Prediction of Proximal Ureteral Stone Clearance After Extracorporeal Shock Wave

Zi-hao Xu, Shuang Zhou, Chun-ping Jia, Jian-lin Lv*

Purpose: The cumulative effect of measurable parameters on proximal ureteral stone clearance following extracorporeal shock wave lithotripsy (ESWL) was assessed via the application of an artificial neural network (ANN).

Methods and patients: From January 2015 to January 2020, 1182 patients with upper ureteral stone underwent ESWL in the supine position. The corresponding significance of each variable inputted in this network was determined by means of Wilks' generalized likelihood ratio test. If the connection weight of a given variable could be set to zero while maximizing the accuracy of the network classification, the variable was not considered as an important predictor of stone removal.

Results: A total of 1174 cases (after excluding 8 cases) were randomly assigned into a training group (813 cases), testing group (270 cases), and keeping group (91 cases). We performed ANN analysis of the stone clearance rate in the training group, and it showed a predictive accuracy of 93.2% (482/517 cases). However, the predictive accuracy for the stone clearance rate in the training group was 75.3% (223 cases/296 cases). The order of importance of independent variables was stone length > course (d) > patient's age > stone width > pH value.

Conclusion: The ANN possesses a huge prediction potential for the invalidation of ESWL.

Keywords: prediction; proximal ureteral stones; artificial neural network

INTRODUCTION

Urolithiasis is one of the most common urological diseases. According to the European Association of Urology (EAU) guidelines for urolithiasis, extracorporeal shock wave lithotripsy (ESWL) remains the primary treatment for symptomatic upper ureteral stone[1]. However, all stones do not respond to this treatment. The early ESWL suitable stones will guide doctors to choose another treatment to avoid unnecessary ESWL. For this purpose, it is necessary to establish or construct a prediction model that includes all variables that may affect the stone-free state.

Artificial neural network (ANN) is a computational method based on a large number of neurons, which loosely simulates the way in which biological brains solve the problem of large clusters of biological neurons connected by axons. Any neuron can have a summation function, which is capable of combining all of its input values. This system is self-learning and training, not explicitly programmed, and performs well in areas where traditional computer programs have difficulty in expressing solutions or feature detection. The network is able to recall the appropriate output for a particular set of inputs after training, which can infer the correct output of a pattern that has never been encountered before. The ANN, as a form of artificial intelligence technology, has been widely used in various fields. Tsao et al.[2] used both neural networks and logistic regression algorithm to predict the clinical stage of prostate cancer indicated by prostate specific antigen levels and Gleason grade. In this study, we hypothesized that the ANN could be a more powerful tool than logistic regression algorithm to predict potential capsular invasion by cancer. The ANN is also a more powerful tool than regression analysis for predicting the survival of liver cancer patients[3].

Therefore, in this study, we used an ANN to assess the cumulative effect of all measurable parameters that affect the removal of stones in the proximal ureter following ESWL.

MATERIALS AND METHODS

From January 2015 to January 2020, patients with upper ureteral stone who underwent ESWL in the supine position were included in this study. All procedures performed in the study were in accordance with the ethical standards of the Affiliated Jiangning Hospital of Nanjing Medical University and the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. This study was approved by the Ethics Committee of the Jiangning Hospital, Nanjing Medical University. The proximal ureter was defined as the segment extending from the pyeloureteral junction to the lower edge of the fourth lumbar spine. The stones were initially diagnosed by abdominal ultrasound and abdom-

Department of Urology, The Affiliated Jiangning Hospital with Nanjing Medical University, Nanjing, Jiangsu 211100, China.
*Correspondence: Department of Urology, Affiliated Jiangning Hospital of Nanjing Medical University, No. 168 Gushan Road, Dongshan Street, Nanjing 211100, China.
Tel: +86-25-52178496. Fax: +86-25-52178496. E-mail: ljlls01@163.com
Received September 2020 & Accepted February 2021

