Prediction of Upper Urinary Tract Calculi Using an Artificial Neural Network

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Objectives : *To evaluate the possibility of using an artificial neural network (ANN) in upper urinary tract calculi prediction.*
Material and Method : *Data of 168 upper urinary tract calculi patients treated in the Division of Urology, Department of Surgery, Songklanagarind Hospital from January 1997 to December 2000 were reviewed and classified into 6 catagories and 20 characteristics. 100 items were used in training and 68 in testing for an ANN designed with 3 layers: 20 nodes for an input layer, 5 nodes for a hidden layer and a node for the output layer.*
Results : *Output data between 0-0.38 indicate free of calculi, 0.65-1 indicate prone to have calculi, 0.38-0.65 indicate probable calculi and further need investigation.*
Conclusion : *An ANN with error back-propagation training can be used in diagnosing the presence of upper urinary tract calculi. The accuracy of prediction depends on a previous history of calculi, nephrocalcinosis, 24 hour urine assay for citrate and urine culture.*

Keywords : *Urinary tract calculi, Neural network*

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Urolithiasis is a serious health problem all over the world. In Thailand, although the incidence of urolithiasis in one region is different from that of others, there are high incidences among both in - and out - patients(1-3), and this needs to be studied further in order to find more effective ways for diagnosis, treatment and prevention of recurrence.

An Artificial Neural Network (ANN) is a system that consists of a large number of simple processing units, called neurons as in the nervous system. A neuron generally has a high-dimensional input vector and a simple output signal. The function to be performed on the input vectors is hence defined by the non-linear function and the weight vector of the neuron. The strength of an ANN is that it trains itself and operates by a pattern of recognition of the data and arrives at a conclusion in an unbiased manner.

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Fig. 1 shows an ANN model where $x_1, x_2,..., x_p$ are the input data; $w_{k1}, w_{k2},..., w_{kp}$ are the synaptic weights of neuron k; u_k is the combiner output; ($_k$) is the threshold; (•) is the activation function and y_k is the output signal of the neuron. In mathematical models, it may describe a neuron k, as follow:

$$uk = \Sigma_{j=1}^{p} w_{ij} x_j + bk \text{ and } y_k = \ (u_k - \ _k) \text{ ....(1)}$$

Fig. 2 shows the structure of a simple ANN. The circles are neurons whereas synapses are presented by the interconnections between the neurons and every neuron is connected to every other in the previous layer through synapses. Many layers can be cascaded, with outputs of one layer connected to inputs of the next layer, to form a hierarchy of network. The circles in the input and output layers are input nodes and output nodes which do not perform any processing function.

The weight vector or weight matrix is adjusted during the training by using a set of training data and a learning rule. The learning rule adapts the weight of

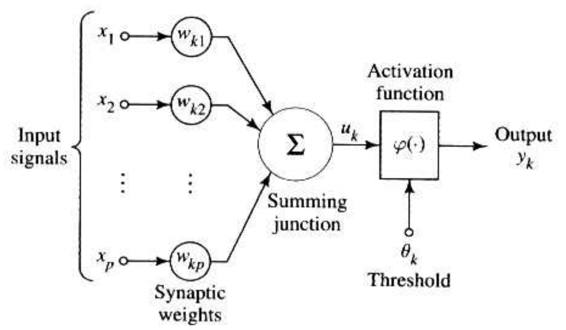

Fig. 1 Model of neuron

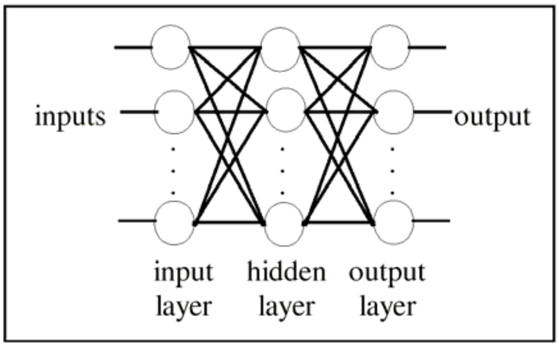

Fig. 2 Simple artificial neural network

all neurons in a neural network in order to learn an underlying relation in the training data.

