Application of Artificial Neural Network for Diagnosing Bladder Outlet Obstruction.

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***Abstract*-This paper presents a neural network system to classify patients of lower urinary tract symptoms (LUTS) and obtain there degree of bladder outlet obstruction (BOO) according to linear passive urethral resistance relation (PURR) nomogram or schäfer grade (0 or 1) for nonobstructed flow, 2 for equivocal and (3,4,5 or 6) for obstructed patient. LUTS patients received routine investigation, consisting of transrectal ultrasonography of the prostate, serum PSA measurement, assessment of symptoms and quality of life by the International Prostate Symptom Score (IPSS),urinary flowmetry with determination of maximum flow rate, voided volume and post-void residual urine and full pressure flow studies (PFS) which are the best available method to distinguish BOO, But PFS are too invasive and time-consuming and expensive to be routinely utilized. So we construct ANN depending on four readings (average flow rate A_F_R, maximum flow rate M_F_R, prostate size as measured by transrectal ultrasound TRUS and residual urine Res_Urin) as input which are most significant and less invasive, and estimate the degree of obstruction of patient as output of ANN.**

?. Introduction

LUTS are Symptoms of prostatic enlargement; previously called "prostatism" include decreased force and size of stream, terminal dribbling hesitancy, urgency, frequency, nocturia and intermittency[1]. Many patients suffer from bladder outlet obstruction (BOO) due to Benign Prostatic hyperplasia (BPH) which is a condition where benign (non-cancerous) nodules enlarge the prostate gland, The incidence of BPH increases with advancing age. BPH is so common that it has been said, "All men will have benign prostatic hyperplasia if they live long enough!" A small amount of BPH is present in 80% of men over 40 years old and over 95% of men 80 years old[2].

Previous studies used traditional regression models to combine the information from several non-invasive diagnostic tests, such as free uroflowmetry, prostatic volume measurement and symptom-score lists, to estimate PFS outcome [3],[4]. Other study used ANN but reached to overall accuracy of system =69% [5]. Other study used I-PSS score to predict degree of obstruction and reached good results [6].

In the beginning we take data of 457 patients with LUTS from the urology and Nephrology Center, Mansoura. and use Minimum distance classifier , K-voting classifier and Neural network classifier which gave best results, in ANN classifier we use 300 randomly selected patients used to train network and 157 patients for testing behavior of network and its output. Each patient contain 5 readings which are (A_F_R, M_F_R, Res_Urin, TRUS, Schäfer grade).

There are two nomograms are commonly used to diagnose bladder outlet obstruction, PURP nomogram which designed by Werner Schäfer and Abrams-Griffiths nomogram, Lim and Abrams superimposed the Abrams-Griffiths nomogram with the linear PURR nomogram and discovered that the line separating obstruction from equivocal obstruction corresponding to the line separating grades 2 and 3 on the PURR nomogram[7]. The milder grade of obstruction (0,1,2) on the linear PURR nomogram were represented in equivocal or unobstructed zones[8].

? . MATERIAL AND METHODS

A. Minimum Distance Classifier

We classify 157 patients (testing vectors) according to nearest vector from learning vectors (300). By calculate the error between unknown vector X from 157 patients and all template vectors T (300 patient), get minimum error to obtain nearest template vector and give X the same class as nearest vector has.

$$\text{Error}= \sqrt{\sum_{i=1}^{i=4}(X_i - T_i)^2} \;\Big/\; \sqrt{\sum_{i=1}^{i=4} X_i^2} \qquad (1)$$

B. Voting K nearest neighbor classifier

This technique is nonparametric, it assigns a test sample to the class of the majority of its K-neighbors is $K= k_1+k_2+k_3$ (where k_i is number of samples from class i in the K-sample neighborhood of the test samples), the test sample is assigned to class m if $K_m = \max\{K_i , i=1,2,3\}$[9]. We take K = 7 neighbors.

C. Neural net work classifier

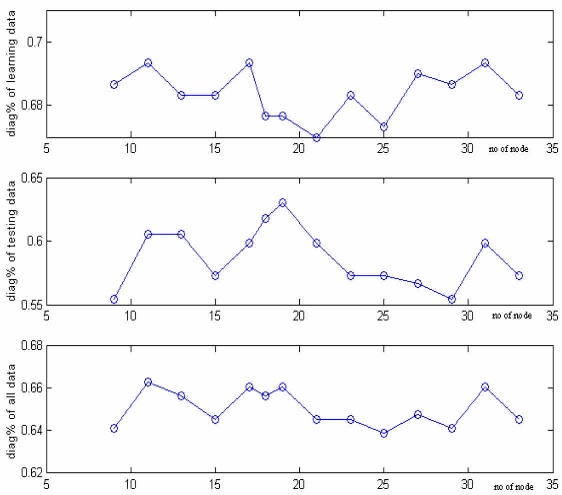
An artificial neural net work can be defined as: A data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain[10].