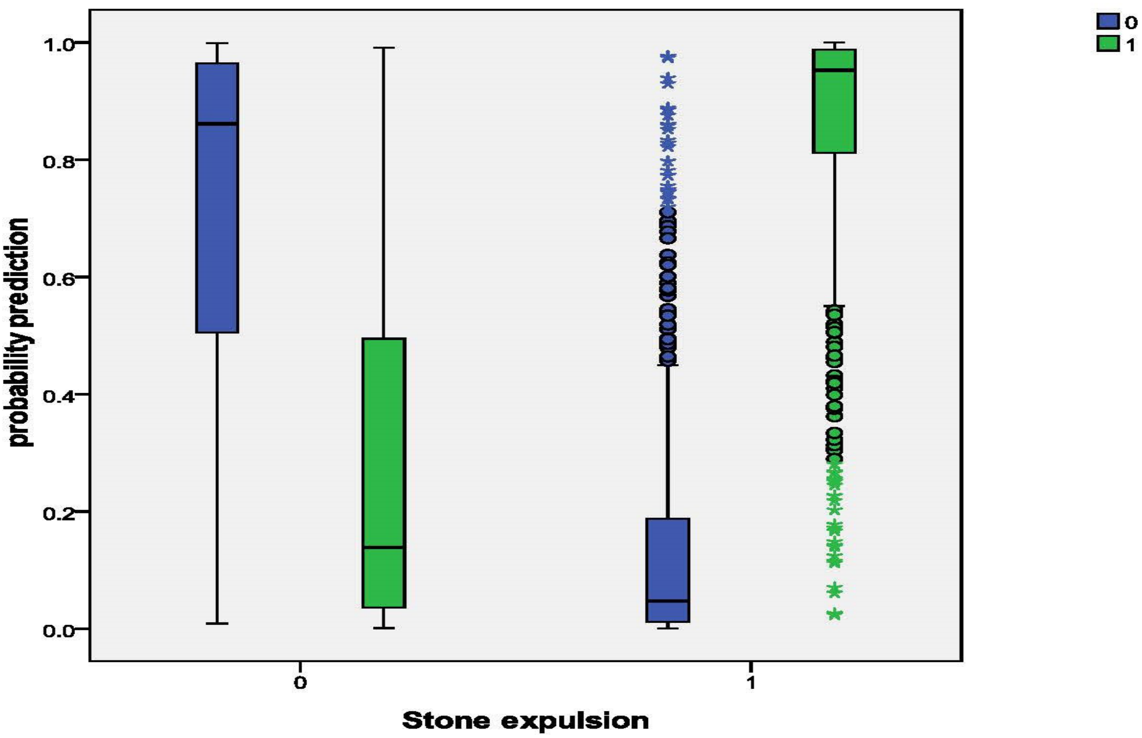

Figure 1. Probability prediction graph

inal roentgenogram of the kidney, ureter, and bladder (KUB). If felt necessary, a simple computed tomography (CT) scan was performed. The lithotripter adopted in this study was electromagnetic Dornier Compact Delta II UIMS (Dornier Medical Systems, Germany). In this work, the stones were fragmented under ultrasonic or fluoroscopic guidance. In each group, shock waves were delivered at 60-90 SW/min. The energy of this machine can be divided into 9 levels ((A, B, C, 1-6), and we usually applied 3-5 levels.

The stone free rate (SFR) was measured on a KUB film obtained 3 months after surgery. Treatment failure was defined as radiologically confirmed persistence of stones (> 4 mm) without rupture after the second session of SWL. The minimum follow-up period was 3 months.

SPSS 22 for Windows software was used to process the acquired data. SPSS software was used to establish a feed-forward and back-propagation error-adjusted neural network. An ANN was used to study the effect of 18 factors on the stone-free state. These factors included sex, age, stone position (left/right), stone length, stone width, body mass index, Alpha receptor blocker or Calcium channel blocker, urinary tract infection, hydronephrosis, daily drinking, hypertension, diabetes, coronary heart disease, PH, course of the disease, history of ipsilateral endoscopy, and ipsilateral stone discharge. When a category existed, an input neuron was allocated to each category value of the category variable, with a value of 1, otherwise 0. The output layer comprised 1 neuron, and the stone-free state was defined as the class value 1, and the nonstone-free state was defined as the class value 0. The value of network output was actually in the range of 0 and 1, and then it was converted to Class 0 (if the output was not more than the decision threshold) or class 1 (if the output was more than the decision threshold) based on the decision threshold. In a separate test set, using the cascade learning paradigm, the number of hidden nodes were selected to obtain the optimal performance.

