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APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PREDICTION OF BLADDER OUTLET OBSTRUCTION: A MODEL BASED ON OBJECTIVE, NONINVASIVE PARAMETERS

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ABSTRACT

Objectives. An artificial neural network model previously described by us that was based on lower urinary tract symptoms yielded a modest prediction of bladder outlet obstruction. The aim of this study was to establish another model, using more objective parameters, that could better predict for bladder outlet obstruction.

Methods. The records of 457 patients were used in the construction of the model. Of the 457 records, 300 were allocated to the training phase and 157 to the testing phase. All patients had the average flow rate, maximal flow rate, postvoid residual urine volume (PVR), and total prostate volume recorded. The results of the pressure flow study of those patients were considered the reference standard against which the artificial neural network was tested.

Results. Three models were tested. Models 1 and 2 were based on a three-output design (ie, nonobstructed, equivocal, and obstructed). The only difference was the number of iterations. The accuracy of the first model was 60.5% compared with 46.5% for the second. For a third model, in which the equivocal pressure flow study results were added to the nonobstructed group, the accuracy rose to 72%. Deletion of equivocal cases (around 19% of the total) was associated with an accuracy of 76% in the prediction of obstruction.

Conclusions. An artificial neural network based on objective and noninvasive parameters could replace the pressure flow study in only 72% of cases. An accuracy of 76% in the detection of bladder outlet obstruction is rather impractical, because an equivocal zone has always been available on pressure flow study nomograms. UROLOGY **68:** 1211–1214, 2006.

On the basis of our previous results, and those of other studies,[1–3] that indicated a failure of statistical correlation between symptom scores and objective measurements of bladder outlet obstruction (BOO), the potential of using an artificial neural network (ANN) in this regard was explored.[4] Because the initial experience with using an ANN as a less-invasive approach to the prediction of BOO did not result in high overall accuracy and sensitivity, another ANN model was constructed using different sets of more objective input parameters in the hopes of increasing the ability to predict for BOO.

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MATERIAL AND METHODS

The records of 457 men with lower urinary tract symptoms were used in this study. The study inclusion criteria were patient age older than 45 years and the presence of lower urinary tract symptoms suggestive of benign prostatic hyperplasia (BPH). Men with an indwelling urethral catheter, previous medical or surgical treatment of BPH, associated bladder pathologic findings, urethral strictures, or neuropathic bladder pathologic features were excluded from the study.

Data previously collected[1] using invasive (pressure flow study [PFS]) and noninvasive urodynamic measurements were used in this investigation. The interpretation of the pressure flow pattern was accomplished using the linear passive urethral resistance relation.[5] Grades 0 and 1 signified no obstruction, grade 2 indicated equivocal obstruction, and grades 3 through 6 indicated increasingly severe obstruction.

The back propagation neural network was the model used in our study. It is a network consisting of a series of processing elements (neurons) arranged in layers.[6] Each of these neurons is capable of simple computational processes. The neurons are

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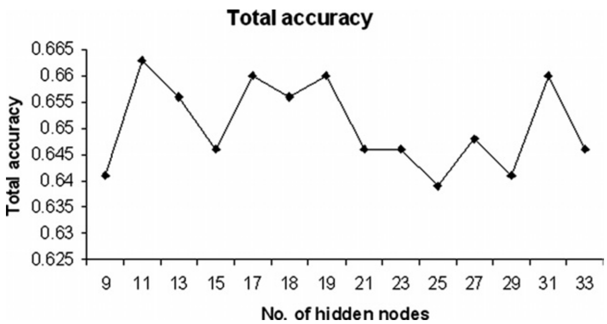

FIGURE 1. *Total accuracy percentages versus number of nodes in hidden layer.*

interconnected with each other and with neurons of the subsequent layer. Connections are given weights, and the process of learning entails changing these weights to obtain a minimal output error. This process is repeated a large number of times (epochs or iterations) to obtain the desired output.[6]

The data were fed to a specially designed ANN that had been constructed using Matlab software, version 6.5 (Mathworks). The backbone of this network is the feed forward-back propagation architecture, with a momentum constant of 0.7. The network consisted of three layers: input, hidden, and output. The input layer was composed of four neurons to which the values of the average flow rate, maximal flow rate (Qmax), postvoid residual urine (PVR) volume, and total prostate volume (using transrectal ultrasonography) were fed.

