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Artificial neural networks improve the prediction of Kt/V, follow-up dietary protein intake and hypotension risk in haemodialysis patients

Luca Gabutti[1], Dario Vadilonga[1], Giorgio Mombelli[2], Michel Burnier[3] and Claudio Marone[4]

[1]Division of Nephrology and [2]Department of Internal Medicine, Ospedale la Carità, Locarno, [3]Division of Nephrology, University Hospital of Lausanne and [4]Department of Internal Medicine, Ospedale San Giovanni, Bellinzona, Switzerland

Abstract

Background. Artificial neural networks (ANN) represent a promising alternative to classical statistical and mathematical methods to solve multidimensional non-linear problems. The aim of the study was to compare the performance of ANN in predicting the dialysis quality (Kt/V), the follow-up dietary protein intake and the risk of intradialytic hypotension in haemodialysis patients with that predicted by experienced nephrologists.

Methods. A combined retrospective and prospective observational study was performed in two Swiss dialysis units (80 chronic haemodialysis patients, 480 monthly clinical observations and biochemical test results). Using mathematical models based on linear and logistic regressions as background, ANN were built and then prospectively compared with the ability of six experienced nephrologists to predict the Kt/V and the follow-up protein catabolic rate (PCR) and to detect a Kt/V <1.30, a follow-up PCR <1.00 g/kg/day and the occurrence of hypotension.

Results. ANN compared with nephrologists gave a more accurate correlation between estimated and calculated Kt/V and follow-up PCR ($P < 0.001$). The same superiority of ANN was also seen in the ability to detect a Kt/V <1.30, a follow-up PCR <1.00 g/kg/day and the occurrence of hypotension expressed as a percentage of correct answers, sensitivity, specificity and predictivity.

Conclusions. The use of ANN significantly improves the ability of experienced nephrologists to estimate the Kt/V and the follow-up PCR and to detect a Kt/V <1.30, a follow-up PCR <1.00 g/kg/day and the occurrence of intradialytic hypotension.

Correspondence and offprint requests to: Luca Gabutti, Division of Nephrology, Department of Internal Medicine, Ospedale la Carità, Via Ospedale, 6600 Locarno, Switzerland. Email: lugabutti@swissonline.ch

Keywords: artificial neural networks; haemodialysis; hypotension risk; Kt/V; prediction; protein catabolic rate

Introduction

Nephrologists treating haemodialysis patients are faced with a large amount of clinical and biochemical historical data that have to be used to make clinical decisions. In this task, the physicians' experience assigning different weights to the known parameters continuously improves, allowing the elaboration of diagnostic and therapeutic strategies. Statistical models as multivariate linear or logistic regressions might ameliorate the outcome of the prediction based on intuition, but even these statistical procedures present limits due to the non-linearity of the multi-dimensional functions studied. In many fields of clinical medicine, artificial neural networks (ANN) have been used successfully to solve complex and chaotic problems without the need of mathematical models and a precise understanding of the mechanisms involved [1–3]. Pharmacodynamic analysis [4–6] (cyclosporin dosage adjustment [7], heparin pharmacokinetics during haemodialysis [8]), time-course and diagnosis of chronic nephropathies (IgA nephropathy [9], glomerular *vs* tubular renal disease [10]), allograft tolerance and function (chronic and acute allograft rejection [11–14]), diagnosis of renal transplant rejection [15], prediction of cytomegalovirus disease after renal transplantation [16], stratification of cardiac risk in renal transplantation [17] and haemodialysis efficiency evaluation (urea kinetic modelling [18,19]) are only a few examples of the artificial intelligence opportunities.

We decided to investigate the ability of an artificial intelligence software based on ANN to predict the Kt/V, the follow-up protein catabolic rate (PCR) and the risk of hypotension during a dialysis session in a

group of chronic haemodialysis patients. The predictions obtained with ANN, built keeping in mind the results of mathematical models based on linear or logistic regressions, were then compared with those obtained after submission of the same data to experienced nephrologists in charge of these patients.

The aim of the study was to verify whether ANN are useful tools in daily clinical practice to predict the dialysis quality, the follow-up dietary protein intake and the risk of hypotension.

