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SCIENTIFIC PAPER

An artificial intelligence-based clinical decision support system for large kidney stone treatment

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Abstract

A decision support system (DSS) was developed to predict postoperative outcome of a kidney stone treatment procedure, particularly percutaneous nephrolithotomy (PCNL). The system can serve as a promising tool to provide counseling before an operation. The overall procedure includes data collection and prediction model development. Pre/postoperative variables of 254 patients were collected. For feature vector, we used 26 variables from three categories including patient history variables, kidney stone parameters, and laboratory data. The prediction model was developed using machine learning techniques, which includes dimensionality reduction and supervised classification. A novel method based on the combination of sequential forward selection and Fisher's discriminant analysis was developed to reduce the dimensionality of the feature space and to improve the performance of the system. Multiple classifier scheme was used for prediction. The derived DSS was evaluated by running leave-one-patient-out cross-validation approach on the dataset. The system provided favorable accuracy (94.8%) in predicting the outcome of a treatment procedure. The system also correctly estimated 85.2% of the cases that required stent placement after the removal of a stone. In predicting whether the patient might require a blood transfusion during the surgery or not, the system predicted 95.0% of the cases correctly. The results are promising and show that the developed DSS could be used in assisting urologists to provide counseling, predict a surgical outcome, and ultimately choose an appropriate surgical treatment for removing kidney stones.

Keywords Artificial intelligence · Classification · Decision support system · Kidney stone treatment · Stone-free rate prediction

Introduction

Kidney stones are one of the most common and costly urinary tract diseases amongst the middle-aged population [1–5]. Its overall prevalence in all age groups is approximately 1–15% [3, 4], which continues to increase mainly due to changes in lifestyle and environmental factors such as diet and climate [2]. The cost of kidney stone disease to an individual and society is relatively high. For example, treatment costs in the United States (prevalence rate ~ 8.8%) are estimated to be several billion dollars per year [6]. Consequently, proper treatment of kidney stones is vital.

Kidney stone treatment depends on its type, shape, size, and location. Small stones (with diameter < 4 mm) can pass naturally, but larger stones (with diameter > 6 mm) require surgical procedure. Shock wave lithotripsy (SWL), ureteroscopy (URS), and percutaneous nephrolithotomy (PCNL) are the frequently used techniques. Of these methods, the PCNL

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is the least invasive, and it has been considered as a standard care for large renal stones treatment [7, 8]. Despite significant advances and success in the management and treatment of kidney stones, there are several serious drawbacks. The rate of success depends on several factors, such as stone features, patient characteristics, and urologist experience. In addition, selecting the optimal treatment procedure is a challenging task as it depends on several factors. Therefore, it calls for a system that can predict postoperative outcome/success of a treatment procedure. Such a system can assist the surgeon to optimize treatment procedure and inform patients about the likelihood of a successful treatment before surgery.

Several methods have been suggested to predict successful status (particularly stone-free rate) of the treatment procedure used for kidney stones [1, 9–17], but there are several shortcomings with the existing methods. Some methods were merely designed according to previous studies findings and experts' opinion, but experimental data were included, and few systems considered a limited number of prognostic variables. In some methods, only a single treatment procedure can be considered, flexibility is limited, and there is no possibility of updating them using a new dataset. Finally, only few methods can be stratified by stone factors (location, size, and density); however, patient characteristics were not considered. Predicting the outcome of a treatment method and then selecting an optimal treatment technique can result in high stone clearance rates, low associated morbidity, and quick recovery. Consequently, developing a reliable and accurate model to estimate the success rate of a treatment procedure is warranted and remains a challenge. Hence, in this work, we developed an artificial intelligence-based system to predict the postoperative outcome of kidney stone treatment procedures and to provide operational support.

Methods

The developing process consists of four main steps: data collection, feature extraction, dimensionality reduction, and classification. Following is a description of these steps.

Data collection

The preoperative, intraoperative, and postoperative variables of 254 patients (mean age: 46.6 ± 12.2 years, 61% men) who underwent kidney stone surgery in Faqihi Hospital, Shiraz, Iran were prospectively collected. Patients with bilateral PCNL or chronic kidney disease were excluded. The detailed information regarding patient demographics, preoperative, and postoperative examination procedures are provided in [9].

