancuronium; vec, vecuronium; atra, atracurium; ABG, arterial blood gas tension; PCA, patient controlled analgesia; PACU, postanaesthesia unit

Systolic pressure more than 160 mmHg/diastolic pressure more than 100 mmHg/antihypertensive medication case was considered intraoperative hypertension.

Systolic pressure less than 80 mmHg/presser medication was considered intraoperative hypotension.

Body temperature was measured at nasopharyngeal area and above 38℃/below 35℃ was considered abnormal temperature.

Intubated state meant the patient had arrived in the PACU without extubation. Complications in the PACU included hypertension, hypotension, hemorrhage, nausea, vomiting and arrhythmia.

Other problems in the PACU included shivering, chills, operation site pain and back pain.

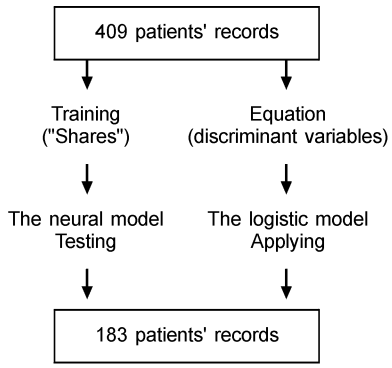

Fig. 1. Schematic flow of procedures. For detailed description, see text.

ral network architecture. The input layer was assigned 22 processing elements (nodes), the hidden layer was set with 20 processing elements by empirical trial, and the output layer had 1 processing element for determining the categorical value of the length of PACU stay. The transfer function was the hyperbolic tangent (similar to sigmoid transfer function, its output range is −1 to +1, as opposed to the sigmoid range of 0 to 1) and the learning rule was the normalized cumulative delta. The root mean square error was displayed above the convergence threshold of 0.001. The confusion matrix was monitored to measure the network performance, allowing a visual display which correlated the actual results with desired results.

After training and testing, we examined the relative predictive importance of the input variables by partitioning the sum of the effects on the output layer. These were represented by "shares" which were a percentage of all the output weights attributable to the given input processing elements by using the following equation:

$$\sum_{j}^{n_H}((Iv_j / \sum_{k}^{n_V} Iv_j) \times O_j) / \sum_{i}^{n_V}(\sum_{j}^{n_H}((Iv_j / \sum_{k}^{n_V} Iv_j) \times O_j))$$

For each n_H, hidden processing element, sum the product formed by multiplying the input-to-hidden connection weight of the input processing element I of variable V for hidden processing element j, times the connection weight of output processing element O for hidden processing element j; then divide by the sum of such quantities for all variables. The result was the percentage of all output weights attributable to the given independent variables, excluding bias weights arising from back-propagation algorithm, thus representing the relative importance of independent variables (8). The neural network predicted values and real categorical values were compared for validation and observed for accuracy. When the output value was less than 0.5, it was categorized as an inaccurate prediction.

A logistic regression analysis technique using SPSS 7.0 (SPSS Inc., Chicago, IL, U.S.A.) for Windows, adopting the forward stepwise variable selection based on the probability of the likelihood statistic, was applied to 409 patients' records in order to determine the contributing variables for the categorical value of the length of stay and prediction. The same inputs and patients' records used to validate performance in the neural network were entered for analysis. Classification output was compared to real categorical values. Continuous variables were classified in the regular range of deviation in 409 patients. Given the estimated coefficients, the logistic regression equation for the probability of a group could be written as follows:

Z = 0.4147 + 1.0913 (sex) − 2.5028 (intraoperative arrythmia) − 16.6885 (abnormal arterial blood gas tension) − 2.2918 (intubated state) + B (duration of anesthesia) − 1.9691 (complications in the PACU)

B: estimated coefficients in each categorical code of variable by time range (deviation)

The probability of the group = $1/(1 + e^{-Z})$

By applying these equations to 183 patients (same patient's record in testing session of the neural network), the estimated probabilities were calculated. If the estimated probability was less than 0.5, the logistic model predicted it as group 1. When it was greater than 0.5, that record was categorized as group 2. Real group and predicted group was compared accurately.