In this paper we construct feed forward artificial neural network using gradient decent adaptive learning rate back propagation training with momentum constant equal to 0.7 with three layer: input, output and hidden layer (Kolmogorov theorem)[11].

Adaptive learning rate is more efficient than fixed learning rate. The learning rate can be thought of size of a step down the error gradient. The heuristic rule state: if training is went well (error decreased) then increase the step size.lr=lr*1.1. if training is poor(error increased)then decrease the step size lr = lr * 0.5[12].

We take four input (AFR,MFR,RES_URIN and TRUS) and normalize it and classify schäfer's grade into 3 categories which is 0,1—nonobstructed , 2---equivocal and 3 to6---obstructed, and construct artificial neural network by using Gradient descent with momentum constant and adaptive learning rate back propagation, and make confusion matrix for output from network and real data an schäfer's grade classified. Trying by several number of node in hidden layer with fixing no of epochs 10000 and momentum constant(0.7),and graph percentage of diagonal of confusion matrix in learning and testing versus number of node to take no of node which has high percentage.

FIGURE 1.GRAPH DAIGONAL PERSENTAGE OF CONFUSION MATRIX VERSUS NUMBER OF NODE IN HIDDEN LAYER



As appear in graph the percentage of correctly (diagonal of confusion matrix / total number of vectors enter net work) which reached to 66%, and number of node give best result is 11 node and its confusion matrix is illustrated as follow, After that we make Another ANN which has 2 output . first activated at milder obstruction second activated at sever obstruction (milder obstruction with Schäfer grade 0,1,2 and Moderate to sever obstruction from grade 3 to 6). Trying by several number of neuron in hidden layer we find 7 node give best results.

? . RESULTS

"table.1" has the result for Minimum distance classifier using 3 classes (no obstructed, equivocal, obstructed), total accuracy of classifier =47% and 65%sensitivity for obstruction.

TABLE 1
CONFUSION MATRIX OF 3 CLASSES ACCORDING TO MINIMUM DISTANCE CLASSIFIER

	Pressure Flow Studies PFS (%)			
Classifier	No obstruction	Equivocal	Obstruction	Totals
No obstruction	1(3)	0	2	3
Equivocal	14	11(41)	31	56
Obstruction	20	16	62(65)	98
Total no	35	27	95	157

Total accuracy of classifier =47%.

"Table.2" has the Result for Minmum distance classifier using 2 classes (milder obstruction with Schäfer grade 0,1,2 and Moderate to sever obstruction from grade 3 to 6). This classfier has total accuracy = 56% with sensitivity 41% for milder obstruction and 65% for sever obstruction.

TABLE 2
CONFUSION MATRIX OF 2 CLASSES ACCORDING TO MINIMUM DISTANCE CLASSIFIER

	Pressure Flow Studies PFS (%)		
Classifier	Milder Obstruction	Sever Obstruction	Totals
Milder Obstruction	26(42)	33	59
Sever Obstruction	36	62(65)	98
Total no	62	95	157

Total accuracy of classifier =56%.

"table.3" has the result for Voting K nearest neighbor classifier using 3 classes (no obstructed, equivocal, obstructed), total accuracy of classifier =61% and 98%sensitivity for obstruction.

TABLE 3
CONFUSION MATRIX OF 3 CLASSES ACCORDING TO VOTING K NEAREST NEIGHPOR CLASSIFIER

	Pressure Flow Studies PFS (%)			
Classifier	No obstruction	Equivocal	Obstruction	Totals
No obstruction	3(9)	2	1	6
Equivocal	1	0(0)	1	2
Obstruction	31	25	93(98)	149
Total no	35	27	95	157

Total accuracy of classifier =61%.

"table.4" has the Result for Voting K nearest neighbor classifier using 2 classes (milder obstruction with Schäfer grade 0,1,2 and Moderate to sever obstruction from grade 3 to 6). This classfier has total accuracy = 65% with sensitivity 29% for milder obstruction and 92% for sever obstruction.

TABLE 4
CONFUSION MATRIX OF 2 CLASSES ACCORDING TO VOTING K NEAREST NEIGHPOR CLASSIFIER

	Pressure Flow Studies PFS (%)		
Classifier	Milder Obstruction	Sever Obstruction	Totals
Milder Obstruction	14(29)	7	21
Sever Obstruction	48	88(92)	136
Total no	62	95	157

Total accuracy of classifier =65%.

IV. NEURAL NETWORK RESULTS

"Table.5" show confusion matrix of learning data for first ANN which constructed by 11 node in hidden layer,10000 epochs, momentum constant =0.7 and adaptive learning rate. First ANN has 40% sensitivity for no obstruction and 95% sensitivity for obstruction in learning set.

