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ARTIFICIAL NEURAL NETWORKS IN PEDIATRIC UROLOGY: PREDICTION OF SONOGRAPHIC OUTCOME FOLLOWING PYELOPLASTY

DARIUS J. BÄGLI, SANJIV K. AGARWAL, SUNITA VENKATESWARAN, BRUCE SHUCKETT, ANTOINE E. KHOURY, PAUL A. MERGUERIAN, GORDON A. MCLORIE, KAI LIU AND CRAIG S. NIEDERBERGER

From the Division of Urology and Department of Radiology, Hospital for Sick Children, University of Toronto, Toronto, Ontario, Canada, and Departments of Electrical Engineering and Computer Sciences, and Urology, University of Illinois, Chicago, Illinois

ABSTRACT

Purpose: Computerized artificial neural networks are analogous to biological neuronal systems. Since they may be trained to recognize the relevance of complex patterns in data, neural networks may be useful for decision making in the multifactorial management of ureteropelvic junction obstruction. We determine the ability of a customized neural network to predict sonographic outcome after pyeloplasty in children with ureteropelvic junction obstruction.

Materials and Methods: A data set was constructed with 242 demographic, clinical, radiological and surgical elements. We analyzed the available retrospective data in 100 consecutive children who underwent unilateral pyeloplasty for ureteropelvic junction obstruction chosen from all 144 surgically treated for ureteropelvic junction obstruction between 1993 and 1995. One radiologist reviewed all film data and provided a final sonographic outcome designation in each case. We wrote a set of computer programs to construct a neural network. A composite 4-layer network was built with output nodes representing 4 possible sonographic outcomes. The 100 patient data set was randomly divided into 84 training and 16 testing examples.

Results: The neural network correctly predicted all 5 of 5 significantly improved, 7 of 7 improved, 2 of 2 same and 2 of 2 worse sonogram results after pyeloplasty. Therefore, sensitivity and specificity were 100% for all 4 outcomes. Linear regression analysis of the data yielded inferior sensitivity and specificity values (52 to 94%), confirming that ureteropelvic junction obstruction is a nonlinear data analysis problem.

Conclusions: The 100% accuracy, sensitivity and specificity of our neural network in this pilot study provide evidence of the value of the neural computational approach for the modern exploration and modeling of the clinical problem of pediatric ureteropelvic junction obstruction.

KEY WORDS: kidney, ureter, outcome assessment (health care)

The management of hydronephrosis in children continues to challenge the clinician. In the past hydronephrosis was assumed to be a pathologically harmful state. Surgical repair was presumed to avert potential renal damage.[1] It is now understood that dilatation or hydronephrosis is not always due to obstruction. Hydronephrosis may result from nonobstructive conditions.[2] Patients may be followed nonoperatively in the absence of decreasing renal function or progressive urinary tract dilatation,[3,4] and hydronephrosis often resolves naturally. Furthermore, current ureteropelvic junction obstruction diagnosis and management require continuous followup of clinical symptoms, infection status and trends in multiple sonograms, nuclear scans, diuretic renograms, half-times and invasive pressure flow studies before a sound demonstration of resolution or surgical indication may be made.[2,5–9] This situation clearly illustrates the lack of precision regarding the management of these cases. Successful management becomes a clinical art that integrates the available literature and pediatric urologist experience. While subjectivity in medicine must continue to have a place in the care of individuals, new approaches to evaluate systematically imprecise clinical problems, such as ureteropelvic junction obstruction, are now available. One such strategy is the artificial neural network.

Neural networks involve a form of machine learning that is a computerized analog of a biological neuronal system.[10] They may be trained to recognize complex data patterns. Unlike conventional statistical software, the essence of neural networks is that they are trained, not programmed, in a manner analogous to how neuronal connections are made and continually revised in the brain. While the potential exists for a neural network to outperform an expert teacher, presently it may serve as an excellent substitute in clinical decision making. Neural networks excel in processes that involve pattern recognition, such as categorization and contrast discrimination.[11] These features, including categorizing cases of infection, changing renographic function and drainage times as well recognizing patterns and grades of hydronephrosis, define ureteropelvic junction obstruction management. Therefore, we reasoned that the neural network approach may be a useful adjunct for decision making in the multifactorial treatment of ureteropelvic junction obstruction.