In our study, patients were randomly allocated by the SPSS software; 69.25% of patients were classified into the total training group, 23.00% into the testing group, and 7.75% into the keeping group. The relative importance of each input variable in the network was determined by means of Wilks' generalized likelihood ratio test. If the connection weight of a given variable could be set to 0 while retaining the accuracy of network classification, the variable was not considered to be a significant predictor of stone removal. Mean ± standard deviation (M ± S.D.) was used to express the result of data. $P < 0.05$ was defined as statistically significant.

RESULTS

A total of 1174 cases (after excluding 8 cases) were allocated into the training group (813 cases), testing group (270 cases), and keeping group (91 cases). In 813 cases (69.2%), the stones were excreted, and the remaining 361 cases (30.8%) needed other treatment due to an inadequate response to lithotripsy. There was no statistical difference in the background data among the three groups. Univariate analysis showed that daily water intake, course of the disease (d), length, width, and age of patients were significantly correlated with stone excretion. The overall accuracy of the ANN analysis in predicting stone removal was 93.2% (482/517 cases) and 75.3% (223 cases out of 296 cases), respectively. The predicted stone removal curve is shown in **Figure 1**. The area under the receiver operating characteristic

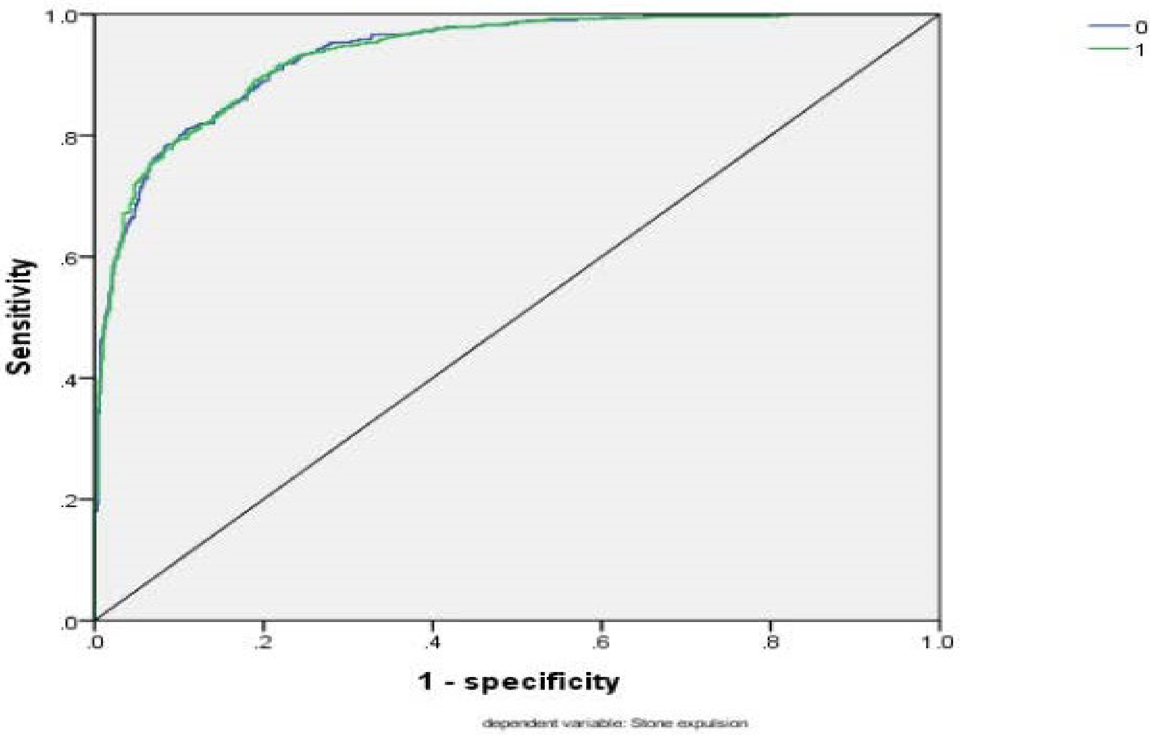

Figure 2. Receiver Operating Characteristic curve for stone-free status (area under the curve = 0.935)