Subjects and methods

A first random sample of chronic haemodialysis patients was selected from two independent dialysis units in south Switzerland in order to collect, retrospectively, the monthly clinical, biochemical and anthropometric parameters necessary to calculate the Kt/V, the theoretical Kt/V, the normalized PCR and to identify the haemodialysis sessions with symptomatic hypotension episodes. In order to estimate the changes of the protein intake, a supplementary column listing the PCR value of 1 month after the basis PCR (follow-up PCR) was added to the data table. With the intention to identify, on the basis of a classical statistical method, the data influencing the chosen dependent variables (Kt/V, follow-up PCR and hypotension episodes) and to build a mathematical estimation model, a linear regression for continuous data (Kt/V and follow-up PCR) and a logistic regression for dichotomous data (hypotension episodes) was performed. Furthermore, with the aim of building non-linear continuous functions exploring and expressing the interdependency between the collected data and the cited dependent variables, a series of ANN were trained until they were successfully tested. Finally, we selected, in a prospective way, a second chronic haemodialysis patient group from the same two independent dialysis centres in order to test the selected ANN and to compare their performance with the prediction of six experienced nephrologists of the same geographical region.

Patients and laboratory tests

We studied two random samples of 60 (control group; 420 biochemical and clinical monthly data) and 20 (experimental group; 60 biochemical and clinical monthly data) chronic haemodialysis patients (older than 17 years) treated for >6 months and without intercurrent illnesses at the moment of the enrolment.

The haemodialysis sessions were performed using a 4008 H bicarbonate-bag machine and a high-flux polysulfone membrane, both from Fresenius Medical Care (Stams, Switzerland).

Calculation of Kt/V, theoretical Kt/V and PCR

The Kt/V was calculated with a second generation single-pool Daugirdas formula [20]:

$$\mathrm{Kt/V} = -\ln(\mathrm{R} - 0.03) + [(4 - 3.5 \times \mathrm{R}) \times (\mathrm{UF/W})]$$

where R = post-dialysis blood urea nitrogen (BUN)/pre-dialysis BUN, UF = net ultrafiltration and W = weight. The theoretical Kt/V was calculated with the following formula [21]:

$$\text{Theoretical Kt/V} = \mathrm{Qb}\frac{\exp[(\mathrm{KoA/Qb})(1 - \mathrm{Qb/Qd})] - 1}{\exp[(\mathrm{KoA/Qb})(1 - \mathrm{Qb/Qd})] - (\mathrm{Qb/Qd})}\mathrm{dT}0.82/\mathrm{W}$$

where Qb = blood flow, KoA = urea mass transfer area coefficient, Qd = dialysate flow, dT = dialysis duration and W = weight. The normalized PCR was calculated with the Jindal and Goldstein formula [22]:

$$\mathrm{PCR} = 0.22 + [0.036 \times (\text{Follow-up BUN} - \text{Post-dialysis BUN}) \times 24]/\text{ID interval}$$

where follow-up BUN = BUN at the beginning of the second dialysis session of the week, post-dialysis BUN = BUN at the end of the first dialysis session of the week and ID interval = time interval between the two dialyses.

The results of the calculated monthly dialysis quality and nutritional parameters were for the control and experimental groups, respectively: Kt/V 1.39 ± 0.31 *vs* 1.38 ± 0.25, theoretical Kt/V 1.41 ± 0.39 *vs* 1.23 ± 0.26 and PCR 1.16 ± 0.26 *vs* 1.07 ± 0.22 g/kg/day.

Definition of symptomatic hypotension during the dialysis treatment

Hypotension episodes were defined as symptomatic falls of the systolic blood pressure below 90 mmHg or sudden and symptomatic falls of the systolic blood pressure of >30% of the previous measured values requiring isotonic saline infusion.

Artificial neural networks

ANN are accepted mathematical methods to translate complex multivariate non-linear relationships into continuous functions. According to Kolmogorov's theorem, paying attention to network structure, any arbitrary continuous function expressing the dependent variable on the basis of the input data may be built. ANN were created, trained (back-propagation algorithm) and tested using the BrainMaker Professional software (California Scientific Software 3.75). On the basis of a constant learning rate, the training tolerance and the percentage of good facts to stop training for each model were at first set at 15% and 95%, respectively. According to the recommendations of the software producer to optimize the performance of the network, the number of hidden layers was limited to one. This was built with the number of neurons equal to the number of input nodes if ≥ 10 or with 10 neurons for a number of input nodes <10 (default settings). Furthermore, to estimate the suitable minimum and maximum numbers of hidden neurons, the following two formulae were used:

$$\text{Minimum number of hidden neurons} = (\text{Number facts}/10) - \text{Input nodes} - \text{Output nodes}$$

$$\text{Maximum number of hidden neurons} = (\text{Number of facts}/2) - \text{Input nodes} - \text{Output nodes}$$