The hidden layer consisted of a variable number of neurons and was the layer at which the computation and differential weighing take place. The number of neurons varied according to the model tested and used several configurations with a fixed number of epochs (10,000) and a fixed momentum constant (0.7). The output layer was the layer at which the results of the PFS were entered. It consisted of three neurons (obstructed, nonobstructed, and equivocal) or two neurons (no obstruction [Schafer grade 0, 1, or 2] and obstruction [grades 3 to 6]). The total accuracy of each configuration was calculated (defined as the number of correctly diagnosed cases per the total number of cases). The configuration with the greatest accuracy was chosen. Figure 1 shows the relation between the total accuracy percentages versus the number of hidden layer nodes for the three-class output system in the initial phase. According to the learning set data, the best configuration for the three-class model was 4-11-3 and that for the two-class output system was 4-7-2.

The training set consisted of the records of 300 patients. The network thus trained was used to predict the pressure flow pattern of an additional 157 patients—the testing set. The distribution of cases among the two groups was similar in terms of the percentage of cases in the three output categories (no obstruction, equivocal, and obstruction).

During training, the ANN is fed with the values of the input parameters of the patients whose pressure flow results are known to the network. During testing, the network is fed with the input only, with output blinded. Diagnostic accuracy was calculated as the ratio of correctly diagnosed cases by the ANN classifier to the total number of cases diagnosed by the pressure flow plot (diagonal row of values in the confusion matrix).

RESULTS

Using four objective parameters and 10,000 epochs (iteration), the accuracy of the model in the training set (using the records of 300 patients) was 69.3%. Table I shows the confusion matrix of a three-output model (model 1), with 10,000 epochs. During testing, the accuracy dropped to 60.5% (Table II). Increasing the number of epochs during training was associated with increased prediction accuracy, but this was associated with "overfitting" of the model, such that when applied to the testing set of data, the accuracy decreased sharply to 46.5%. Tables III and IV demonstrate the confusion matrices of the ANN classifier at 1,000,000 epochs (model 2).

The accuracy of the classifier in detecting equivocal cases was consistently low, ranging from 26% to 48% in the previous models. Accordingly, a two-output model was created, with patients with a grade 2 linear passive urethral resistance relation pressure flow included in the "no obstruction" output. The accuracy of the thus-constructed models increased to 76.7% and 72% in the training and testing sets, respectively. Tables V and VI show the results of the prediction using a two-output nodes model (model 3).

Using the two-output model (deletion of the equivocal cases from the training and testing sets) and 10,000 epochs was associated with a significant increase in the accuracy of the model, at the same momentum constant (0.7). In the training set (239 patients), the accuracy was 88% and in the testing set (100 patients), it was 76%.

COMMENT

The diagnosis of BOO attributable to BPH has been always challenging. Although the reference standard test for the diagnosis of BOO is the PFS,[7] the routine application of PFS to all men with lower urinary tract symptoms and BPH is practically impossible, because it is invasive, time consuming, and costly. Symptom scores have been widely used in the quantification of symptomatic BPH, in combination with other parameters with poor correlation.[8] This has also been documented by us in an earlier study.[1,4] Accordingly, another approach was used in an attempt to improve the predictability of BOO using noninvasive parameters commonly available for patients with lower urinary tract symptoms attributable to BPH.

