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Predicting hypotensive episodes during spinal anesthesia with the application of artificial neural networks

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ABSTRACT

Hypotension is one of the most frequent adverse effects of spinal anesthesia. Several factors might be related to the occurrence of hypotension. Predictions of the hypotensive event, however, had been addressed by only a few authors using logistic regression (LR) models. Artificial neural networks (ANN) are pattern-recognition tools that can be used to detect complex patterns within data sets. The purpose of this study was to develop the ANN-based predictive model to identify patients with high risk of hypotension during spinal anesthesia. From September 2004 to December 2006, the anesthesia records of 1501 patients receiving surgery under spinal anesthesia were used to develop the ANN and LR models. By random selection 75% of data were used for training and the remaining 25% of data were used as test set for validating the predictive performance. Five senior anesthesiologists were asked to review the data of test set and to make predictions of hypotensive event during spinal anesthesia by clinical experience. The ANN model had a sensitivity of 75.9% and specificity of 76.0%. The LR model had a sensitivity of 68.1% and specificity of 73.5%. The area under receiver operating characteristic curves were 0.796 and 0.748. The ANN model performed significantly better than the LR model. The prediction of clinicians had the lowest sensitivity of 28.7%, 22.2%, 21.3%, 16.1%, and 36.1%, and specificity of 76.8%, 84.3%, 83.1%, 87.0%, and 64.0%. The computer-based predictive model should be useful in increasing vigilance in those patients most at risk for hypotension during spinal anesthesia, in allowing for patient-specific therapeutic intervention, or even in suggesting the use of alternative methods of anesthesia.

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1. Background

Although spinal anesthesia (SpA) has long been considered a safe technique, it is not without risk or adverse effects. Hypotension is one of the most frequent adverse effects of spinal anesthesia with reported incidence of 15–33% [1,2]. The clinical importance of this side effect had been shown in several studies which proved that hypotensive episodes clearly correlated with morbidity and mortality [3,4]. Identification of patients with high risk of hypotension would be an important step in the rational selection of anesthetic techniques and adoption of therapeutic interventions. Certain factors related to patient history, basal clinical state, or anesthetic technique might be associated with an increased risk for hypotensive episodes. History of hypertension [5], basal heart rate [6], and obesity [7,8] have been considered to be possible predisposing factors for hypotension during spinal anesthesia. Predictions of the hypotensive event, however, have been addressed by only a few studies using logistic regression models which have limited discriminating power [9].

Artificial neural networks (ANN) are pattern-recognition tools that can be used to detect complex patterns within data sets. In recent years ANN has been widely applied in computer-aided diagnosis [10,11,21], in medical signal processing [12,13], and in outcome prediction [14,15,22]. The purpose of this study was to develop the ANN-based predictive model to predict patients with high risk of hypotension during spinal anesthesia. Furthermore, we compare the predictive performance of the ANN model to those of the logistic regression model and the prediction of clinicians.

2. Materials and methods

2.1. Study population

From January 2004 to December 2006, the anesthesia records of 1611 patients receiving surgery under spinal anesthesia were reviewed. Records with missing data were excluded. A total of 1501 data were included in the study for model construction and performance evaluation. The Hospital Ethics Committee had approved the protocol. Because the study entailed no interventions in patient care, informed consent was not required.

The predictive power of 8 patient-related, 2 surgical, 1 anesthesia-related variables and 3 hemodynamic variables was recorded and studied:

1. Patient-related variables included: age, gender, height, weight, hematocrit, American Society of Anesthesiologist (ASA) physical status, history of hypertension, history of diabetes.
2. Surgical variables included: emergency or elective surgery, surgical category (orthopedics, plastic surgery, general surgery, obstetrics, and urology).
3. Anesthetic variables included: dose of local anesthetics (0.5% bupivacaine).
4. Hemodynamic variables included: basal systolic blood pressure (SBP), basal diastolic blood pressure (DBP), and basal heart rate (HR).