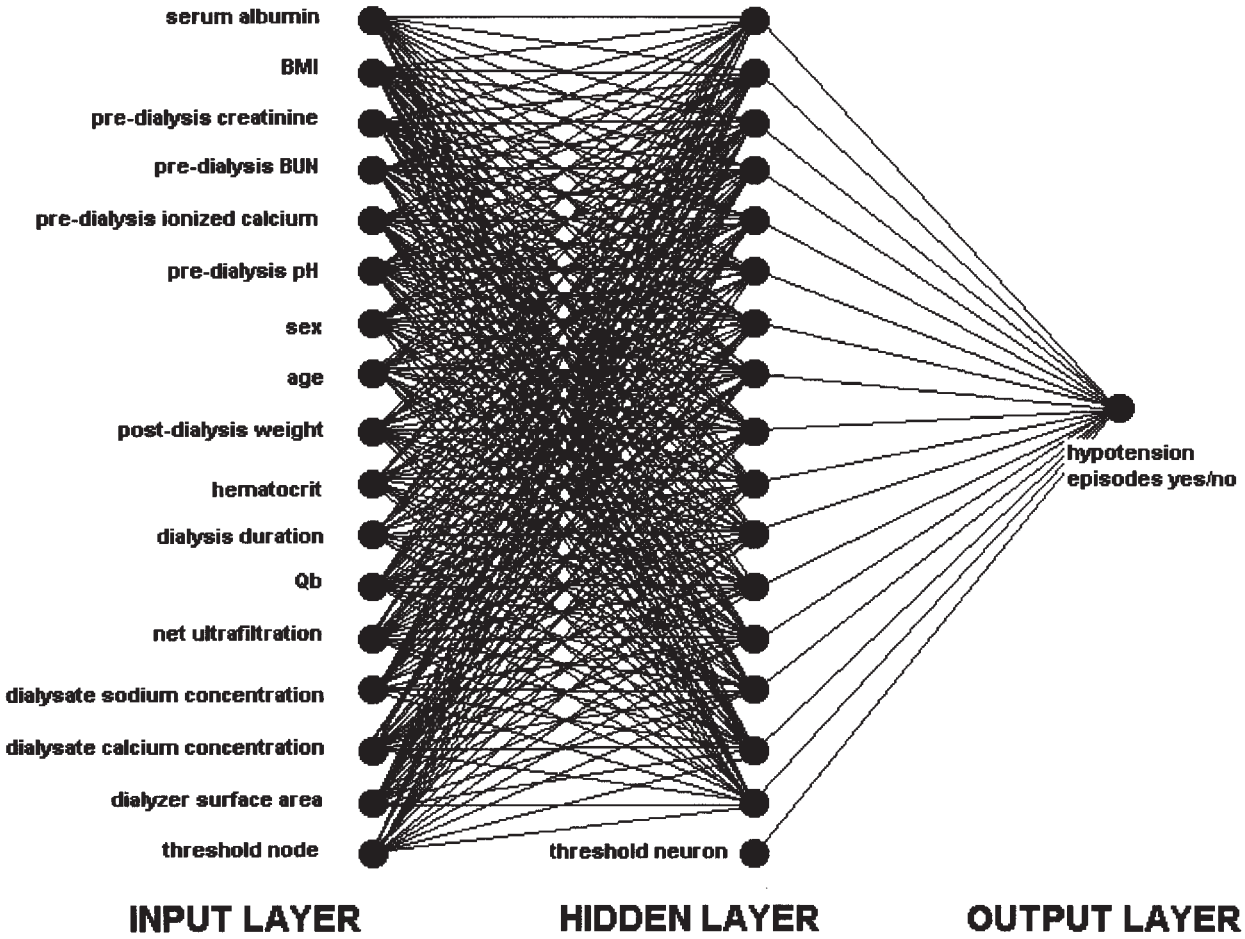

Fig. 1. Schematic representation of the ANN used to predict the occurrence of hypotension episodes: $16 + 1^{a}$ input variables, $16 + 1^{a}$ hidden neurons and 289 connections ([a]threshold node and neuron added to avoid a zero output in the following layer).