No patient undergoes precisely the same number or type of studies during the evaluation of ureteropelvic junction obstruction. Similarly the duration, timing, type, number and results of postoperative studies and surgical events also vary in each case. Since a neural network is designed to deal with incomplete data sets, it is theoretically ideally suited to modeling clinical ureteropelvic junction obstruction scenarios. In this pilot study we report the ability of a customized neural network to predict renal sonographic outcomes after pyeloplasty in children with ureteropelvic junction obstruction. We found that our neural network performed with great accuracy when predicting postoperative sonography after ureteropelvic junction obstruction repair.

MATERIALS AND METHODS

Our study population comprised 144 patients who underwent pyeloplasty at 1 institution between 1993 and 1995. Only patients with unilateral primary ureteropelvic junction obstruction were included in the study. Thus, available data in each of 100 consecutive children undergoing pyeloplasty for ureteropelvic junction obstruction were collected by a retrospective review of medical records.

Data set. A database was constructed with 242 variables, including demographic, clinical, preoperative and postoperative radiological studies, pressure flow studies when available and surgical data. We included all available studies in each case, although in some fewer or more preoperative or postoperative studies had been done than in others. The 14 demographic and clinical variables included patient age, gender and urinary tract infection parameters. The 35 radiographic variables included voiding cystography and excretory urography data. The 125 ultrasound variables included kidney size, pelvic dimensions, cortical thickness of the upper, mid and lower poles, hydronephrosis grade according to Society of Fetal Urology criteria, evaluation of the ureter, and the presence or absence of scars and stones. The 45 nuclear renography variables of dimercapto-succinic acid and diethylenetetramine pentaacetic acid scans were differential renal function, scarring and half-time drainage. The 23 surgical variables included surgeon, incision type, stent usage, leakage and postoperative complications.

Since a neural network does not process the qualitative difference between or meaning of variables, data must be numerically transformed before being entered into the network. Neural networks only deal with numerical data. In other words, a neural network does not understand why or how grades 1 and 3 hydronephrosis differ, nor the difference between 3 years and grade 3 hydronephrosis. For this reason variables are transformed to binary (yes and no equal 0 and 1), categorical (hydronephrosis grade equals 0 to 4) or normalized forms for entry into the neural network. Normalization reduces continuous variables to a range between 0 and 1 depending on the highest value of that variable in the data set. For example, for the continuous variable age, oldest patient age in the data set is assigned a value of 1.00. If the oldest age is 15 years and entered as 1.00, then 3 years is entered as 0.20 or 3/15. One radiologist reviewed all film and nuclear data, and provided the final sonographic outcome designation using the latest postoperative renal ultrasound study after pyeloplasty in each patient. The 4 ultrasound outcome categories reflecting the most recent state of hydronephrosis in the ipsilateral renal unit were designated as significantly improved, improved, no change or worse.

Neural network design. Neural networks were built using neUROn (neuronal computational environment for urological numericals) in a set of computer programs that we wrote. In neUROn neural network architecture and learning algorithms are tailored to urological classification problems by preprocessor directives in the C programming environment. We encoded 242 linear, binary and categorical variables into 580 linear and binary input nodes. A composite 4-layer network was built with corresponding output nodes, representing the 4 possible sonographic outcome variables of significantly improved, improved, no change and worse. The significantly improved subnetwork contained 50 hidden nodes, whereas the remaining subnetworks contained 30. Each subnetwork layer of the composite network was individually trained using the canonical back propagation method.[12] The 100-exemplar (patient) data set was randomly divided into 84 training and 16 testing examples using a randomization algorithm that preserved outcome frequencies in the training and testing sets. In this way the neural network was not over trained to recognize 1 outcome more reliably than another. The 16-patient test set data were not used for network training.

