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Conversion of Laparoscopic Cholecystectomy to Open Cholecystectomy in Acute Cholecystitis: Artificial Neural Networks Improve the Prediction of Conversion

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Abstract. Laparoscopic cholecystectomy is now also performed for acute cholecystitis. In the presence of inflammatory conditions, technical difficulties leading to conversion to open cholecystectomy may occur and overshadow the advantages of the laparoscopic approach. Factors associated with these undue events combined with techniques capable of learning from them may help in determining when to completely avoid the laparoscopic procedure. In this study we determined predictors of conversion in acute cholecystitis and tested their predictive ability by means of statistical multivariate analysis and artificial neural networks. Between January 1994 and February 1997, 225 patients underwent laparoscopic cholecystectomy for acute cholecystitis. Preoperative and operative data were prospectively collected on standardized forms. The first 180 laparoscopically approached cases entered the training set, which was learned by both the statistical and the artificial neural networks methods. Conversion was first studied in relation to a set of preoperative data. Prediction models were then fitted by both of these methods. The last 45 operated cases, which remained unknown to the learning systems, served for testing the fitted models. The forward stepwise logistic regression technique, the forward stepwise linear discriminant analysis, and the artificial neural networks method enabled positive prediction of conversion in 0%, 27%, and 100% of the cases, and a negative prediction in 80%, 85.5%, and 97% respectively, in the training set. A positive prediction of conversion in 0%, 25%, and 67% of the cases, and a negative prediction in 82%, 88%, and 94%, respectively, in the untrained, validation set of patients. An artificial neural networks based model provides a practical tool for the prediction of successful laparoscopic cholecystectomies and their conversion. The high degree of certainty of prediction in untrained cases reveals its potential, and justifies, under appropriate conditions, the complete avoidance of laparoscopy and turning directly to open cholecystectomy.

Laparoscopic cholecystectomy (LC) is established as the treatment of choice for cholecystolithiasis, and it is now being proposed for the treatment of acute cholecystitis (AC) as well [1, 2]. However, technical difficulties may occur in the presence of inflammatory conditions, and in 20% to 30% of cases conversion to open cholecystectomy may be inevitable [3, 4]. Under these circumstances, the conversion and its consequences may overshadow all advantages of the laparoscopic procedure, making this approach unsafe, uneconomic, inefficient, and possibly inferior to the traditional open cholecystectomy. In about three-quarters of the cases of acute cholecystitis laparoscopic cholecystectomy can be performed safely, while in the remaining quarter open cholecystectomy may be preferable, illustrating how important it is, preoperatively, to be able to discriminate between these two groups. By identifying the subset of patients with a high potential for conversion, the laparoscopic attempt can be avoided by proceeding directly to an open operation. Appropriate study of the acute cholecystitis cases approached laparoscopically, including analysis of the factors associated with undue events, may serve to define predictors of conversion, may assist in planning a more effective and more efficient approach toward laparoscopic cholecystectomy, and may help in determining when to completely avoid the procedure.

The multivariate statistical discriminant analysis (MVA) [5] and the multilayered artificial neural networks (ANNs) [6] are two techniques capable of deriving information from labeled data and then generalizing this knowledge so that the outcome of further unseen but similar cases can be predicted. The MVA has the power of observation, analysis, and prediction of events, as well as defining factors associated with them. The ANNs perform, in addition, multiple nonlinear transformations, using their many parallel components; they constitute a model of computation that is stronger than the conventional statistical computation models [7, 8]. Because of their proven accuracy in pattern recognition [9, 10], the ANNs have gradually been introduced over the last 5 years into various laboratory and clinical settings in medicine. Applications include diagnostic [11–13], imaging [14–17], and outcome prediction [18–25]. Although the potential of this new tool has not yet been fully perceived, some of the reported results are impressive and promising.

This study was initiated to find factors associated with conversion to open cholecystectomy (by univariate analysis), then to identify predictors of conversion (by the MVA method), and finally to compare the effectiveness of the MVA and the ANN methods in predicting conversion. In our comparative study, data for both methods were derived from examples of a learning set of patients (training set), but the interpolative capabilities were ver-

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ified with data from a new and untrained group of patients (validation set).