(guideline 2 of the BrainMaker Professional reference manual). The number of connections was then calculated as follows (Figure 1):

$$[(\text{Input nodes} + 1) \times \text{Hidden neurons}] + [(\text{Hidden neurons} + 1) \times \text{Output nodes}]$$

The '1' added optionally to both the input and the hidden layers represents a threshold neuron; an extra neuron that always fires at full strength allows the neurons in the next layer to have a non-zero output even if all inputs are zeros. A sigmoid transfer function was chosen for each neuron. An ANN was then designed and trained with the training tolerance and the percentage of good facts to stop training set, respectively, at 15% and 95% for the first attempt to obtain a successfully testable ANN, modifying then the tolerance stepwise from alternately plus or minus 0.5% until five ANN for each of the three dependent variables (Kt/V, follow-up PCR and hypotension episodes) were successfully tested ($>85\%$ of correct answers with a tolerance of 20%). As input nodes, the variables known or supposed to influence the value of the desired prediction (according to literature data, intuition and results of the linear and logistic regressions) have been used: nutritional (pre-dialysis serum phosphate, serum albumin, pre-dialysis creatinine, pre-dialysis BUN, pre-dialysis potassium and pre-dialysis ionized calcium), anthropometric (sex, age and body mass index), biological (haematocrit) and dialysis quality (post-dialysis weight, net ultrafiltration, Qb × dialysis duration and dialyser surface area) parameters to predict Kt/V (15 input variables, 15 hidden neurons and 255 connections), nutritional (pre-dialysis serum phosphate, serum albumin, net ultrafiltration, pre-dialysis BUN and PCR) and dialysis quality (Kt/V) parameters to predict follow-up PCR (six input variables, 10 hidden neurons and 81 connections) and nutritional (serum albumin, body mass index, pre-dialysis creatinine, pre-dialysis BUN, pre-dialysis ionized calcium and pre-dialysis pH), anthropometric (sex, age and post-dialysis weight), biological (haematocrit) and dialysis (dialysis duration, Qb, net ultrafiltration, dialysate sodium and calcium concentrations and dialyser surface area) parameters to predict the occurrence of hypotension (16 input variables, 16 hidden neurons and 289 connections). The study was designed according to the prescriptions of Cross *et al.* [3].

Statistical and data analysis

Statistical and data analysis was performed using two different statistical software packages (Systat 7.0 and SPSS 11.0; SPSS Inc.). Systat was used to perform the multivariate

logistic regression involving the hypotension substudy, whereas SPSS was used to elaborate the multivariate linear regression of the Kt/V and follow-up PCR substudies. Non-parametric kernel density estimators were used to show the distribution of the relative error generated from the estimation of the Kt/V and follow-up PCR. The differences between kernel curves were judged with a repeated-measure analysis of variance (ANOVA) and a post-hoc Bonferroni test. In all cases a P-value of ≤ 0.05 was considered statistically significant. Accuracy is expressed by the combined root mean square error calculated as the square root of [(mean difference in estimate – observed)^2 + (SD of the difference)^2]. Agreement between the predictions and the basis data is expressed by 'limits of agreement', '95% confidence interval for the bias' and '95% confidence interval for the lower and upper limits of agreement', according to Bland and Altman [23]. For Kt/V and follow-up PCR, results were expressed using a cut-off of, respectively, 1.30 and 1.00 g/kg/day to define correct answers and consequently sensitivity, specificity and predictivity (= positive predictive value) of the ANN or nephrologists estimations. The differences between these data were judged with a two samples Student's t-test. Values are presented as means ± SD.

Comparison with experienced nephrologists

Six nephrologists from three different Swiss dialysis centres were shown the monthly clinical, biochemical and anthropometric data of the experimental group and they were asked to predict the Kt/V, the follow-up PCR and the occurrence of hypotension. The distribution of the error in the prediction (for Kt/V and follow-up PCR), the amount of correct answers, the sensitivity, the specificity and the predictivity were than compared with the results obtained with the selected ANN.

Results

The characteristics of the studied populations, the haemodialysis prescriptions and the results of the monthly biochemical parameters in the experimental and control groups are listed in Table 1. Table 2 shows the results of the logistic regression for the estimation of occurrence of hypotension during dialysis ($P < 0.001$) and of the linear regressions for the estimation of the Kt/V ($P < 0.001$) and the follow-up PCR ($P < 0.001$). The model for the estimation of occurrence of hypotension gives a significant correlation only for age, net ultrafiltration, serum phosphate and dialysate sodium; that for the estimation of Kt/V demonstrates a significant correlation only for body mass index, net ultrafiltration and serum pH, BUN and creatinine and, finally, only serum phosphate and BUN, basis PCR and dialysate calcium show a significant correlation for follow-up PCR.