2.2. Hypotension

Hypotension was defined if SBP fell below 90 mmHg or if the patient developed the associated symptoms (nausea/vomiting) within 15 min after induction of spinal anesthesia. The dichotomous variable “hypotension” was used as target criterion and was defined as “1” if hypotension occurred and “0” if hypotension not occurred.

2.3. Logistic regression (LR)

Data analysis and statistics were performed using the commercial software SAS (SAS for Windows, Version 9.0, SAS Inc.). Randomly selected 75% data were used for model construction and the remaining 25% data were used as test set for validating the predictive performance.

First, variables were checked with univariate analysis for associations with hypotension. We calculated mean value, standard deviation, median, inter-quartile range, and 95% confidence interval as metric variables. Metric variables were analyzed by Mann–Whitney *U*-test. Categorical variables were assessed for a significant association by either Chi-square statistics or Fisher’s exact test.

Second, the stepwise algorithm was used for the construction of the multivariate model. At each step, independent variables not yet included in the equation were tested for possible inclusion. The variable with the strongest significant contribution to improving the model was included. Variables already included in the logistic regression equation were tested for exclusion on the basis of the probability of a log likelihood test ratio. The analysis ended when no further variables for inclusion or exclusion were available. Furthermore, logistic regression was used to estimate the coefficients (β) of these variables. On the basis of the results, the probability of hypotension may be estimated with the logistic equation.

2.4. Artificial neural network

We used the NeuroShell 2 (Release 4.0, Ward systems Group Inc.) to develop the ANN model. The architectures selected in this study were the multilayer perceptron and 1 hidden layer with 12 hidden nodes were defined due to the complexity of the data set. There were 14 parameters chosen as input variables according to the related literatures and clinical experiences (Table 1). Randomly selected 75% data were used for training and the remaining 25% data which were not involved in the training process were used as test set for validating the predictive performance.

2.5. Simplified artificial neural network (SANN)

To study the predictive performance of the ANN model with lesser input nodes, the seven variables selected in the logistic regression model (surgical category, weight, height, ASA physical status, emergency, basal SBP, and dose of local

Table 1 – Variables used for training of the ANN model

Variable	Coding
Age	Years
Gender	0: female; 1: male
Weight[a]	kg
Height[a]	cm
Hematocrit	%
ASA physical status[a]	0: class 1, 2; 1: class 3, 4
Basal SBP[a]	mmHg
Basal DBP	mmHg
Basal HR	Beat per minute
History of hypertension	0: no; 1: yes
History of diabetes	0: no; 1: yes
Surgical category[a]	c1(1,0,0,0,0): ORT; c2(0,1,0,0,0): PS; c3(0,0,1,0,0): GS; c4(0,0,0,1,0): OBS; c5(0,0,0,0,1): URO
Emergency[a]	0: no; 1: yes
Dose of local anesthetics[a]	mg

ORT: Orthopedics, PS: plastic surgery, GS: general surgery, OBS: obstetrics, URO: urology.

[a] Used for training of the SANN model.

anesthetics) were used as input variables to develop the "simplified" ANN model. The architectures selected were the multilayer perceptron and 1 hidden layer with 8 hidden nodes were defined. The data set and training process were the same as the ANN model with all 14 input variables.

2.6. *Prediction of clinicians*

The data of test set were presented to 5 senior anesthesiologists. They were asked to make predictions about whether the patient may have a hypotensive episode after spinal anesthesia induction case by case. The results of their predictions were computed and then compared to the other predictive models.

2.7. *Performance evaluation*

The test data set was used to evaluate predictive performance. Accuracy, sensitivity, specificity, and likelihood ratios for positive and negative tests were calculated for each model. Receiver operating characteristic (ROC) curves were plotted and the areas under ROC curve were calculated. The ROC curve represents a graphical display of the true-positives (sensitivity) plotted against the false-positive (1 − specificity) for various thresholds. The area under the curve could indicate the discriminating power of the model. This may be interpreted as the probability of correct patient classification in one of the two categories for hypotension.