Materials and Methods

Study Group

Between January 1994 and February 1997, 225 patients aged 18 to 92 years (mean 54.3 ± 16) were treated for clinical acute cholecystitis in the Department of Surgery, at Bnai Zion Medical Center. The clinical diagnosis was based on right upper quadrant pain and tenderness, fever and/or leukocytosis, and was supported by ultrasound findings in 210 cases (93%), by HIDA studies in 34 cases (15%), and/or by computed tomography (CT) scan in 4 cases (2%). In 125 cases (56%) this was the first presentation of biliary pathology, whereas 100 patients (44%) reported previous biliary disease. In all cases, as soon as the diagnosis was made, IV cephazolin was initiated, and the patient underwent emergency laparoscopy. In each procedure, one of four senior surgeons, each with an experience of at least 200 laparoscopic cholecystectomies, was involved. Hydrops and empyema of the gallbladder were intraoperative clinical diagnoses, while acute and gangrenous cholecystitis were pathologically confirmed. During surgery, the standard four-trocar technique was slightly modified for the inflammatory condition, as previously reported [2, 26], mainly to enable handling of the edematous and friable gallbladder.

The first 180 laparoscopically approached cases were entered into the study group (training set), which was studied by both the statistical and the artificial neural networks methods. The last 45 operated cases served for testing the generalization of the findings obtained by the fitted models of the two modalities (validation set). The characteristics, the clinical and laboratory findings, and the postoperative outcome of the two groups are comparatively presented in Table 1.

Data Collection

Data sheets containing demographic, preoperative, and operative information were prospectively generated. The preoperative notes included history of gall stones; duration of gallbladder complaints (as an indication of the onset of the disease); the presence of associated diseases (cardiac ischemia, hypertension, cerebrovascular accident, diabetes mellitus); the finding of a palpable gallbladder; temperature; and laboratory results of WBC count, serum bilirubin, diastase, and alkaline phosphatase. Operative data of concern were macroscopic intraoperative findings (of acute or gangrenous cholecystitis, hydrops, or empyema of the gallbladder), duration of surgery, and conversion of LC to open cholecystectomy. Gangrenous cholecystitis and empyema of the gallbladder were reported as "advanced cholecystitis," while acute cholecystitis and hydrops of the gallbladder were termed early cholecystitis."

All collected information was entered into a database as either continuous (quantitative data) or categorical (qualitative data) variables. The variables that were studied with relevance to conversion by the MVA and the ANN are presented in Table 2.

Table 1. Characteristics, clinical findings, and laboratory data of the training set and the set of cross-validation

	Training set (n = 180)	The set of cross-validation (n = 45)	p value
Age range (years)	18–92	23–80	
Median (years)	58	54	0.23
Gender: male/female	77/103	20/25	0.97
With/without associated disease	74/106	17/28	0.81
Abdominal scar present/absent	30/150	7/38	0.96
History of gallbladder disease positive/negative	83/97	17/28	0.40
Duration of complaints (hours)			
Range	6–480	6–450	
Median	64	52	0.93
Palpable/nonpalpable gallbladder	62/118	9/36	0.09
Range of temperature (°C)	36–40	36–40	
Median (°C)	37.5	37.5	0.76
Range of WBC × 1000 (/cc^3)	5.8–29	4.5–20.6	
Median (/cc^3)	12.25	12	0.35
Range of alkaline phosphatase (U/L)	35–313	35–350	
Median (U/L)	79	75	0.33
Range of bilirubin (mg/dL)	0.1–5.8	0.5–3.0	
Median (mg/dL)	0.8	0.9	0.37
Range of diastase (U/dL)	22–2865	28–1350	
Median (U/dL)	79	73	0.55
Stage of gallbladder disease			
Acute cholecystitis	72	22	
Gangrenous cholecystitis	57	13	
Hydrops of gallbladder	25	4	
Empyema of gallbladder	26	6	0.68
Advanced cholecystitis/acute cholecystitis	58/122	13/32	0.80
Duration of surgery			
Range (minutes)	15–225	30–300	
Median (minutes)	60	60	0.64
Converted/non-converted cases	36/144	8/37	0.90
Complicated/non-complicated cases			
Total complications	32/148	5/40	0.39
Infectious complications	12/168	1/44	0.43
Bile leak	8/172	1/44	0.80

WBC: white blood cells.