Figure 2 depicts graphically the distribution of the absolute error for the estimation of Kt/V predicted from ANN, nephrologists and obtained with the

Table 1. Characteristics of the studied populations, haemodialysis prescriptions and results of the monthly biochemical parameters in the experimental and control groups

Characteristic	Control group	Experimental group
Age (years)	70 ± 13	69 ± 13
Dry weight (kg)	68 ± 11	69 ± 8
Body mass index (kg/m^2)	25 ± 3	25 ± 3
Net ultrafiltration (ml)	1490 ± 1220	1400 ± 1040
Male/female ratio	1	1
Haemodialysis duration (h)	3.28 ± 0.47	3.06 ± 0.28
Dialyser effective surface area (m^2)	1.8 ± 0.3	1.8 ± 0.3
KoA urea (ml/min)	1242 ± 97	1239 ± 95
Effective blood flow (ml/min)	307 ± 71	302 ± 62
Dialysis fluid temperature (°C)	36.5 ± 0	36.5 ± 0
Dialysis fluid flow rate (ml/min)	600 ± 0	600 ± 0
Dialysis fluid sodium (mmol/l)	139 ± 1	139 ± 1
Dialysis fluid potassium (mmol/l)	2.4 ± 0.9	2.5 ± 0.7
Dialysis fluid calcium (mmol/l)	1.42 ± 0.19	1.47 ± 0.18
Dialysis fluid bicarbonate (mmol/l)	31 ± 1	31 ± 1
Dialysis fluid magnesium (mmol/l)	0.5 ± 0	0.5 ± 0
Dialysis fluid acetate (mmol/l)	3.0 ± 0	3.0 ± 0
Dialysis fluid glucose (g/l)	1.0 ± 0	1.0 ± 0
Pre-dialysis creatinine (μmol/l)	698 ± 213	693 ± 219
Post-dialysis creatinine (μmol/l)	273 ± 83	273 ± 80
Pre-dialysis BUN (mmol/l)	24.9 ± 6.6	22.5 ± 5.7
Post-dialysis BUN (mmol/l)	7.7 ± 3.0	6.9 ± 2.4
Pre-dialysis potassium (mmol/l)	5.3 ± 0.8	5.1 ± 0.6
Post-dialysis potassium (mmol/l)	3.8 ± 0.3	3.8 ± 0.4
Pre-dialysis phosphate (mmol/l)	1.69 ± 0.52	1.58 ± 0.64
Pre-dialysis ionized calcium (mmol/l)	1.23 ± 0.13	1.15 ± 0.10
Pre-dialysis pH	7.38 ± 0.04	7.37 ± 0.05
Pre-dialysis haematocrit (%)	33.7 ± 4.1	34.8 ± 4.0
Pre-dialysis albumin (g/l)	36.9 ± 3.5	35.5 ± 3.7

Values are means ± SD.

Table 2. Results of the logistic regression for the estimation of occurrence of hypotension during dialysis and of the linear regressions for the estimation of Kt/V and follow-up PCR

Dependent variable Statistical method	Hypotension Logistic regression		Kt/V Linear regression		Follow-up PCR Linear regression	
	Odds ratio	*P*-value	Beta coefficient (standardized)	*P*-value	Beta coefficient (standardized)	*P*-value
Sex	2.48	0.100	0.03	0.157	0.45	0.452
Age	1.06	0.002	−0.01	0.795	−0.08	0.112
Body mass index	1.62	0.386	−0.34	0.010	−0.50	0.089
Dry weight	0.81	0.432	0.28	0.028	0.62	0.072
Ultrafiltration	0.85	0.000	0.16	0.000	0.00	0.978
Dialysis duration	1.61	0.830	0.05	0.429	−0.04	0.807
Blood flow	1.00	0.965	−0.20	0.388	−0.08	0.900
Phosphate[a]	2.46	0.012	0.01	0.605	−0.09	0.031
Potassium[a]	0.74	0.367	−0.02	0.325	0.05	0.407
Ionized calcium[a]	12.8	0.147	−0.02	0.308	0.03	0.460
pH[a]	0.29	0.748	0.05	0.002	−0.02	0.653
Creatinine[a]	1.00	0.506	0.17	0.000	0.25	0.065
BUN[a]	0.99	0.955	0.66	0.000	−0.41	0.015
Haematocrit	1.06	0.244	0.03	0.070	−0.05	0.220
Albumin[a]	0.98	0.764	−0.03	0.108	0.05	0.291
Kt/V	11.2	0.196	N/A	N/A	0.09	0.523
PCR	0.53	0.695	N/A	N/A	0.66	0.000
Potassium[b]	1.62	0.153	0.00	0.968	−0.05	0.403
Sodium[b]	1.38	0.010	0.01	0.500	−0.05	0.259
Calcium[b]	0.57	0.521	−0.01	0.650	0.08	0.041
Dialyser area	0.23	0.191	−0.03	0.122	0.06	0.253

[a]In serum at the beginning of the dialysis session; [b]in dialysate. N/A, not available for estimation.