After the network was trained it was tested with the remaining 16 testing examples. The frequency of the 4 possible outcomes in the training set was maintained in the testing set, which reflected the fact that the neural network was required to predict outcomes in a testing population of 16 patients with the same outcome frequency as in the 84-patient training set with which it was programmed. Since we knew the outcomes in the testing set, we could evaluate network performance.

RESULTS

Table 1 shows the neural network predictions of final sonographic outcome after pyeloplasty in 16 unknown patients. Classification accuracy was 100% for all subnetworks, and sensitivity and specificity were 100% in all 4 outcomes. Thus, after training with data from 84 of 100 patients the neural network accurately predicted the final sonographic outcome after pyeloplasty when we provided it with data on the remaining 16 of 100 unknown patients.

Given the 100% sensitivity and specificity of the neural network performance we determined whether the high degree of accuracy resulted because there were simple linear relationships between the input data variables and outcome categories (sonogram results). If this were true, a sophisticated neural network would be expected to perform perfectly. Furthermore, simple logistic regression techniques would reveal any such linear relationship. Logistic regression attempts to produce a linear equation plotting a curve that divides data points into simple groupings. In other words, if a linear relationship exists between the input data variables and the 4 sonographic outcome categories, a single equation could separate and classify the data set cleanly into the 4 sonogram categories.[13]

We subjected the data set to 4 forms of logistic regression that may be directly compared to neural network analysis.[12] A full description of this analysis is beyond the scope of the present report. These simple linear regression tests produced classification sensitivity and specificity far below that of the trained neural network (table 2).[12] Table 2 illustrates the critical negative finding that sonographic outcome after pyeloplasty is indeed a nonlinear, multifactorial data analysis problem. Furthermore, this data model indicates that a neural network correctly associated clinical and radiographic data with a corresponding postoperative sonogram classification using a series of training ureteropelvic junction obstruction cases to predict accurately the final postoperative renal ultrasound reading of such cases unknown to the neural network.

DISCUSSION

The imprecise nature of ureteropelvic junction obstruction management lends itself to exploration with novel analysis

TABLE 1. *Neural network predictions of final postoperative renal sonography after pyeloplasty for ureteropelvic junction obstruction*

	Sonogram Category (No. pts.)			
	Significantly Improved	Improved	No Change	Worse
Radiologist	5	7	2	2
Trained neural network*	5	7	2	2

* Sensitivity, specificity, and positive and negative predictive values were 100%.

TABLE 2. *Relative performance of 4 logistic regression analysis models[12] for categorizing the ureteropelvic junction obstruction data set into the 4 sonogram categories*

Neural Network Regression No.	% Sensitivity	% Specificity	% Pos. Predictive Value	% Neg. Predictive Value
1	100	100	100	100
	57	79	75	62
2	100	100	100	100
	52	94	92	59
3	100	100	100	100
	72	81	76	78
4	100	100	100	100
	67	86	80	76

techniques designed for clinical categorization and decision making. The artificial neural network is a computational computer modeling strategy that may assimilate and integrate nonlinear data structures into reproducible and recognizable patterns. Our study demonstrates that the ureteropelvic junction obstruction management experience of 4 pediatric urologists at 1 center was accurately imparted to a customized artificial neural network. This network may be successfully trained to recognize multivariate patterns in the clinical, radiographic and surgical data in a series of patients and use this so-called experience to predict accurately the postoperative sonogram in a different series of new or unknown patients.

How neural nets work. Training the neural network involves associating input data with a corresponding known outcome.[13] The internal architecture of the neural network software automatically develops relationships between the variables as it is being trained. Variables are weighted internally in the software in a manner analogous to dynamic or real-time multivariate analysis, in which the weight of the variables constantly shifts as the neural network is trained. The basic neural network processing element has characteristics similar to those of a neuron. It sums negative (inhibitory) and positive (excitatory) inputs to produce a single output (action potential). In turn, this element synapses with 1 or more similar processors.