Table 2. The predicting variables that served the study of conversion in the logistic regression and discriminant analysis (MVA) and the multilayered artificial neural networks (ANN) analysis and their validation.

Variable 1, gender (male vs. female)
Variable 2, age[a]
Variable 3, with vs. without a history of gallbladder disease
Variable 4, with vs. without associated disease
Variable 5, duration of disease[a]
Variable 6, with vs. without an abdominal scar (indicating previous surgery)
Variable 7, temperature °C[a]
Variable 8, palpable vs. non-palpable gallbladder
Variable 9, WBC/cc^{3}[a]
Variable 10, bilirubin (mg%)[a]
Variable 11, alkaline phosphatase (IU/dL)[a]
Variable 12, diastase (U/dL)[a]

[a]Continuous data. All remaining variables are categorical data.

Statistical Methods

The Kolmogorov Smirnov test was used to define normal and non-normal distributions of variables. For comparison of the two groups, Chi-square analysis and Fisher's exact test were used when appropriate for qualitative data, and Student's t-test (for normal variables) or the Mann Whitney U-test (for non-normal variables) were used for quantitative data. Equality of variances in normally distributed variables was examined by the Levene test. For multivariate analysis and to enable prediction of conversion, the forward stepwise logistic regression technique and the linear discriminant analysis technique were applied. A probability of 0.05 or less was accepted as statistically significant.

Multilayered Artificial Neural Networks (ANNs)

The ANNs are computer programs that can be used to discover complex relations within data sets. They permit the recognition of patterns in complex biological data sets that cannot be detected by other means. The ANNs constitute parallel interconnections of simple processors, each of which computes a nonlinear function of its input. We recognize an input layer (composed of various data), hidden layers (calculated by various algorithms), and an output layer (computed by the ANNs and trying to resemble the desired output). The way the processors are interconnected and the algorithms in use determine their properties. Weights of input as well as calculated data, at different neurons and at various layers, are tuned and updated to bring the calculated output closer to the desired output. The ANNs are discussed in greater detail in the appendix. The neural networks were trained on a training set of 180 patients and evaluated using the validation set of 45 patients. The neural networks were generated with 12 input neurons, 4 hidden neurons, and 2 output neurons (Fig. 1). The variables 1 to 12 of Table 2 correlated to the input neurons. Each input variable (link) was multiplied by an appropriate constant (weight) and the result was then passed through a set of nonlinear functions of the 4 hidden neurons to 2 output neurons, generating the outcome—non-conversion (0), conversion (1). The learning process (training) involved repeated iteration cycles. With each iteration the constants (weights) were corrected according to a back-propagation algorithm in an effort to minimize the error between the calculated outcome and the observed outcome. The best weights obtained finally from the training process were introduced into the (ANNs) system to compute the predicted outcome of the validation group.

Results

*In the Study (Training) Set of Patients (*n *= 180)*

Of the 180 cases laparoscopically approached, 36 required conversion (20%). Most characteristics, preoperative clinical data, and laboratory data were comparable in the nonconverted and converted groups. Statistically significant differences between the two groups are presented in Table 3. Male gender, comorbidity, and older age were univariately associated with conversion.

By applying the MVA to the study group, it was noted that of all the preoperative data, male gender was the only independent factor associated with conversion ($p = 0.037$, odds ratio = 2.2). Based on this single factor, the forward stepwise logistic regression technique could predict conversion with a specificity of 100%, a sensitivity of 0%, a negative predictive power of 80%, and a positive predictive power of 0%, while the forward stepwise discriminant analysis predicted it with a specificity of 61%, a sensitivity of 58%, a positive predictive power of 27%, and a negative predictive power of 85.5%.

When our three-layered ANN was trained on the 180 patients of the study group, all the variables (of Table 2) served the prediction. The model achieved a specificity of 100%, a sensitivity of 89%, a positive prediction of conversion of 100%, and a negative prediction of conversion of 97%. These results are graphically illustrated in Fig. 2. The solid line in the figure illustrates the mode by which the ANN system builds up its learning curve, using the input information embedded in the training data set. With each iteration (learning step) the error domain narrows (Fig. 2A) and the predictive accuracy improves (Fig. 2B).

Table 4 summarizes the sensitivity, specificity, positive predictive value, negative predictive value, and total accuracy achieved in the training set with each of the study modalities.