Brenner and Drukker formula. The ANOVA of the absolute value of the error for the three predictions reaches a significant level, which is compatible with the curves behaviour. The differences between the ANN curve and the other two is significant according to a post-hoc Bonferroni test. Similarly, Figure 3 shows the same curves for the estimation of follow-up PCR predicted from ANN and nephrologists. The ANOVA

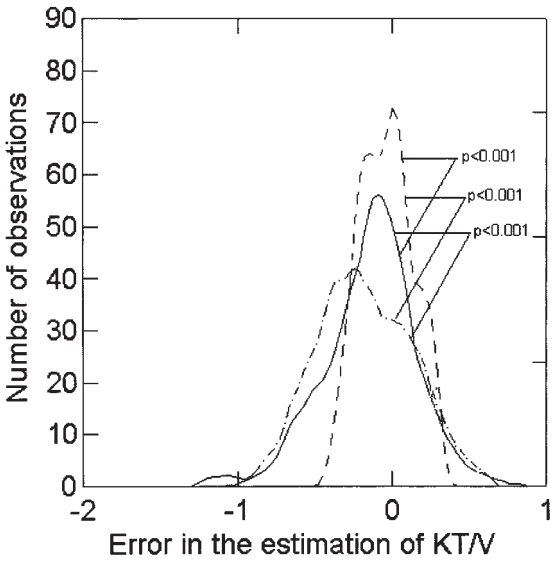

Fig. 2. Non-parametric kernel density estimator (analogous to a continuous histogram that shows where the data are most concentrated in the sample) showing the distribution of the absolute error for the estimation of Kt/V. Dashed line, ANN; solid line, nephrologists; dashed and dotted line, theoretical Kt/V obtained with the Brenner and Drukker formula. *P*-values for the differences between the curves have been superimposed on the graph.

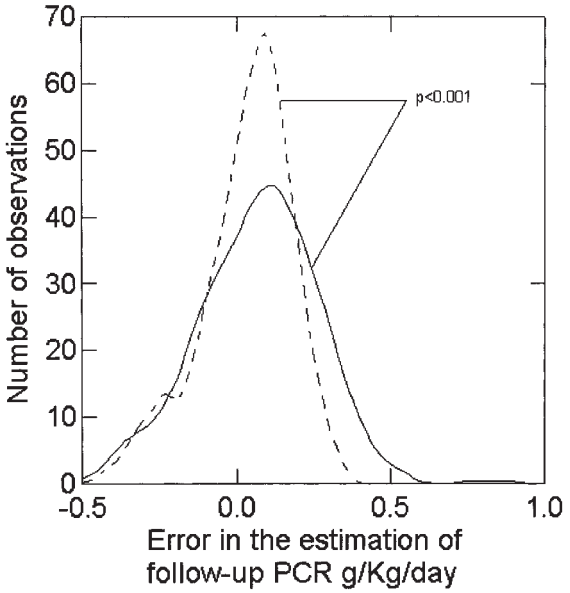

Fig. 3. Non-parametric kernel density estimator (analogous to a continuous histogram that shows where the data are most concentrated in the sample) showing the distribution of the absolute error for the estimation of follow-up PCR. Dashed line, ANN; solid line, nephrologists. *P*-values for the differences between the curves have been superimposed on the graph.

Table 3. Accuracy expressed by the combined root mean square error, agreement expressed by the 'limits of agreement', the '95% confidence interval for the bias' (95% bias) and the '95% confidence interval for the lower (95% lower) and upper (95% upper) limits of agreement' in the estimation of Kt/V and follow-up PCR. *P*-values are specified only if differences are signifcant