Different less-invasive objective parameters have been assessed for their association/correlation with BOO detected by PFS. Vesely *et al.*[9] found that Qmax, prostate volume, and PVR showed significant differences among groups of men with PFS-proved obstruction. Others[10] have demonstrated a 100% positive predictive value for a Qmax of less than 10 mL/s in a small cohort of asymptomatic men but found that a PVR of greater than 50 mL yielded no predictive value at all in the same group. However, the Qmax cutoff threshold of 10 mL/s was studied in a larger sample (1271 patients from

TABLE I. ***Confusion matrix of learning set of ANN with four input variables* to predict three output variables with configuration 4-11-3 with 10,000 epochs***

Classifier	PFS Results: No Obstruction	Equivocal	Obstruction	Total
No obstruction	20	10	6	36
Equivocal	5	8	3	16
Obstruction	25	43	180	248
Total	50	61	189	300

Key: ANN = artificial neural network; PFS = pressure flow study; Qave = average urinary flow rate; Qmax = peak urinary flow rate; PVR = postvoid residual urine volume; TRUS = transrectal ultrasound.
Accuracy (ratio between diagonal [correct data] and total number) was 69.3%.
** Qave, Qmax, PVR, and TRUS-determined prostate volume.*

TABLE II. ***Confusion matrix in testing set of ANN with four input variables* to predict three output variables with configuration 4-11-3 with 10,000 epochs***

Classifier	PFS Results: No Obstruction	Equivocal	Obstruction	Total
No obstruction	20	1	1	22
Equivocal	6	28	12	46
Obstruction	24	32	176	232
Total	50	61	189	300

Abbreviations as in Table I.
Accuracy was 60.5%.
** Qave, Qmax, PVR, and TRUS-determined prostate volume.*

TABLE III. ***Confusion matrix in learning set of ANN with four input variables* to predict three output variables with configuration 4-11-3 with 1,000,000 epochs***

Classifier	PFS Results: No Obstruction	Equivocal	Obstruction	Total
No obstruction	12	6	6	24
Equivocal	9	7	13	29
Obstruction	14	14	76	104
Total	35	27	95	157

Abbreviations as in Table I.
Accuracy was 74.6%.
** Qave, Qmax, PVR, and TRUS-determined prostate volume.*

multiple centers) by Reynard *et al.*[11] and was found to have a specificity of 70%, positive predictive value of 70%, and sensitivity of 47% for BOO.

Clearly, a single parameter of those mentioned is not reliable enough to replace the PFS. Our results demonstrated that the accuracy of model 1 in the testing set of data was 60.5%. Increasing the number of training cycles (epochs) in model 2 substantially increased the accuracy of the prediction during training (74.6%), but a major decline in accuracy (46.5%) during testing clearly invalidated the application of such a technique. Model 3 had the greatest accuracy at 72% in the testing set when Schafer grade 2 PFS cases were added to the nonobstructed ones. However, deleting the equivocal cases altogether resulted in 76% accuracy. Nevertheless, this is a mere theoretical context, because, in reality, investigators do have patients with equivocal cases of BOO, which is delineated in every pressure flow nomogram available.[12] In the experimental model by Sonke *et al.*,[13] a comparison was made between a linear regression model and an ANN model. The input parameters were prostate volume, Qmax, voided volume, PVR, patient age, prostate-specific antigen level, International Prostate Symptom Score, and quality-of-life score. Both linear regression analysis and the ANN displayed an area under the curve of 0.78, using receiver operating characteristic curves. However, the PFS parameter they used was the Abrams-Griffiths number and the number of input data was greater than in the present study (eight parameters).

TABLE IV. ***Confusion matrix in testing set of ANN with four input variables* to predict three output variables with configuration 4-11-3***

	PFS Results			
Classifier	No Obstruction	Equivocal	Obstruction	Total
No obstruction	10	3	4	17
Equivocal	18	13	41	72
Obstruction	7	11	50	68
Total	35	27	95	157

Abbreviations as in Table I.
Accuracy was 46.5%.
** Qave, Qmax, PVR, and TRUS-determined prostate volume.*

TABLE V. ***Confusion matrix in learning set of ANN with four input variables* to predict two output variables with configuration 4-7-2***

	PFS Results		
Classifier	Milder Obstruction	Severe Obstruction	Total
No obstruction	64	23	87
Obstruction	47	166	213
Total	111	189	300