*In the New and Untrained (Validation) Set of Patients (*n *= 45)*

To test the general validity of the predictive equations, fitted by the different techniques on the study group (training group, n = 180), we tested them on a completely new and yet untrained similar group (n = 45). Of the 45 cases laparoscopically approached, 8 required conversion (18%). The calculated conversions (according to the various predictive methods) were compared with the true conversions.

When the equation of the logistic regression technique was tested on the untrained population of the last 45 acute cholecystitis cases operated laparoscopically, positive prediction of conversion was completely unsuccessful and negative prediction of conversion was successful in 82% of cases. When the equation of the discriminant analysis was similarly tested, a positive prediction of conversion was noted in 25% of cases, and a negative prediction was seen in 88% of the cases. When the ANN was applied to an untrained set, the positive and negative predictions of conversion were 67% and 94%, respectively. Figure 2 illustrates the performance of the network in the training (solid line) as well as in the testing (dotted line) groups.

Table 5 summarizes the sensitivity, specificity, positive predictive value, negative predictive value, and total accuracy achieved for the validation set with each of the study modalities.

Discussion

It is now beyond dispute that laparoscopic cholecystectomy can be safely performed in the majority of acute cholecystitis cases, and when uneventfully completed, the advantages over open cholecystectomy are maintained. This was recently discussed by Kiviluoto et al., who noted a higher postoperative complication rate, a prolonged postoperative hospital stay, and a longer sick leave period in the group with open cholecystectomy as opposed to the group with laparoscopic cholecystectomy [27]. However, in about 20% to 30% of the cases, because of the inflammatory process, the procedure may be complicated and unsafe, demanding conversion [3, 4]. Under these circumstances, this inefficient, uneconomic, and sometimes time-consuming mishap proves to be inferior to the traditional open approach. Discrimination analysis between the group successfully operated by laparoscopy and the converted group will enable us to define characteristics associated with

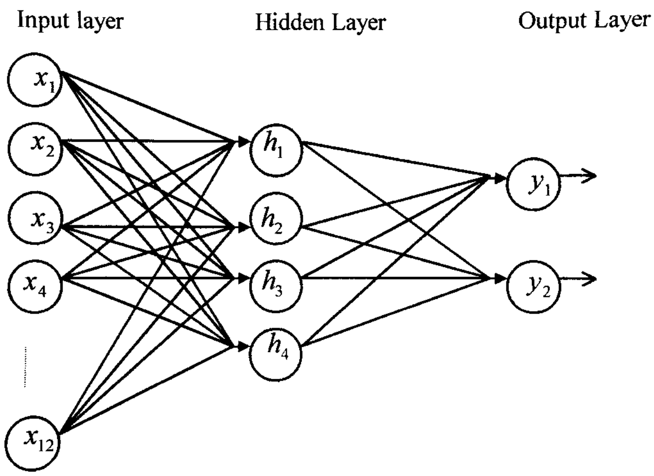

Fig. 1. Our feedforward neural network. Variables 1–12 of Table 2 are fed as x_1 to x_{12} in the input layer.