	Estimation of Kt/V			Estimation of follow-up PCR	
	ANN	Nephrologists	Theoretical Kt/V	ANN	Nephrologists
Accuracy	0.17 ± 0.01	0.30 ± 0.04	0.37	0.15 ± 0.01	0.21 ± 0.04
	P < 0.001			P < 0.01	
LA	0.37 ± 0.03	−0.65 ± 0.10	0.03	−0.26 ± 0.06	−0.32 ± 0.09
	P < 0.001				
	0.30 ± 0.04	0.38 ± 0.15	0.06	0.32 ± 0.02	0.45 ± 0.09
				P < 0.001	
95% Bias	–0.07 ± 0.02	–0.18 ± 0.08	–0.25	0.00 ± 0.03	0.03 ± 0.02
	P < 0.01			P < 0.05	
	–0.01 ± 0.02	–0.09 ± 0.09	–0.14	0.06 ± 0.03	0.10 ± 0.02
	P < 0.05			P < 0.01	
95% Lower	–0.42 ± 0.03	–0.73 ± 0.11	–0.91	–0.31 ± 0.06	–0.38 ± 0.10
	P < 0.001				
	–0.32 ± 0.02	–0.57 ± 0.09	–0.72	–0.22 ± 0.05	–0.26 ± 0.08
	P < 0.001				
95% Upper	0.25 ± 0.04	0.31 ± 0.14	0.34	0.28 ± 0.02	0.40 ± 0.08
				P < 0.001	
	0.35 ± 0.05	0.46 ± 0.16	0.53	0.37 ± 0.02	0.51 ± 0.11
				P < 0.001	

Values are means ± SD. LA, limits of agreement.

of the absolute value of the error for the two predictions also reaches a significant level for these distributions.

According to Bland and Altman, agreements between the predictions and the basis data expressed by 'limits of agreement', '95% confidence interval for the bias' and '95% confidence interval for the lower and upper limits of agreement' are given in Table 3. These results are concordant with the previous statistical analysis and confirm the overall reduction in the magnitude of the error by the use of ANN.

Histograms showing the percentage of correct answers, sensitivity, specificity and predictivity in the estimation of the occurrence of hypotension, of the Kt/V (lower or higher than 1.30) and of follow-up PCR (lower or higher than 1.00 g/kg/day) for the ANN and the nephrologists are presented in Figure 4, whereas the absolute numbers of correct answers, true and false positive and false negative in the same estimations are listed in Table 4.

Discussion

In the evaluation of chronic haemodialysis patients, biochemical data determined at monthly intervals, as well as clinical parameters registered at each dialysis session, hide important information that could be very useful for the management of the patients and for the continuing education of the nephrologist himself. Our data show that the use of ANN enables to achieve a better prediction of Kt/V, follow-up PCR and occurrence of intradialytic hypotension than the intuitive prediction of experienced nephrologists.

Mathematical models based on usual statistics are often disappointing when used to analyse multidimensional non-linear data. In fact, logistic regression applied to the risk of hypotension (dichotomous data) and linear regressions used to estimate Kt/V and follow-up PCR (continuous variables), on the one hand, did not permit building a model that could be used in the daily clinical practice and, on the other,

Table 4. Ability to detect a Kt/V < 1.30, a PCR < 1.00 g/kg/day and hypotension episodes expressed as correct answers, true and false positive and false negative ($n = 60$). *P*-values are specified only if differences are significant

	Kt/V < 1.30 ($n = 19$)		PCR < 1.00 g/kg/day ($n = 24$)		Hypotension episodes ($n = 13$)	
	ANN	NEPH	ANN	NEPH	ANN	NEPH
Correct answers	48.7 ± 0.5	34.0 ± 3.8	49.8 ± 1.3	41.6 ± 3.4	46.7 ± 2.3	45.0 ± 2.6
	P < 0.001		P < 0.001			
True positive	16.0 ± 0.0	14.3 ± 3.9	17.4 ± 0.9	8.8 ± 1.9	9.7 ± 1.0	2.5 ± 2.4
			P < 0.001		P < 0.01	
False positive	8.2 ± 0.5	21.3 ± 5.0	3.6 ± 0.6	3.2 ± 2.4	10.0 ± 3.2	4.5 ± 2.1
	P < 0.01				P < 0.05	
False negative	3.0 ± 3.0	4.7 ± 3.9	6.6 ± 0.9	15.2 ± 1.9	3.2 ± 1.0	10.5 ± 2.4
			P < 0.001		P < 0.01	

Values are means ± SD. NEPH, nephrologists.