In contrast to conventional computer systems, artificial neural networks have multiple processors working in tandem that serve simultaneously as memory and processing elements.[14] At regular intervals during training the trainer-programmer requires the neural network to provide an outcome result based only on familiar input variables. Whether the response is correct or incorrect is entered into the neural network. This result is saved, and in this way the neural network learns. After this training process is complete the neural network is challenged with unknown data, in this case patient data to which it was never exposed during training but for which the output is known, and it is required to provide output responses. Neural network performance is compared to the actual expected output, permitting its evaluation by conventional sensitivity and specificity analysis. In this manner a neural network successfully trained to greater than 95% reliability theoretically may be trusted by novice users who provide the neural network with completely unknown input data for which no output or result is already available. A correct output or prediction should be returned in greater than 95% of cases.

Artificial neural networks offer a way to assimilate actively past and present knowledge, extract information, map correlations and produce inferences from a large number of data variables.[15] Because they generalize from exemplars, neural networks are intolerant to noise that may exist in data, which is frequently present in individual ureteropelvic junction cases. In medical data noise is defined as interobserver and intra-observer variation, differences in data acquisition, laboratory, radiographic or scanning techniques, such as diuretic renography, irregularities in testing intervals and variations in disease or clinically inapparent conditions. The disadvantage of the neural network is that training may take considerable time. Furthermore, neural network performance results depend on the quality of neural network computer software. While generic neural network software is commercially available and useful for introducing the concept of neural network computation, it performs specific, specialized tasks poorly.[16] Conversely the neural network software that we used in this study was specifically designed to deal with urological data sets but it requires training by individuals experienced in neural network architecture.

Neural networks handle incomplete data. In our neural network there were frequently empty variables (individual data sets with fewer than 242 possible elements), since no case involved all expected clinical events or possible evaluations. This finding is expected and it accurately reflects daily clinical experience. Naturally since no 2 patients have an identical clinical course or evaluation, the nonempty variables in individual data sets also vary. Despite incomplete data sets our neural network performed accurately. The neural network process is similar to the manner in which a child learns to distinguish between a cat and dog.[14] After being presented with many examples of each animal and feedback on whether the correct identification was made a child eventually learns to identify each animal correctly and reliably. At no time in this process are the many specific animal characteristics or variables explicitly identified. Although the overlapping features of these 2 animals are substantial, the human brain has no difficulty telling them apart, even when a portion of the animal is obscured from view (incomplete data). Hence, even with incomplete data the pattern recognition capability of the brain is clearly enormous. Urologists use these processes to make clinical diagnoses and select treatment for ureteropelvic junction obstruction. Our artificial neural network similarly learns, recognizes and identifies patterns based on past experience without explicitly identifying the basis on which this task is performed, even in the presence of incomplete data.

Neural networks in general urology. More than 400 biomedical applications of artificial neural networks have been described in computational, engineering, biological and medical journals. The diversity of applications is remarkable, ranging from neural networks built directly on computer chips to act as smart electrocardiograph readers to programs that determine the 3-dimensional structure of protein from its amino acid sequence, formulate diagnoses from radiographic images and measurements or prognosticate various diseases.[17] In urology there have been several successful attempts to incorporate this computational approach. Recently Krongrad et al used a neural network to examine the relative value of various available analytical methodologies for modeling general quality of life in benign prostatic hyperplasia and prostate cancer.[18] Snow et al used neural networks with greater than 85% overall accuracy to predict transrectal biopsy results from prostate specific antigen profiles, digital rectal examination and transrectal ultrasound findings.[10] They also used a similar neural network to predict cancer recurrence after radical prostatectomy with greater than 90% overall accuracy. Input data included patient demographic parameters, tumor grade and stage, and preoperative prostate specific antigen parameters. Others reported encouraging results using neural networks to predict semen analysis results after varicocelectomy, testis biopsy results from clinical and hormonal profiles, and gamete micromanipulation outcomes.[19,20]