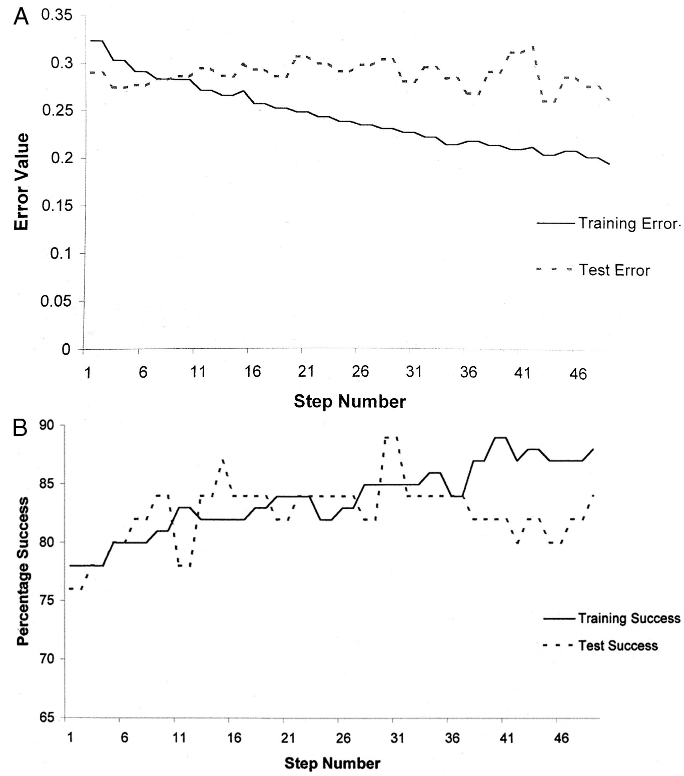

Fig. 2. Error estimates of the neural network training and testing (validation) sets following the learning process as a function of the iteration cycles (**A**). Approximation performance of the neural network training set and generalization performance of the test (validation) set as a function of the iteration cycles (**B**).

Table 3. Results of the predictive variables in the non-converted and converted groups (univariate analysis).

Variables	Non-converted group (n = 144)	Converted group (n = 36)	p-value/ Odds ratio
Males/females	56/88 (39%/61%)	21/15 (58%/42%)	0.035/2.2
Median age (range) (years)	55 (18–92)	63 (29–71)	0.05
History of gallbladder disease	66 (46%)	17 (47%)	0.88
Associated diseases	54 (37.5%)	20 (55.5%)	0.05/2
Median duration of complaints (range) (hours)	63 (6–480)	72 (10–240)	0.8
Abdominal scar	26 (18%)	4 (11%)	0.3
Median temperature (range) (°C)	37.5 (36–40)	37 (36.2–39.5)	0.09
Gallbladder palpation	53 (37%)	9 (25%)	0.18/1.75
Median WBC (range) (×1000/cc)	12 (5.9–29)	13 (5.8–20.6)	0.24
Median bilirubin (range) (mg%)	0.8 (0.1–5.8)	1.0 (0.38–2.9)	0.35
Median alkaline phosphatase (range) (U/L)	79 (35–313)	78.5 (38–203)	0.67
Median diastase (range) (U/L)	79 (22–2865)	80 (37–350)	0.4

Table 4. Sensitivity, specificity, positive predictive value, negative predictive value, and total accuracy of the trained group according to the various study modalities.[a]

Group	Sensitivity	Specificity	PPV	NPV	Total accuracy
Logistic regression	0	100	0	80	80
Discriminant analysis	58	61	27	85.5	60.5
ANN	89	100	100	97	98

PPV: positive predictive value; NPV: negative predictive value.
[a]Total number of cases = 180; converted cases = 36 (20%).

conversion and to use them to construct predictors. In this way, predictors can be used so that laparoscopy may be avoided altogether, thereby avoiding the conversion and its negative consequences.

A number of studies have attempted to define criteria of conversion of laparoscopic cholecystectomy to open cholecystectomy in acute cholecystitis [3, 28, 29]. All were based on statistical analysis. Elevated white blood cell count and gangrenous cholecystitis were reported as such criteria [3, 28, 29]. In two of our recent studies [26, 30], we extended the range of the conversion criteria. In the first study [26], factors such as age, a history of biliary disease, and a nonpalpable gallbladder were added. In the second study [30], based on an expanded pool of patients similar to that in the present study, male gender and a prolonged duration of disease were found to be associated with conversion. However, it remained uncertain whether these results were of any practical predictive use [30].

In the present study, we address this issue of practicality. Based on three statistical methods (the forward stepwise logistic regression, the forward stepwise linear discriminant analysis, and the multilayered artificial neural networks), mathematical models were fitted to associate conversion of laparoscopic cholecystectomy to open cholecystectomy in acute cholecystitis. The resultant sensitivity, specificity, positive predictive value, negative predictive value, and total accuracy obtained by the different models on

Table 5. Sensitivity, specificity, positive predictive value, negative predictive value, and total accuracy of the untrained group according to the various study modalities.[a]

Group	Sensitivity	Specificity	PPV	NPV	Total accuracy
Logistic regression	0	100	0	82	82
Discriminant analysis	62.5	59.5	25	88	60
ANN	75	92	67	94	89

[a]Total number of cases = 45; converted cases = 8 (18%).

the study (training) set (Table 4) are expressions of the significance, applicability, and practicality of these findings.