Abbreviations as in Table I.
Accuracy was 76.7%.
** Qave, Qmax, PVR, and TRUS-determined prostate volume.*

TABLE VI. ***Confusion matrix in testing set of ANN with four input variables* to predict two output variables with configuration 4-7-2***

	PFS Results		
Classifier	Milder Obstruction	Severe Obstruction	Total
No obstruction	40	22	62
Obstruction	22	73	95
Total	62	95	157

Abbreviations as in Table I.
Accuracy was 72%.
** Qave, Qmax, PVR, and TRUS-determined prostate volume.*

CONCLUSIONS

The ANN model, based on free flow parameters (average flow rate and Qmax), PVR, and total prostate volume), can accurately determine whether a patient had obstruction in 72% of cases without performing PFS. If the equivocal zone of the nomogram were ignored, the accuracy would be 76%. This result, compared with the accuracy of the model previously described (73%), in utilizing objective parameters thus described, did not provide an advantage compared to symptoms, as rated by the International Prostate Symptom Score. When clinically important, PFSs are unavoidable.

REFERENCES

1. Wadie BS, Ibrahim EI, de la Rosette JMCH, *et al:* The relationship of International Prostate Symptom score and objective parameters for diagnosing bladder outlet obstruction. Part I: when statistics fail. J Urol **165:** 32–34, 2001.
2. Bosch JLHR, Hop WCJ, Kirkels WJ, *et al:* The International Prostate Symptom Score in a community-based sample of men between 55 and 74 years of age: prevalence and correlation of symptoms with age, prostate volume, flow rate, and residual urine volume. Br J Urol **75:** 622–630, 1995.
3. Ko DSC, Fenster HN, Chambers K, *et al:* The correlation of multichannel urodynamic pressure-flow studies and the American Urological Association Symptom Index in the evaluation of benign prostatic hyperplasia. J Urol **154:** 396–398, 1995.
4. Wadie BS, Badawi AM, and Ghoneim MA: The relationship of International Prostate Symptom score and objective parameters for diagnosing bladder outlet obstruction. Part II: the potential usefulness of artificial neural network. J Urol **165:** 35–37, 2001.
5. Schäfer W: Analysis of bladder-outlet function with the linearized passive urethral resistance relation, linPURR, and a disease-specific approach for grading obstruction: from complex to simple. W J Urol **13:** 47–58, 1995.
6. Armoni A: Use of neural networks in medical diagnosis. MD Comput **15:** 100–104, 1998.
7. Griffiths DJ: Pressure-flow studies of micturition. Urol Clin North Am **23:** 279–297, 1996.
8. Madersbacher S, Pycha A, Klingler CH, *et al:* The International Prostate Symptom Score in both sexes: a urodynamic-based comparison. Neurourol Urodyn **18:** 173–182, 1999.
9. Vesely S, Knutson T, Fall M, *et al:* Clinical diagnosis of bladder outlet obstruction in men with lower urinary tract symptoms: reliability of commonly measured parameters and the role of idiopathic detrusor overactivity. Neurourol Urodyn **22:** 301–305, 2003.
10. Botker-Rasmussen I, Bagi P, and Jorgensen JB: Is bladder outlet obstruction normal in elderly men without lower urinary tract symptoms? Neurourol Urodyn **18:** 545–551, 1999.
11. Reynard JM, Yang Q, Donovan JL, *et al:* The ICS-BPH study: uroflowmetry, lower urinary tract symptoms and bladder outlet obstruction. Br J Urol **82:** 619–623, 1998.
12. Grifiiths DJ, Hofner K, Van Mastrigt R, *et al:* Standardization of terminology of lower urinary tract function: pressure-flow studies of voiding, urethral resistance and urethral obstruction. Neurourol Urodyn **16:** 1–18, 1997.
13. Sonke GS, Heskes T, Verbeek ALM, *et al:* Prediction of bladder outlet obstruction in men with lower urinary tract symptoms using artificial neural networks. J Urol **163:** 300–305, 2000.