In brief, at first, PCNL procedure was applied for all patients. Then, during postoperative period, kidneys were examined using computerized tomography (CT) scan to evaluate stone free status. Ancillary procedures (such as URS, SWL, or re-PCNL) were considered in case of any clinically significant residual stones (> 4 mm). The success of the second treatment was examined, too. Postoperative complications such as the need for blood transfusion or the need for stenting to manage postoperative urine leakage were also compiled.

Out of 254 patients, 194 (76.4%) were treated successfully using PCNL surgery in the first stage. Ancillary procedures such as re-PCNL ($n = 12$ (4.7%)), SWL ($n = 15$ (5.9%)) ,and URS ($n = 27$ (10.6%)) had to be performed to remove residual stones. In 67 (26.4%) patients, prolonged urine leakage was seen and was managed with a Double-J catheter insertion. In 58 (22.8%) patients, significant blood loss occurred, requiring blood transfusion. The preoperative, intraoperative, and postoperative data for the patients are provided in Appendix 1.

Feature extraction

A quantitative vector containing 26 features from three categories including patient history, kidney stone features, and laboratory data were used to represent each patient in the feature space. Detailed characteristics of these features are summarized in Table 1. As shown, the first 12 features are related to patients' history; and13 features are pertinent to kidney stone parameters, kidney's characteristics, and skeletal abnormalities, obtained through CT-scan. One feature is the patient preoperative hemoglobin.

Dimensionality reduction

To remove irrelevant and redundant features, two supervised dimension reduction methods were examined; one is an existing feature selection method, i.e., the sequential forward selection (SFS) method; and the other is a newly developed dimensionality reduction method. These two methods are described below.

In the SFS approach, the objective is to find d desirable features out of 26 available features so that an objective function is optimized. The objective function used here was the classification accuracy (the wrapper method) [18]. Detailed description of the SFS algorithm can be found in [19], but in short, this algorithm starts with an empty feature set, then repeatedly finds the most discriminant feature with respect to the current subset, and finally adds it to the subset until there is no significant improvement in the objective function.

The second dimension reduction method was developed by combining the SFS algorithm and the Fisher discriminant

Table 1 List of the features used to represent each patient

Feature category	Index	Preoperative and intraoperative features	
Patient history	1	Age	
	2	Gender (male–female)	
	3	Previous surgery in target kidney	
	4	History of PCNL	
	5	History of TUL	
	6	History of SWL	
	7	History of dialyses	
	8	History of diabetes	
	9	History of hypertension	
	10	Single kidney	
	11	Body mass index (kg/m^2)	
	12	Another problems (heart problems, thyroid,…)	
Kidney stone/characteristics and skeletal abnormalities	13	Stone location	Upper calyx
	14		Mid calyx
	15		Lower calyx
	16		Renal pelvis
	17		Ureter
	18	Stone characteristics	Side (right–left)
	19		Size (mm)
	20		Volume (mm^3)
	21		Staghorn
	22		Multiple
	23	Renal anomy	
	24	Skeleton anomy	
	25	Degree of hydronephrosis	
Laboratory data	26	Preoperative hemoglobin	

analysis (FDA) approach [20] in a cascade manner. At each stage of the SFS algorithm, to evaluate a subset, the FDA technique was applied to the subset and then the mapped features were fed to a classifier. The process was repeated as classical SFS approach to find the best set of features that provides the highest classification accuracy and sensitivity. This newly developed dimension reduction algorithm was called the SFSFDA.

Classification

Four different classification methods were explored: (1) quadratic discriminant analysis (QDA), (2) K-nearest NEIGHBORS (KNN), (3) multilayer perceptron neural network (MLPNN), and (4) support vector machine (SVM).

QDA classifier

QDA classifier is the general version of linear classifiers. In QDA classifier, the class conditional distribution of each class is modeled as a multivariate Gaussian distribution, and no assumption is made on the covariance matrix of each class, which leads to quadratic decision surfaces. Details of the QDA classifier can be found in [21]. We used QDA classifier, since it is easy to implement and fast. For each class, sample mean and sample covariance matrix are used as an estimation of the mean and covariance matrix of the class.