While the MVA bases its prediction of conversion on a few selected variables, for the same process, the ANN uses all available variables. In the present study for example, MVA based its predictability on the "gender only" entry in Table 2, while the ANN used all 12 factors of Table 2 for the same prediction of conversion. This difference is one possible explanation for the fact that the ANN-based model generated the best predictive characteristics for conversion (Table 4). The diagnostic accuracy of this ANN model may have been improved simply by detecting information in the clinical input that was not apparent to the MVA.

In regard to predictive means (methods or tools), an optimal predicting tool is one that has experienced an unbounded large training set. However, in any practical study the training set will be of limited size, and the limited training set may not be a good representative of the world. In specific cases of ANN, it may further be possible that a predicting tool has too many weights and although it would study any training set well, it will not be in the position to generalize well to unseen data (i.e., overtraining, excessive biasing).

To verify that our model is not too rich in weights, and that we are not in the situation of studying well only the training set, we tested our prediction on untrained data. In this way we carried the study a step further, constructing a more reliable predicting tool. The same three predictive models were tested on a new population, comparable to the training set (Table 1), but yet unexposed to the models (validation group). It is striking how the MVA results of the new population were comparable to those of the studied population, and how the ANN kept its superiority in this set as well (Table 5), thus supporting its strength to predict conversion from laparoscopic cholecystectomy to open cholecystectomy in acute cholecystitis. These findings may emphasize the robustness of the models.

The negative predictive value (NPV) and the positive predictive value (PPV) of Tables 4 and 5 relate to the prediction of a successful laparoscopic cholecystectomy and that of conversion, respectively. In the case of the untrained group (Table 5), the NPV of 94% expresses a very good ability to predict successful laparoscopic cholecystectomy. The PPV of 67%, on the other hand, expresses a less satisfactory ability to predict conversion. The current performance of the ANN-based model results in overestimation of the cases that will undergo successfully laparoscopic cholecystectomy, and underestimation of the cases demanding conversion. Practically, however, it reduces by two-thirds the cases that are attempted laparoscopically and then converted to open cholecystectomy.

The end point of this study is a computerized decision supporting system that will guide the individual approach to laparoscopic cholecystectomy in acute cholecystitis. Based on preoperative information that will be fed into the ANNs system, the probability for conversion will be calculated and the individual approach will be suggested. This will make the operative approach to acute cholecystitis safer, more efficient, and more economic in the majority of the cases.

To summarize, in our study an ANN-based model was shown to constitute a practical tool for evaluating the preoperative condition of patients with acute cholecystitis, under which LC is expected to be successful or may fail and need conversion. Its applicability stems from the high degree of certainty, of an order of about 67% to 94% of the prediction, achieved in groups unknown to the system. This prediction justifies the complete bypassing of laparoscopy under the appropriate conditions and turning instead to open cholecystectomy.

Résumé. De nos jours, la cholécystectomie laparoscopique est souvent réalisée pour la cholécystite aiguë. En présence d'inflammation, on peut rencontrer des difficultés techniques obligeant à convertir, annulant les avantages du procédé laparoscopique. Les facteurs associés aux évènements adverses ainsi que les techniques capables de prédire dans quel cas il faut éviter la laparoscopie sont donc utiles. Dans cette étude, nous avons déterminé les facteurs prédicteurs de conversion dans la cholécystite aiguë, et avons testé leur prédictibilité grâce à une analyse multivariée et un réseau d'intelligence artificielle. Entre janvier 1994 et février 1997, 225 patients ont eu une cholécystectomie laparoscopique pour cholécystite aiguë. On a cueilli des données prospectivement sur des formes standardisées. Les 180 premiers cas abordés par laparoscopie ont été entrés dans un modèle d'entranement animé par des méthodes statistiques et par un système d'intelligence artificielle. On a étudié la conversion d'abord par rapport aux données préopératoires. Les 45 derniers cas, inconnus par les systèmes d'apprentissage, ont servi ensuite pour tester les modèles.