RESULTS

A total of 592 clinical sets of records (409 patients' records in the training session, additional 83 records, nearly half the number of training session, in the testing session) were included. Patients' mean (±SD) age was 38.9 (±14.4) years old and there were 94 males and 89 females in the testing of 183 records. At the end of the training session, the neural network showed input variables which had more effect on output. Four influential variables ("shares") were included: intubated state (5.46), sex (5.40), neuromuscular blocker (5.39), and intraoperative use of opioid (5.17). The predictive classification of the length of stay is shown in Table 2. Overall accuracy was 81.4% (149/183). The accuracy of group 1 (a stay of more than 30 min but less than 60 min) was 90.6% (106/117), and group 2 (a stay of more than 60 min) was 65.2% (43/66).

The logistic regression model revealed prominent variables as sex (p=0.01), intraoperative arrhythmia (p=0.04), abnormal arterial blood gas tension (p=0.01), intubated state (p<0.01), duration of anesthesia (p<0.01) and complications in the PACU (p<0.01). Overall classification performance was 85.6% (350/409) in 409 patients' records. The equation using prominent variables was

Table 2. Comparison of prediction results

Real categories	The neural network [n (%)]		Logistic regression analysis [n (%)]	
	Gr 1	Gr 2	Gr 1	Gr 2
Gr 1	106 (57.9)	11 (6.0)	89 (48.6)	28 (15.3)
Gr 2	23 (12.6)	43 (23.5)	36 (19.7)	30 (16.4)

Gr 1, more than 30 but less than 60 min; Gr 2, more than 60 min (n=183)

applied to 183 records which were same data in neural networks for predictive classification of the length of stay. Accuracy rate was 65.0% (119/183) for 183 patients' records as a whole. The accuracy of group 1 was 76.1% (89/117), while that of group 2 was 45.5% (30/66).

DISCUSSION

This study was actually designed as a part of an ongoing quality improvement program to the overall length of stay for patients, to improve utilization of resources, and to advance the quality of care provided in the PACU. To achieve this goal, we needed to develop a prediction model using efficient statistical techniques to find out lengths of stay following general anesthesia in adult patients. We planned to redistribute our resources: e.g. arrangement of operating room schedule to optimize admission rate, nurse needed for the PACU, consideration of anesthetic regimen and to implement the optimal utilization of time based on the model's accuracy. The successful prediction of lengths of stay might ensure a more appropriate use of resources, including the provision of better services, more effective scheduling and planning of resources, more timely initiation of treatment, and improved cost control management which is so vital in an era of diminishing fiscal budgets.

The determinants in the neural network and logistic regression analysis were quite different. But some of these discriminatory variables were thought to be controllable in managing the length of stay in the PACU. The logistic regression model performed poorly in classifying both groups. This model indicated prominent predictors: sex, intraoperative arrhythmia, abnormal arterial blood gas tension, intubated state, duration of anesthesia, and complications in the PACU: e.g. wound bleeding, respiratory difficulty, high blood pressure, whereas the predictors indicated by the neural network were: intubated state, sex, neuromuscular blocker and intraoperative use of opioid, determined in a single pass of all 183 records from recall. Only two variables, sex and intubated state, overlapped in both models. The exact explanation was not apparent, but the dependence of the analytic techniques on different mathematical algorithms seemed to be one reason. Waddle et al. studied PACU length of stay at a 900-bed tertiary-care academic hospital and identified factors (10). Major influencing predictors were anesthetic time, anesthetic technique and amount of intraoperative fluid by logistic analysis. They admitted their observations were restricted to the largest phase 1 PACU. Different circumstances of hospital and study design including variables might produce different results. We did not include regional anesthesia because discharge criteria after regional anesthesia were not the same as general anesthesia. This was reevaluated by Cohen et al. (11). Residual block and spinal opioid affected the majority of unnecessary stays.