(ROC) curve of the applied ANN analysis model was 0.935 (**Figure 2**). The relative weights of the 18 key variables were assigned by the ANN analysis for predicting proximal ureteral stone clearance (**Figure 3**), the importance of independent variables was as follows: the length of stone > course (d) > patient's age > stone width > Ph value. The cumulative and gain plots predicted by ANNs for proximal ureteral stone clearance

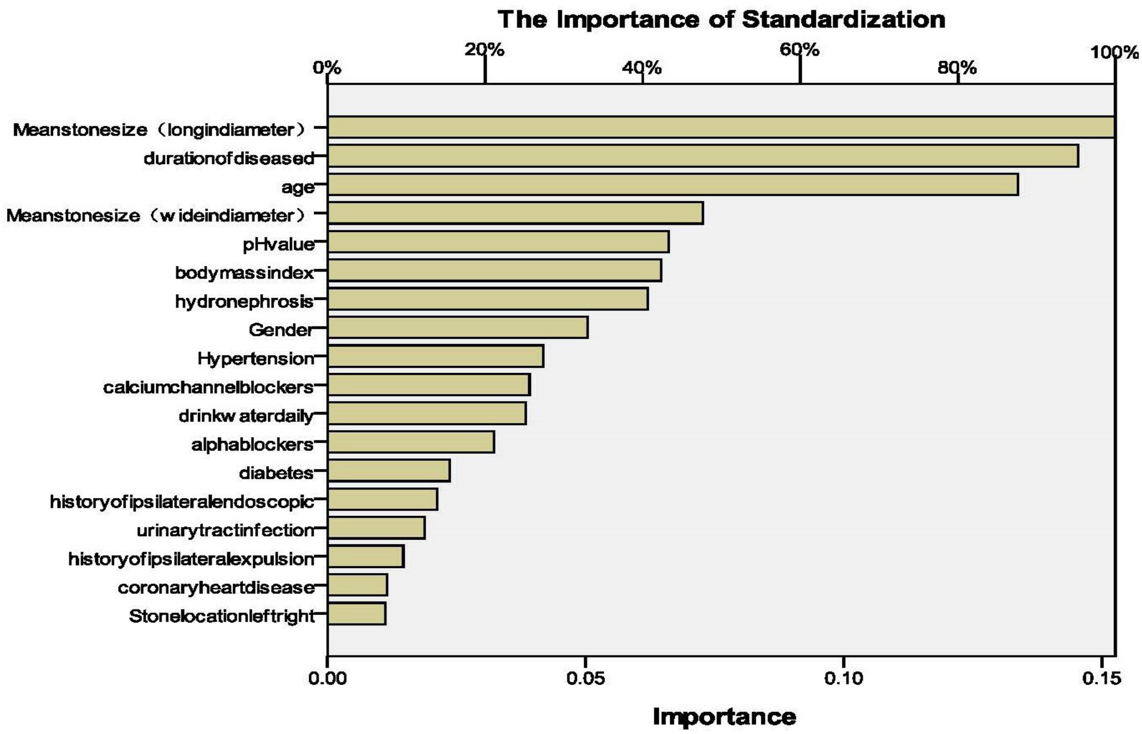

Figure 3. Independent variable importance graph

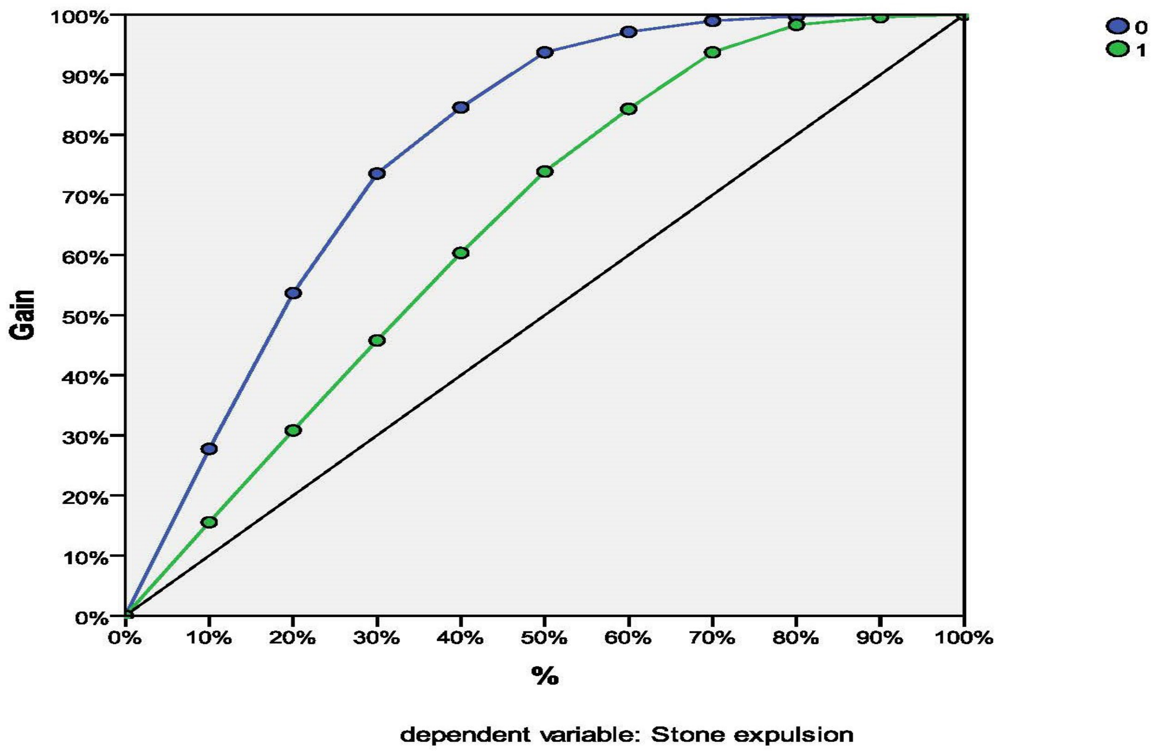

Figure 4. The cumulative gain graph for stone expulsion

are shown in **Figures 4 and 5**.

DISCUSSION

Proximal ureteral stone is one of the most common stone diseases in modern society. Stones smaller than 4-6 mm can initially be treated by monitoring. ESWL is generally the first choice for the treatment of an upper ureteral stone, especially for stones less than 1 cm. However, effective treatment management decisions depend on the nature of the stones, as well as patient factors. The patient's position also affects the stone clearance after ESWL[4]. Although ESWL has been found to be effective for treating ureteral stones, some ureteral stones do not respond to this treatment. Wher-