Resumen. En la actualidad, la colecistitis aguda es también subsidiaria de una colecistectomía laparoscópica. Sin embargo, la reacción inflamatoria puede producir tales dificultades técnicas que obligen a una reconversión, lo que disminuye las ventajas del procedimiento laparoscópico. Los factores que acompañan a este irreparable hecho junto con las técnicas que permitan detectarlos previamente, pueden ser útiles a la hora de establecer las contraindicaciones de la laparoscopía. En este estudio se pretende detectar, en las colecistitis agudas, los factores de reconversión y evaluar mediante un análisis multivariante y merced al empleo de una red y de un programa que emule métodos de razonamiento análogos a los de los humanos, dichos factores pronósticos. Entre enero de 1994 y febrero de 1997 se trataron, mediante colecistectomía laparoscópica, 225 enfermos con colecistitis aguda. Los hallazgos pre e intraoperatorios se registraron prospectivamente de una forma estándar. Los primeros 180 casos tratados por laparoscópia se asignaron al grupo de adiestramiento/entrenamiento y fueron estudiados, no sólo mediante métodos analíticos sino también, para la programación del sistema computarizado de información. Los factores determinantes de la reconversión se estudiaron analizando, en primer término, el conjunto de hallazgos preoperatorios. Los modelos pronósticos se obtuvieron utilizando tanto los métodos analíticos como el sistema computarizado de información programada. Como control de los modelos adaptados, utilizamos los últimos 45 casos operados cuyas características desconocían los sistemas de adiestramiento.

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Appendix

Multilayered Artificial Neural Networks (ANNs)

The ANNs constitute parallel interconnections of simple processors, each of which computes a scalar nonlinear function of its input. The model of interest in this work is the feedforward network, characterized by the layer structure and the directionality of the computational flow from the input layer, through a couple of hidden layers and up to the output layer. Our working network had one hidden layer only and was built with 12 input neurons, 4 hidden neurons, and 2 output neurons [9, 10] (see Fig. 1). The input neurons distribute their values forward, these values corresponding to the patient's variables, as described in Table 2. The hidden neurons receive their input from the input layer, multiply it by the weights attached to their links, and pass it through the nonlinear activation function. The next layer receives its input from the hidden layer and outputs its results to the environment.

The architecture is fixed; the only adaptable parameters are the numerical values (weights) associated with links between neurons. Analysis is done by tuning the weights in the following manner. For each training example that consists of input I and its desired output D, I enters the network and the actual response A is compared against the desired response D. The weights of both the hidden and the output layers are updated in the direction of bringing A closer to D. The numerical update for tuning the weights was done in our implementation by means of gradient descent using the backpropagation algorithm [9, 10]. This is the most commonly used analytical algorithm for feedforward neural networks when training examples (I,D) are known, but without other extra "hints". It is known to be one of the fastest and most accurate algorithms for such cases. We used the activation function suggested by LeCun et al. [31], and applied on-line changes to both the study rate and the momentum. The tuning process is iterated on all training patterns a few times (Fig. 2). The goal, however, is not to load up the training input–output examples to an optimum, but rather to learn the "concept" and to generalize it to new cases of similar statistics.