Neural network considerations in pediatric urology. Our present report, which is the first of a 2-part design, involves the ability of a customized neural network to predict renal sonographic outcomes after pyeloplasty in children with ureteropelvic junction obstruction. In part 2 we will train a neural network to provide a clinical decision to continue observation, perform pyeloplasty or discharge the patient to the primary care physician. To our knowledge our report represents the first application of artificial neural networks in pediatric urology as well as the first application to the protean management of ureteropelvic junction obstruction. We chose to test the suitability of the neural network approach for predicting sonographic appearance after pyeloplasty. Admittedly the postoperative sonogram is at best a poor reflection of absolute renal function. However, stable or decreased hydronephrosis, represented in our study by no change or improvement in the sonogram, is an accepted means of ensuring that pyeloplasty has been successful. However, even at a referral center the sonographic result is not necessarily known with certainty regardless of the preoperative or intraoperative course. Our neural network categorized the final sonogram correctly in all 16 cases. Furthermore, simple linear regression models did not attain this level of performance, underscoring the nonlinear nature of this problem. We caution that the relatively small data sets used in training and testing the neural computational model must be considered when evaluating the 100% performance of our model. However, the 100% accuracy, sensitivity and specificity of the neural network model in our pilot study illustrate the value of neural computational approach for the clinical management of ureteropelvic junction.

Our ureteropelvic junction obstruction neural network provides several intriguing possibilities for pediatric urology. Prospective validation of its performance with a new cohort of patients who undergo surgery for ureteropelvic junction obstruction at our institution and for whom no output result is known even to the clinician may allow earlier intervention or treatment planning if a future sonogram result is predicted well in advance. Similarly the neural network strategy may make possible more rational development and testing of clinical care pathways or algorithms. In our second ureteropelvic junction obstruction neural network currently under construction we will attempt to train a network to discriminate between patients who require further observation only or surgery, or who may be safely discharged from the care of the pediatric urologist.

Current economic trends are reshaping patient care at an alarming rate. Neural network techniques may permit more objective, rational and testable care pathways before they are implemented. Thus, expert opinion or clinical guidelines may be captured by a neural network system, and used for training residents or advising physicians and public health observers who are less experienced in clinical pediatric urological evaluation and outcome. For study purposes identical patient cohorts may be theoretically treated using different experiences captured in neural networks, permitting the comparison of clinical approaches. Neural networks may provide artificial pediatric urology intelligence in the absence of the experts, for example where expert opinion may not be accessible. A neural network may learn to recognize equivocal Doppler flow patterns that are compatible with testicular torsion versus epididymo-orchitis. They may be programmed to relate fetal urine electrolytes or hydronephrosis patterns to postnatal renal function. Such a strategy would aid in prenatal counseling and intervention. In the setting of reflux neural networks may associate appropriate pre-infection and post-infection clinical and radiological variables with the potential for scarring in the individual, thus, helping to refine patient selection and timing for ureteroneocystostomy. Neural networks may also prove helpful for predicting clinical and quality of life outcomes in neurogenic bladder and exstrophy, which are further major multifactorial and imprecise clinical challenges in pediatric urology.

CONCLUSIONS

We demonstrate that a computerized artificial neural network may be trained to assimilate multivariate management data derived from a large cohort of pediatric patients treated with pyeloplasty for ureteropelvic junction obstruction. After training the neural network was provided only with input data from a further group of 16 unknown patients. The neural network correctly categorized (predicted) the final postoperative renal sonographic appearance in all 16 cases with 100% sensitivity and specificity. Logistic regression testing confirmed the nonlinear nature of the prediction required from the neural network. These results support the neural network computational approach for the modern exploration and modeling of the clinical problem of pediatric ureteropelvic junction obstruction.

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