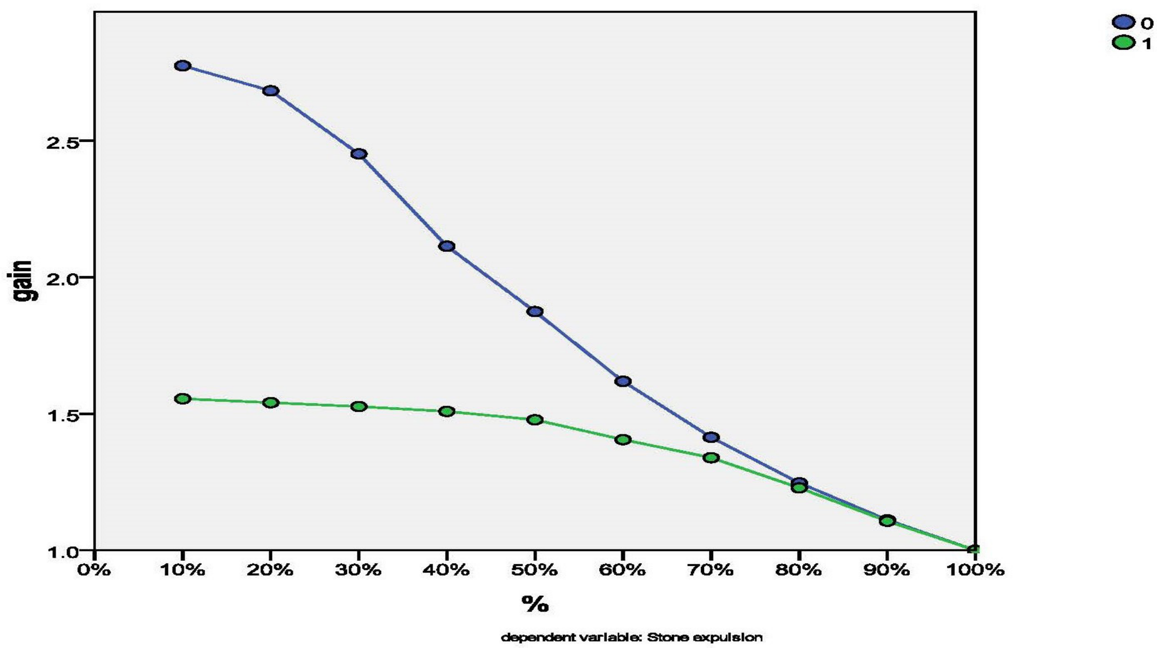

Figure 5. The gain graph for stone expulsion

ever possible, allowing the stone to pass spontaneously is probably the most popular option. Accurate prediction of the passage of a stone in an individual's body will allow timely intervention in patients who need it. An accurate prediction can also prevent unnecessary surgery and potential complications in patients who do not require stone management or lithotripsy.

It is crucial to identify patients with failed ESWL and ensure earlier and better treatment options, which can be achieved by building predictive models. Among a wide range of expert systems (ES), an ANN may be suitable for the stone channel prediction of ESWL for upper ureteral stone. The ANN analysis is a complex nonlinear mathematical model, which is inspired by the closely connected parallel structure inside the human brain. The ANN analysis is capable of stimulating the human brain to process, analyze, and learn relationships between data without the need to provide any known associations or rules[5-9]. ANNs can assist in building prediction models, classifing biomedical events, and making a decision. On the other hand, some applications of neural networks have been applied in many fields of urology[10-12].

Complicated interactions and relationships among individual predictive variables could be detected via an ANN. Although expert systems are based on accurate expert-defined rules, there is no need for neural networks to know the data in advance[13,14]. They learned by exposure to data and expected responses so that after the learning and testing phases, the ANN can be applied to be a decision-making helper. Compared with the statistical method, the ANN has several advantages. Predictions of individuals, rather than assumptions about correlations among variables, and determination of relationships among variables are important to the results. The ANN can accurately predict 2 classes with a higher average classification rate (sensitivity + specificity)/2, which can take into account the ability of the model to predict the two categories, regardless of the number of cases per category[15].

The ANN analysis can be used as an assistant for making a clinical decision, and on that basis a trained ANN can usually provide better prediction than standard multiple regression analysis. In the current study, we analyzed the application of the ANN analysis to predict the proximal ureteral stone clearance rate following extracorporeal shock wave lithotripsy. The accuracy of the neural network in predicting stone removal reached an unprecedented 93.2% (482 out of 517 cases), and the overall accuracy was 75.3% (223 out of 296 cases). Through the gain diagram, we found that the predicted success rate of stone removal will be increased by more than 2.5 times. The area under the ROC curve was 0.935.

In this study, an ANN analysis was performed to specify the relative weights of the 18 key variables for the prediction of proximal ureteral stone clearance. The results of the constructed neural network indicated that the length, course, age, width, PH value, and body mass index were the most relative variables affecting the output decision. The correlation ranged from large to small: stone length, course of the disease, patient age, stone width, urine PH value, and body mass index. On further validation in a prospective group of patients, the ANN could help guide the selection of patients with ureteral stones treated with ESWL. However, the results of the current study are only preliminary explorations. Identification and inclusion of more critical variables in the input, such as rock brittleness, may improve the efficiency and usefulness of the neural network. However, further prospective studies are needed to assess the potential of ANN analysis for the prediction of the proximal ureteral stone clearance rate.