References

1. Wiesen SM, Unger SW, Barkin JS, Edelman DS, Scott JS, Unger HM: Laparoscopic cholecystectomy: the procedure of choice for acute cholecystitis. Am. J. Gastroenterol. 1993;88:334–337
2. Zucker KA, Flowers JL, Bailey RW, Graham SM, Buell J, Imbembo AL: Laparoscopic management of acute cholecystitis. Am. J. Surg. 1993;165:508–514
3. Cox MR, Wilson TG, Luck AJ, Jeans PL, Padbury RT, Touli J: Laparoscopic cholecystectomy for acute inflammation of the gallbladder. Ann. Surg. 1993;218:630–634
4. Kum CK, Goh PMY, Isaac JR, Tekant Y, Ngoi SS: Laparoscopic cholecystectomy for acute cholecystitis. Br. J. Surg. 1994;81:1651–1654
5. Fisher LD, van Belle G: Biostatistics: A methodology for the Health Sciences. New York: Wiley-Interscience, pp. 630–665, 1993
6. Cross SS, Harrison RF, Kennedy RL: Introduction to neural networks. Lancet 1995;346:1075–1079
7. Siegelmann HT, Sontag ED: Analog computation via neural networks. Theoretical Computer Science 1994;131:331–360
8. Siegelmann HT: Computation beyond the tuning limit. Science 1995; 268:545–548
9. Bishop CM: Neural Networks for Pattern Recognition. Oxford: Clarendon, 1997, pp. 1–32
10. Haykin S: Neural networks—A Comprehensive Foundation, 2nd Ed., Prentice-Hall, Englewood Cliffs, NJ, 1999, pp. 156–175
11. Eberhart RC, Dobbins, RW, Hutton, LV: Neural network paradigm comparisons for appendicitis diagnosis. In Proceedings of the Fourth Annual IEEE Symposium on Computer-Based Medical Systems. Los Alamitos, CA, 1991:298–304
12. Patil S, Henry JW, Rubenfire M, Stein PD: Neural network in the clinical diagnosis of acute pulmonary embolism. Chest 1993;104:1685–1689
13. Baxt WG: Application of artificial neural networks to clinical medicine. Lancet 1995;346:1135–1138
14. Reinus WR, Wilson AJ, Kalman B, Kwasny S: Diagnosis of focal bone lesions using neural networks. Invest. Radiol. 1994;29:606–611
15. Wu Y, Giger ML, Doi K, Vyborny CJ, Schmidt RA, Metz CE: Artificial neural networks in mammography: application to decision making in the diagnosis of breast cancer. Radiology 1993;187:81–87
16. Hare BJ, Prestegard JH: Application of neural networks to automated assignment of NMR spectra of proteins. J. Biomol. NMR 1994;4: 35–46
17. Datz FL, Rosenberg C, Gabor FV, Christian PE, Gullberg GT, Ahluwalia R, Morton KA: The use of computer-assisted diagnosis in cardiac perfusion nuclear medicine studies: a review (part 3). J. Digit. Imaging. 1993;6:67–80
18. Doyle HR, Dvorchic I, Mitchell S, Marino IR, Ebert FH, McMichael J, Fung JJ: Predicting outcomes after liver transplantation: a connectionist approach. Ann. Surg. 1994;219:408–415
19. Ebell MH: Artificial neural networks for predicting failure to survive following in-hospital cardiopulmonary resuscitation. J. Fam. Pract. 1993;36:297–303
20. Buchman TG, Kubos KL, Seidler AJ, Siegforth MJ: A comparison of statistical and connectionist models for the prediction of chronicity in a surgical intensive care unit. Crit. Care Med. 1994;22:750–762
21. Grigsby J, Kooken R, Hershberger J: Simulated neural networks to predict outcomes, costs, and length of stay among orthopedic rehabilitation patients. Arch. Phys. Med. Rehabil. 1994;75:1077–1081
22. Snow PB, Smith DS, Catalona WJ: Artificial neural network in the diagnosis and prognosis of prostate cancer: a pilot study. J. Urol. 1994;152:1923–1926
23. Burke HB: Artificial neural networks for cancer research: outcome prediction. Semin. Surg. Oncol. 1994;10:73–79
24. Ravdin PM, Clark GM: A practical application of neural network analysis for predicting outcome of individual breast cancer patients. Breast Cancer Res. Treat. 1992;22:285–293
25. Wilding P, Morgan MA, Grygotis AE, Shoffner MA, Rosato EF: Application of backpropagation neural networks to diagnosis of breast and ovarian cancer. Cancer Lett. 1994;77:145–153
26. Eldar S, Sabo E, Nash E, Abrahamson J, Matter I: Laparoscopic cholecystectomy for acute cholecystitis: a prospective trial. World J. Surg. 1997;21:540–545
27. Kivilluoto T, Sirén J, Lluukkonen P, Kivilaakso E: Randomized trial of laparoscopic versus open cholecystectomy for acute and gangrenous cholecystitis. Lancet 1998;351:321–325
28. Rattner DW, Ferguson C, Warshaw AL: Factors associated with successful laparoscopic cholecystectomy for acute cholecystitis. Ann. Surg. 1993;217:233–236
29. Singer JA, McKeen RV: Laparoscopic cholecystectomy for acute or gangrenous cholecystitis. Am. Surg. 1994;60:326–328
30. Brodsky A, Matter I, Sabo E, Cohen A, Abrahamson J, Eldar S: Laparoscopic cholecystectomy for acute cholecystitis: can the need for conversion and the probability of complications be predicted? Surg. Endosc. 2000;14:755–760
31. LeCun Y: Generalization and network design strategies. In, Connectionism in Perspective. Pfeifer, R., Schreter, Z., Fogelman, F., Steels, L., editors. Zurich: Elsevier; 1989, pp. 143–156