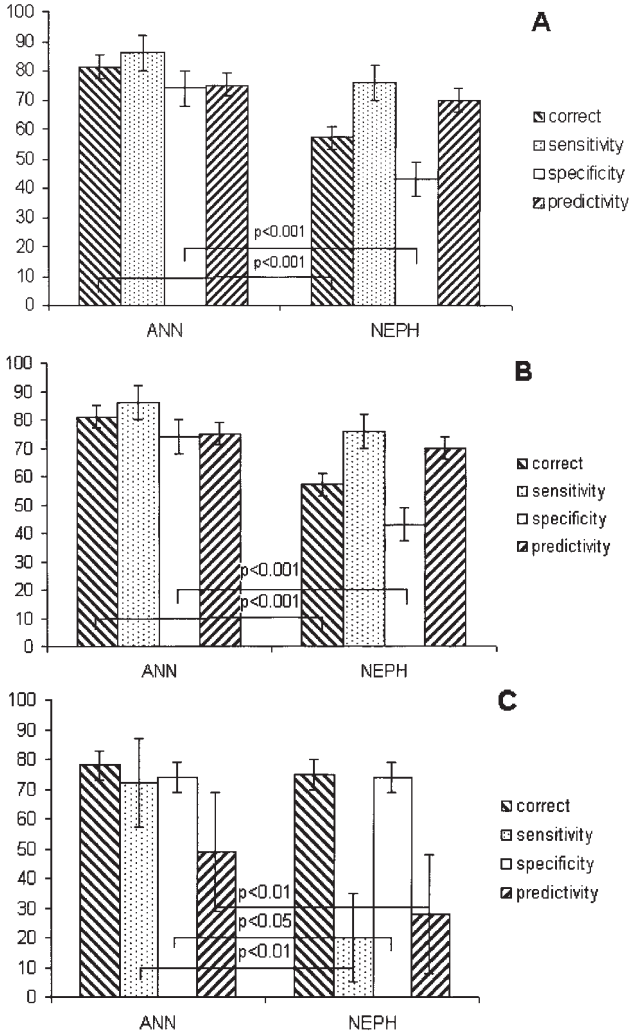

Fig. 4. Histograms showing the percentage of correct answers, the sensitivity, the specificity and the predictivity in the estimation of (**A**) the Kt/V (lower or higher than 1.30), (**B**) the follow-up PCR (lower or higher than 1.00 g/kg/day) and (**C**) the occurrence of hypotension episodes for, respectively, the ANN and the nephrologists (NEPH). Significant differences are highlighted (*P*-values are specified).

sometimes gave disconcerting results. For instance, in the linear regression using Kt/V as the dependent variable, body mass index, dry weight, ultrafiltration and pre-dialysis BUN, creatinine, pH and haematocrit contrary to blood flow, dialyser area and dialysis duration surprisingly gave no significant correlations. Keeping in mind that for the calculation of Kt/V we used a single-pool model that gave an estimation of the true value based only on BUN, dry weight and ultrafiltration and that the variability in the distribution of the data for blood flow, dialyser area and dialysis duration in the studied population was low, the beta-coefficients and the *P*-values of the linear regression are not as strange as they appear at first sight. Furthermore, linear regressions, as expressed by their name, are not able to show positive correlations based on non-linear functions, such as logarithmic, exponential or polynomial.

Data multidimensionality and non-linearity are the typical application fields for artificial intelligence and, in particular, for ANN. These programs have been successfully utilized in various medical specialties and the number of published studies demonstrates that the subject is in continuous rapid expansion [4–19].

Our data, in the absence of previous comparable studies, show that:

(i) The information contained in the historical biochemical results and clinical parameters of the patients might significantly improve the ability of nephrologists to predict the occurrence of intradialytic hypotension episodes. This means that our intuition, even if supported by long experience and the classical statistical methods, misses out on an important part of the usually available information.

(ii) The useful experience of the nephrologists enables a more accurate prediction of Kt/V than the algorithm proposed by Brenner and Drukker [22].

(iii) Nevertheless, in the estimation of Kt/V, artificial intelligence can further improve the prediction.

(iv) Even in the prediction of follow-up PCR, which in day to day experience might resemble an unsolvable task, ANN demonstrate their positive performance and potential usefulness.

In conclusion, our data show that ANN can give a significant contribution and be helpful tools in clinical practice for the nephrologist treating chronic haemodialysis patients. The correct appreciation of the intradialytic hypotension risk and of the trend in the evolution of the nutritional state are two capital challenges that could be solved by an ANN approach, thus permitting the application of prophylactic measures.

Future studies will show in which way the ANN performance could be further improved by increasing the extension of the retrospective data-pool and/or by the application of the method to the clinical course of a single patient.

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Conflict of interest statement. None declared.

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