The neural network distinguishes the group as a pattern of parallel weights, but the logistic regression technique is nonlinear, it is an iterative algorithm, which estimates the group by probability. Despite getting "share" value, we could not determine the simultaneous contribution of each variable to the connection because those variables had been interacted upon by weights being changed through the backpropagation of error. The interconnection of processing elements could support input variables to develop a pattern which provides a basis for making a decision in favor of one outcome over another in the pattern match. The neural network was better than the logistic regression technique in distinguishing between the two groups but logistic regression was informative in identifying discriminatory variables. The neural network correctly identified 81.4% of 183 sets of patient records during testing. A similar study for predicting the lengths of stay in a post-coronary care unit was performed and the predicted stays compared to the actual stays were 72% accurate within 1 day (6). These preliminary results were an encouraging example of neural network application in the field of prediction compared to 65.0% for logistic regression analysis. The neural network showed significant differences in accuracy compared to the logistic regression method in both groups. Input data were likely less noisy and well fitted to logistic regression analysis. However, the estimated probabilities of 183 records were inconsistent. The neural network found that a few of the presented records seemed to cause a wide swing in weights which contributed to the inaccuracy of the prediction. This could be explained by the small number of trained samples and data impurities included in the training session. The neural network needed sufficient, consistent data to produce an accurate response. Generally, it is recommended that there be at least 10 to 40 examples for each input variable, although some networks may require fewer depending on the complexity of the problems. Our result was fairly useful in both groups and was thought to be promising if training samples were fully supported. But the neural network was superior in classification performance and showed better results in applying this model in the PACU. The logistic regression model generally assumes exact and nonlinear functional forms for classification and is known to be more sensitive to noise. On the other hand, the neural network can be nonlinear and relatively durable to noise data. Therefore, the neural network model may be potentially more suitable to this typical form of data, especially for a dependent variable such as a category.

The neural network has a certain capacity to learn trends and realize a functional connectivity in the pattern among coupled interactive variables. This connectivity in patterns indicates that the neural network may be able to synthesize patterns of clinical sets of data carried out for prediction. Recent studies have suggested that neural networks are useful in recognizing sets of clinical data (7-9). The neural network may be used to classify patients on the basis of putting their variables into categories. Like many other statistical techniques, the neural network is a nonlinear modelling tool that relates inputs to prediction but has a basically non-parametric nature which requires data not to be assumed. It allows data to be analyzed at the same time its more complex interaction of inputs is being parameterized by its weights on a grid. Based on the adjustment of weight values, the neural network learns the pattern rules from the sample data, distinguishing the neural network from a rule-based expert system which processes the knowledge by an inference engine. The neural network can be trained with samples presented to the network by adjusting to a learning rule. Therefore, it is important to remove noise and specific outlier in samples during training to obtain the desired response. Neural computing systems are more adept at many pattern recognition tasks than traditional statistical methods or expert systems. To solve complex, real-world problems, neural networks can be used in classification and pattern recognition. However, the neural network has some disadvantages, which are the meaninglessness of numeric weight values changed by backpropagated error, the relative lack of explicit structural information where these values are exposed out of the system and the difficulty in verifying a decision criteria by even an expert (12). Interconnected nodes and coefficients of the neural networks have to be determined empirically. This point enables the neural system to become too flexible and therefore less consistent. Despite those problems, neural networks are widely applied in the field of anesthesiology such as prediction analysis, clinical monitoring, capnogram analysis, depth of anesthesia control and integration of alarm (13-17).

A limitation of our study was that a larger sample size was not used to improve the accuracy in the neural network and detailed subsets of variables should have been searched, such as complications in the PACU. The model would be more plausible if a prediction could be made for each patient on the operating list at the start of the day using only information available pre-operatively: e.g. age, sex, type of surgery and planning of anesthesia. Further research is required to make this clear. The results of our study indicated that the trial of a neural network-based model for the prediction of lengths of stay in the PACU following general anesthesia and in identifying the major discriminant variables was an encouraging endeavor. The neural network's performance compared to the widely-used logistic regression analysis was proved to be a fairly good classification method for predicting resource utilization. We suggest it would be useful in clinical practice in recognizing interactive variables that have dynamic patterned data.

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