CONCLUSIONS

The accuracy of the neural network in predicting the removal of upper ureteral stone after ESWL is high. In the analysis of prognostic variables, the model of stone clearance was determined by ANN analysis. The length of stone was the strongest predictor of stone clearance, followed by the course of the disease, patient's age, and stone width. Identification and inclusion of more critical variables in the input may improve the efficiency and usefulness of the neural network. However, it needs to be validated by other researchers, preferably by using a prospective randomized approach.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

1. Türk C, Petřík A, Sarica K, et al. EAU Guidelines on Interventional Treatment for Urolithiasis. Eur. Urol. 2016;69:475-82.
2. Tsao C-W, Liu C-Y, Cha T-L, et al. Artificial neural network for predicting pathological stage of clinically localized prostate cancer in a Taiwanese population. J. Chin. Med. Assoc. 2014;77:513-8.
3. Qiao G, Li J, Huang A, Yan Z, Lau WY, Shen F. An artificial neural networking model for the prediction of post-hepatectomy survival of patients with early hepatocellular carcinoma. J. Gastroenterol. Hepatol. 2014;29:2014-20.
4. Ziaee S, Hosseini S, Kashi A, Samzadeh M. Impact of sleep position on stone clearance after shock wave lithotripsy in renal calculi. Urol.Int. 2011;87:70-4.
5. Madbouly K, Sheir K, Elsobky E. Impact of lower pole renal anatomy on stone clearance after shock wave lithotripsy: fact or fiction? J. Urol. 2001;165:1415-8.
6. Ackermann D, Fuhrimann R, Pfluger D, Studer U, Zingg E. Prognosis after extracorporeal shock wave lithotripsy of radiopaque renal calculi: a multivariate analysis. Eur. Urol. 1994;25:105-9.
7. Snow P, Rodvold D, Brandt J. Artificial neural networks in clinical urology. Urology. 1999;54:787-90.
8. Robert M, Marotta J, Rakotomalala E, Muir G, Grasset D. Piezoelectric extracorporeal shock-wave lithotripsy of lower pole nephrolithiasis. Eur. Urol. 1997;32:301-4.
9. Pace KT, Tariq N, Dyer SJ, Weir MJ, D'A. HONEY RJ. Mechanical percussion, inversion and diuresis for residual lower pole fragments after shock wave lithotripsy: a prospective, single blind, randomized controlled trial. J. Urol. 2001;166:2065-71.
10. Lamb D, Niederberger C. Artificial intelligence in medicine and male infertility.

World J. Urol. 1993;11:129-36.
11. Moul JW, Snow PB, Fernandez EB, Maher PD, Sesterhenn IA. Neural network analysis of quantitative histological factors to predict pathological stage in clinical stage I nonseminomatous testicular cancer. J. Urol. 1995;153:1674-7.
12. Zlotta AR, Remzi M, Snow PB, Schulman CC, Marberger M, Djavan B. An artificial neural network for prostate cancer staging when serum prostate specific antigen is 10 ng./ml. or less. J. Urol. 2003;169:1724-8.
13. Gomha MA, Sheir KZ, Showky S, Abdel-Khalek M, Mokhtar AA, Madbouly K. Can we improve the prediction of stone-free status after extracorporeal shock wave lithotripsy for ureteral stones? A neural network or a statistical model? J. Urol. 2004;172:175-9.
14. Cummings JM, Boullier Ja, Izenberg Sd, Kitchens Dm, Kothandapani Rv. Prediction of spontaneous ureteral calculous passage by an artificial neural network. J. Urol. 2000;164:326-8.
15. Michaels EK, Niederberger CS, Golden RM, Brown B, Cho L, Hong Y. Use of a neural network to predict stone growth after shock wave lithotripsy. Urology. 1998;51:335-8.