TABLE 5
CONFUSION MATRIX OF LEARNING DATA

	Pressure Flow Studies PFS (%)			
Neural Network	No obstruction	Equivocal	Obstruction	Totals
No obstruction	20(40)	10	6	36
Equivocal	5	8(13)	3	16
Obstruction	25	43	180(95)	248
Total no	50	61	189	300

We find that ratio between diagonal (correct data) to total number in Learning data is =69.3%.

"Table.6" show confusion matrix of testing data data for first ANN with 34% sensitivity for no obstruction and 80% sensitivity for obstruction in testing set. First ANN has total accuracy = 66%.

TABLE 6
CONFUSION MATRIX OF TESTING DATA

	Pressure Flow Studies PFS (%)			
Neural Network	No obstruction	Equivocal	Obstruction	Totals
No obstruction	12(34)	6	6	24
Equivocal	9	7(26)	13	29
Obstruction	14	14	76(80)	104
Total no	35	27	95	157

We find that ratio between diagonal (correct data) to total number in Testing data is =60.5%.

"table.7" has confusion matrix for learning data of second ANN which constructed by 7 node in hidden layer,10000 epochs, momentum constant =0.7 and adaptive learning rate. Second ANN has sensitivity 58% for milder obstruction and 88% for sever obstruction in learning set.

TABLE 7
CONFUSION MATRIX OF LEARNING DATA

	Pressure Flow Studies PFS (%)		
Neural Network	Milder Obstruction	Sever Obstruction	Totals
Milder Obstruction	64(58)	23	87
Sever Obstruction	47	166(88)	213
Total no	111	189	300

We find that ratio between diagonal (correct data) to total number in learning data is =76.7%.

"Table.8" has confusion matrix for testing data of second ANN With sensitivity 65% for milder obstruction and 77% for sever obstruction in testing set. We get in second ANN total accuracy = 75% which better than previous study [5].

TABLE 8
CONFUSION MATRIX OF TESTING DATA

	Pressure Flow Studies PFS (%)		
Neural Network	Milder Obstruction	Sever Obstruction	Totals
Milder Obstruction	40(65)	22	62
Sever Obstruction	22	73(77)	95
Total no	62	95	157

We find that ratio between diagonal (correct data) to total number in learning data is =72%.

V. CONCLUSION

After we construct several classifier to predict Bladder Outlet Obstruction BOO and get best result from Neural network Classifier which classifies patients to two classes first class has milder obstruction (schäfer grade = 0,1,2) and second class has moderate or sever obstruction (schäfer grade = 3 to 6). This ANN classifier reached to result better than the previous study [5].

REFERANCES

[1] Abrams, p.: New words for old: lower urinary tract symptoms for "prostatism". BMJ 308:929, 1994 a.

[2] http:// Benign prostatic hyperplasia (BPH).htm

[3] Madersbacher, S., Klingler, H. C., Djavan, B., Stulnig, T., Schatzl, G., Schmidbauer, C. P. And Marberger, M.: Is obstruction predictable by clinical evaluation in patients with lower urinary tract symptoms? Br J Urol, 80: 72, 1997.

[4] Van Venrooij, g. e. and Boon, T.A.: the value of symptom score, quality of life score, maximal urinary flow rate, residual volume and prostatic size for the diagnosis of obstructive benign prostatic hyperplasia: a urodynamic analysis. JUrol, 155: 2014, 1996.

[5] Gabe S. Sonke, Tom Heskes,Andre L.M. Verbeek, Jean J. M. C. H. Dela R osette and Lamertus A. L. M. Kiemeney.: Prediction of bladder outlet obstruction in men with lower urinary tract symptoms using artificial neural network. J Urol, 163, 300-305, 2000.

[6] Bassem S Wadie, Ahmed M. Badawi and Mohamed A. Ghoneim.: The relationship of the international prostate symptom score and objective parameters for diagnosing bladder outlet obstruction .part2: the potential usefulness of ANN. J Urol, 165, 35-37, 2001.

[7] Lim. C. S. and Abrams, P.: The Abrams Griffiths nomogram. World J. Urol, 13:34, 1995.

[8] Joseph M. Khoury, Lesley Marson and Culley C. Carson,III: A comparative study of the Abrams-Griffiths nomogram and the linear PURR to determine Bladder Outlet Obstruction. J. Urol. 159. 758-760. 1998.

[9] Yasser M. Kadah, Aly A. Farag, Jacek M. Zurada, Ahmed M. Badawi and Abou-Bakr M. Youssef.: Classification algorithms for quantitative tissue characterization of diffuse liver disease from ultrasound image, IEEE, Transaction on medical imaging.,15,no 4.1996.

[10] Lefteri H. Tsoukalas, Robert E. uhrig.: Fuzzy and Neural approaches in engineering. John Wiley& sons, New York, 1997.

[11] R Beale, T Jackson.: Neural Computing: An Introduction .Adam Hilger, New York,1990.

[12] J. Wesley Hines.: Matlab Supplement to Fuzzy and Neural approaches in engineering. John Wiley& sons, New York,1997.