Multi-layer perceptron (MLP) with error back-propagation (BP) training is a well-known algorithm for diagnostic and prognostic clinical information because it is able to implicitly detect complex nonlinear relationships between dependent and independent variables, detect all possible interactions between predictor variables and the availability of multiple training data. BP is not serious with over-parameterization or over-fitted models. It can ensure accuracy and precision using a gradient descent (∇E) technique to minimize the differences between clinical data and computation data (E), follow as:

$$\Delta\omega_{ij}(n) = -\varepsilon * \frac{\partial E}{\partial \omega_{ij}} + \alpha * \Delta\omega_{ij}(n-1) \quad \text{.....................(2)}$$

$$\Delta b_{ij}(n) = -\varepsilon * \frac{\partial E}{\partial b_{ij}} + \alpha * \Delta b_{ij}(n-1) \quad \text{.....................(3)}$$

When:

- $\omega_{ij}(n)$ and $b_{ij}(n)$ are weight and bias which is the i - th element of the j - th element and n - th iteration
- ε and α are two non negative constant parameters called learning rate and momentum
- $\frac{\partial E}{\partial \omega_{ij}}$ is partial derivatives of descent by derivative of weight i, j called performance index

To date, ANNs have been succesfully used for mass screening in many fields in medicine[4]. The objective of this study was to evaluate the possibility of using an artificial neural network (ANN) in recurrent upper urinary tract calculi prediction.

Material and Method

A study was conducted on data of recurrent renal or ureteral calculi (upper urinary tract calculi; UUT) patients receiving treatment at the Division of Urology, Department of Surgery, Songklanagarind Hospital from January 1997 to December 2000. The inclusion criteria were patients who had 1) available X-ray film or ultrasonographic result confirmed for the first diagnosis and the recurrence of UUT calculi, and 2) a stone analysis from an infrared spectrometer. The data used for the ANN analysis were the recurrent episodes of calculi.

Data management

Data from 168 patients with recurrent UUT calculi were divided into a set of 100 training records and a set of 68 testing records. All records were reviewed and classified into 6 categories and 20 characteristics (Table 1).

In the present study, the records were normalized/equalized with each data range and mapped to the closest unit interval [0,1] to resemble probability information in statistical models:

$$\tilde{x}_m = \frac{x_m}{x_{m,\,\max} - x_{m,\,\min}}$$

(when x_m denotes the m - th element of input vector X)

For binary input, zero meant “Yes” and one meant “No”. Each record was applied to an input layer, and formed a vector 1 column by 20 rows.

Modeling

Five nodes in the first hidden layer networks and a node in the second hidden layer network gave a

Table 1. Data management for ANN

Catagory	Characteristics
1. Patient profiles	Age, sex, history of previous calculi
2. Radiologic type	Staghorn and non-staghorn
3. Location/position of calculi	Calyx, lower pole, renal pelvis, ureter, parenchyma (nephrocalcinosis)
4. Composition of previous calculi	Calcium and non-calcium
5. Investigation	24 hour urine assay for citrate, hypercalciuria, hyperuricosuria and urine culture
6. Treatment	Herb, Allopurinol, Thiazide and others

choice of 100 synaptic weights forming a matrix with 20 columns and 5 rows.

Log-Sigmoid $(n) = \frac{1}{1 + exp(n)}$ was chosen for activation because it is a differentiable function and correspond with nonlinear/correlation variables.

Processing

Weight and bias vectors or matrices were initialized with zeros. The authors assigned 0.05 for a learning rate and 0.9 for momentum. In each iteration, weights and biases were automatically adjusted and cycling tuned for 10 times until the total actual gradient descent converged to 0.01 percent error or less. The model was continuously computed using "TRAINBPX" toolbox in MATLAB software and verified with NeuNet Pro 2.2 software.