3. Results

The characteristics, surgical and anesthesia data, along with the distribution of hypotension of the training set and the test set are shown in Table 2. The incidence of hypotension of the training set and test set were 32.8% and 31.5%, respectively.

Table 2 – Characteristics of patients

	Training set ($n = 1126$)	Test set ($n = 375$)	p-Value
Hypotension (%)	32.8	31.5	–
Age (years)	49.5 ± 18.5	50.6 ± 18.8	0.2091
Gender: male (%)	54.4	54.7	–
Height (cm)	162.9 ± 7.5	163.2 ± 8.0	0.4933
Weight (kg)	67.3 ± 12.7	67.5 ± 12.3	0.5416
Hematocrit (%)	39.0 ± 7.8	38.9 ± 5.9	0.9247
Basal SBP (mmHg)	139.3 ± 24.5	138.4 ± 25.1	0.0823
Basal DBP (mmHg)	84.6 ± 13.4	85.9 ± 15.1	0.0765
Basal HR (bpm)	79.8 ± 15.5	78.1 ± 14.7	0.0534
History of hypertension (%)	19.0	20.5	-
History of diabetes (%)	11.5	11.5	-
Emergency (%)	15.5	13.1	-
Dose of local anesthetics	10.6 ± 1.8	10.5 ± 1.7	0.2547

Data are mean ± S.D.

Of the total of 1501 patients, 1126 were selected for training the predictive model and the rest (375 patients) were available for testing. There was no significant difference in the demographic data between both data sets.

The results of logistic regression analysis are summarized in Table 3. There are seven variables included in the final logistic regression model—surgical category, weight, height, ASA physical status, emergency, SBP, and dose of local anesthetics. The probability of hypotension could be calculated by the following logistic equation:

$$\text{probability} = \frac{1}{1+e^{-\beta}}, \quad \text{with}\ \beta$$
$$= 2.9 + 2.4458 \times (\text{surgical category}) + 0.0254 \times (\text{weight}) - 0.0061 \times (\text{height}) + 0.7406 \times (\text{ASA physical status}) + 0.5388 \times (\text{emergency}) + 0.0107 \times (\text{basal SBP}) + 0.18 \times (\text{dose of local anesthetics})$$

The ANN had an overall accuracy of 77.6% in predicting hypotension. The sensitivity was 75.9% and specificity was 76.0%. The accuracy of the SANN model was 76.5%; the sensitivity was 73.1%, with a specificity of 77.5%. The logistic regression model had an accuracy of 71.2%. The sensitivity

Table 3 – Coefficient of the logistic regression model

Parameter	Coefficient (β)	Standard error	p-Value
Intercept	2.9000	2.0482	0.1568
Surgical category	2.4458	0.2011	<0.0001
Weight	0.0254	0.0078	0.0012
Height	−0.0061	0.0133	<0.0001
ASA physical status	0.7406	0.2463	0.0026
Emergency	0.5388	0.2131	0.0115
Basal SBP	0.0107	0.0037	0.0040
Dose of local anesthetics	0.1800	0.0515	0.0005

Table 4 – Comparison of the different models

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Area under ROC curve	LR+	LR−
ANN	77.6	75.9	76.0	0.796	3.17	0.32
SANN	76.5	73.1	77.5	0.798	3.26	0.35
LR	71.2	68.1	73.5	0.748	2.95	0.33
Clinician 1	62.9	28.7	76.8	–	–	–
Clinician 2	66.4	22.2	84.3	–	–	–
Clinician 3	65.3	21.3	83.1	–	–	–
Clinician 4	63.5	16.1	87.0	–	–	–
Clinician 5	56.0	36.1	64.0	–	–	–

LR+: Likelihood ratio for positive test. LR−: Likelihood ratio for negative test.

was 69.1% and specificity was 73.5% (Table 4). The ANN had the highest accuracy and sensitivity among all predictive models. The SANN model which are developed with seven variables has similar predictive performance to the ANN model. The receiver operative characteristic curves were plotted in Fig. 1. The area under ROC curves of ANN, SANN and LR models were 0.796, 0.798, and 0.748, respectively. It revealed that the ANN and SANN models have better discriminating power than the LR model to identify the patient with high risk to develop hypotension during spinal anesthesia. The accuracy of the prediction of clinicians were 62.9%, 66.4%, 65.3%, 63.5, and 56.0. The sensitivity were 28.7%, 22.2%, 21.3%, 16.1%, and 36.1%; the specificity were 76.8%, 84.3%, 83.1%, 87.0%, and 64.0%. The clinician had the lowest predictive accuracy and sensitivity.

4. Discussion

In our study the ANN and SANN demonstrated the power in detecting whether hypotension occurred after induction of spinal anesthesia. The ROC curves were plotted to summarize the findings of the multivariate analysis. The predictive performance of the ANN and SANN models were superior to those of the LR model and the clinicians' prediction.

The ANN and SANN models which were developed by the parameters available before induction of spinal anesthesia had good predictive performance. When applied in clinical practice, we can identify the patient with high risk of hypotension before spinal anesthesia is performed. We could undertake some therapeutic interventions to prevent the occurrence of hypotension or consider if other anesthesia techniques could be used.

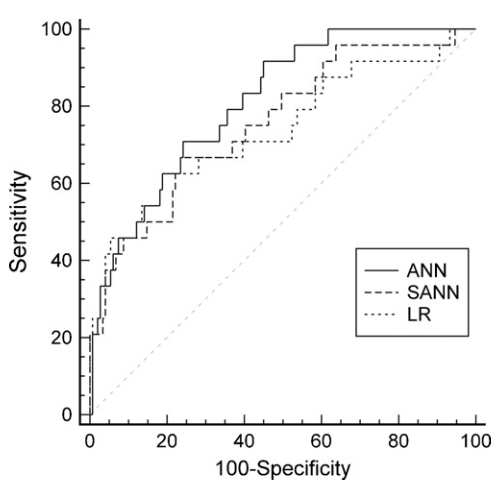

Fig. 1 – ROC curves of ANN, SANN, and LR models.

In this study, we use the 7 variables selected in the logistic regression model to construct the SANN model. The SANN model with the 7 variables presented a good predictive performance similar to the ANN model which was developed by 14 variables. In clinical practice, the SANN model which need less parameters would be easier to use and probably more acceptable.

The prediction of clinician had very low sensitivity and high specificity. It indicted that it was very difficult for a clinician to identify the risk of hypotensive episode according to the concomitant parameters. When many determinant factors exist, it is impossible for a clinician to consider every factor simultaneously before making decision. In this study the computer-based ANN model presented the power in predicting the occurrence of hypotensive episode much better than just clinical judgment.

In recent years Hanss et al. had concluded that heart rate variability (HRV) analysis could be used to predict the occurrence of hypotension during spinal anesthesia [16,17]. Because fast Fourier transformation analysis requires stationary data, patients were asked to lie calmly in the supine position during HRV measurements. Artifacts during HRV data recording, e.g., due to movements of the patient, were inevitable to some degree. The application of HRV to a clinically routine setting is currently not possible so it was not included in our predictive models. If HRV analysis could be applied and included in the construction of predictive model it could improve the predictive performance of the models.

In conclusion, the knowledge of these risk factors and the computer-based predictive models should be useful in increasing vigilance in those patients most at risk for hypotension, in allowing for patient-specific therapeutic intervention [18–20], or even in suggesting the use of alternative methods of anesthesia, such as epidural anesthesia or general anesthesia.

Conflict of interest

We certify that all the authors of the manuscript have no commercial association or funding support that might post a conflict of interest in connection with this report.

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