Results

After calibrating the ANN with a set of 100 data, the program correctly predicted the presence of calculi at the time of diagnosis. The testing data of 68 records gave 100% accuracy for predicting calculi (Table 2).

The evaluation of relative weights by applied statistic math functions (means, median, correlation and covariance) was found that some input data had minimal relative weight in diagnosis. The data input which had the greatest relative weight in the ANN was history of previous calculi. Other high relative weights were nephrocalcinosis, composition of calculi, 24 Hr urine assay for citrate, and urine culture.

Table 2. Output data and meaning

Output data		Meaning
$0.00 \leq$ Output value	< 0.38	Free from calculi
$0.38 \leq$ Output value	< 0.65	Probable calculi, need further investigation
$0.65 \leq$ Output value	$= 1.00$	Calculi

Discussion

The artificial neural network is useful for prediction in many fields of medicine because it can be easily and quickly calibrated for pattern recognition, and can reach conclusions in an unbiased manner[5]. In urology, ANN has been used in discrimination of benign from malignant lower urinary tract lesions[4], predicting quality of life in patients with benign prostatic hyperplasia or prostatic cancer[6], predicting stone growth after ESWL[7], and predicting spontaneous ureteral calculi passage[5]. The present series of UUT calculi was analysed using an artificial neural network without knowledge about association of data, such as sex, age, history of previous calculi, stone type, location/position of calculi, composition of calculi, investigation, and treatment. The study revealed that the ANN predicted the presence of calculi in recurrent UUT calculi patients with 100% accuracy. The ANN model was easily changed to a binary decision by adjusting the threshold value to 0.5 at the activation of the output layer, but the accuracy then decreased to 82%. The data input which had the greatest relative weight was history of previous calculi.

Conclusion

The ANN model with error back-propagation training can be used in diagnosing the presence of upper urinary tract calculi. The accuracy of prediction depends on previous history of calculi, nephrocalcinosis, 24 hour urine assay for citrateand urine culture.

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การใช้โครงข่ายประสาทเทียมทำนายการเกิดนิ่วทางเดินปัสสาวะ

มณฑิรา ตัณฑนุช, สาวิตร์ ตัณฑนุช

วัตถุประสงค์ : เพื่อศึกษาความเป็นไปได้ในการใช้โครงข่ายประสาทเทียมทำนายการเกิดนิ่วในผู้ป่วยนิ่วทางเดินปัสสาวะส่วนบน
วัสดุและวิธีการ : ศึกษาข้อมูลผู้ป่วยนิ่วทางเดินปัสสาวะส่วนบน (นิ่วในไตและท่อไต) ที่เป็นนิ่วเกิดซ้ำซึ่งเข้ารับการรักษาใน โรงพยาบาลสงขลานครินทร์ ระหว่างเดือนมกราคม 2540 ถึงธันวาคม 2543 จำนวน 168 ราย โดยใช้ข้อมูลผู้ป่วย 100 ราย ฝึกโครงข่ายประสาทเทียม และ 68 ข้อมูลเป็นส่วนทดสอบผลการทำนาย
ผลการศึกษา : ผลการทำนายที่มีค่าระหว่าง 0-0.38 หมายถึงผู้ป่วยไม่มีนิ่วในช่วงที่ทำการเก็บข้อมูล, 0.38-0.65 หมายถึงผู้ป่วยอาจจะมีนิ่ว และต้องตรวจวินิจฉัยเพิ่มเติม, 0.65-1 หมายถึง ผู้ป่วยมีนิ่วในขณะเก็บข้อมูล
สรุป : โครงข่ายประสาทเทียมสามารถใช้ในการวินิจฉัยการเกิดนิ่วในผู้ป่วยนิ่วทางเดินปัสสาวะส่วนบนได้ โดยปัจจัยที่มีความสำคัญในการทำนาย ได้แก่ ประวัติการเกิดนิ่วในอดีต ภาวะ nephrocalcinosis ผลการตรวจซิเตรทในปัสสาวะ 24 ชั่วโมง และผลเพาะเชื้อปัสสาวะ