KNN classifier

KNN classifier categorizes a given sample based on the class labels of its *K*-closest neighbors [21], in which the sample is assigned to the class that possesses the most votes in the *K* nearest neighbors. In using the KNN classifier, two important parameters should be defined by the user; the similarity metric for finding the neighbors, and the value of *K*. In this study, Euclidean distance was chosen as similarity metric; the value of parameter *K* was also estimated through cross-validation by which the accuracy of the KNN classifier was estimated for a range of values of *K*. Then, the *K* that led to maximized classification accuracy was selected as the best value for the parameter *K*.

MLPNN classifier

MLPNN is a feedforward artificial neural network model, which associates input vector to appropriate outputs. In using MLPNN for a pattern recognition problem, two sets of parameters are required to determine (a) architecture (number of layers and number of neurons in each layer); and (b) the value of weights connecting the neurons. In this work, we used a three-layer MLPNN with an input layer, a hidden layer, and an output layer. The number of input nodes equals to the number of features used to represent each subject. The number of neurons in the hidden layer was determined experimentally, using cross-validation. We used the back-propagation algorithm to estimate the value of weights.

SVM classifier

SVM model is a frequently used supervised learning model for classification and regression [22]. In designing an SVM-based classifier, we used cross-validation approach to find the regularization parameter as well as the type of kernel function and its parameter (s). The sequential minimal optimization (SMO) method was used to train the SVM.

In summary, the combination of the two-feature selection algorithms and four classifiers that we used in this work resulted in eight DSSs. These systems are summarized in Table 2.

As discussed in "Data collection," the PCNL procedure was performed at first for all patients. After that if the treatment was not successful and stones were not completely removed, one of the following procedures URS, SWL, or PCNL was utilized as ancillary procedure. Hence, we developed two sets of decision support systems to assist a surgeon in treating kidney stones. One system was to predict the stone-free status of the PCNL after surgery in the first stage of the treatment. In other words, whether the PCNL in the first step of the treatment was successful or not. The second system was to predict which treatment (URS, SWL, or PCNL) should be used in the second stage of the treatment, if needed. As the classifier discussed in Table 2, is a binary classifier, we used one versus the other strategy to design the second DSS.

Table 2 Summary of eight examined machine learning systems

Feature selection method	Classifier method	Developed system
SFS	QDA	QDA_SFS
	KNN	KNN_SFS
	MLP	MLP_SFS
	SVM	SVM_SFS
SFS and FDA	QDA	QDA_SFSFDA
	KNN	KNN_ SFSFDA
	MLP	MLP_ SFSFDA
	SVM	SVM_ SFSFDA

In addition to these two DSSs that assist physicians in choosing the proper treatment technique, we developed two other systems that can help to provide operational support. One system predicts whether the patient needs stent placement after the removal of a stone or not, and the other system shows whether the patient might require a blood transfusion during the surgery or not. An overview of the developed DSSs and their outputs is shown in Fig. 1.

Evaluation

The performance of the proposed system was assessed using three performance indices: sensitivity, specificity, and accuracy. The stone-free status for all 254 patients after treatment was determined in CT scans, thus this finding was used as "actual value" in training and evaluating the system. To ensure an unbiased evaluation of the developed systems, we performed "leave-one-patient-out cross-validation" scheme [23]. In this technique, the data for one patient was randomly picked as the test set. A model was built on the remaining patterns; thereafter it was evaluated on the holdout patient. A generalization estimate of the performance was obtained by repeating this process for each patient and ultimately averaging the results.

Results

The classification performances of the developed DSSs are summarized in Tables 3, 4, 5 and 6. For each individual classifier, its parameter(s) were determined experimentally, and the obtained results are listed in the second column of each table. As mentioned in the methodology section, we used cross-validation approach to estimate these user-defined parameters.

Table 3 presents the accuracy of the developed DSSs in predicting the stone-free status of a kidney after the first treatment, conducted by PCNL method. As shown, the integration of FDA and SFS in finding the best feature subset and ultimately reducing the dimensionality of the data was effective. In comparison to only the SFS method, except for the SVM classifier, this integration resulted in improving classification accuracy by at least 6%, which is a significant improvement, particularly in medical applications. According to this table, the best methods for predicting the outcome of PCNL surgery are those that were developed using the SVM classifier. There is a tradeoff between using SFS or SFSFDA for reducing the dimensionality of the feature space. The sensitivity with the latter method was improved, but the specificity was reduced. For medical application, the sensitivity of a system is more important than its specificity; hence, the developed SVM-based decision support system in which the SFSFDA algorithm was used for dimensionality reduction is recommended.

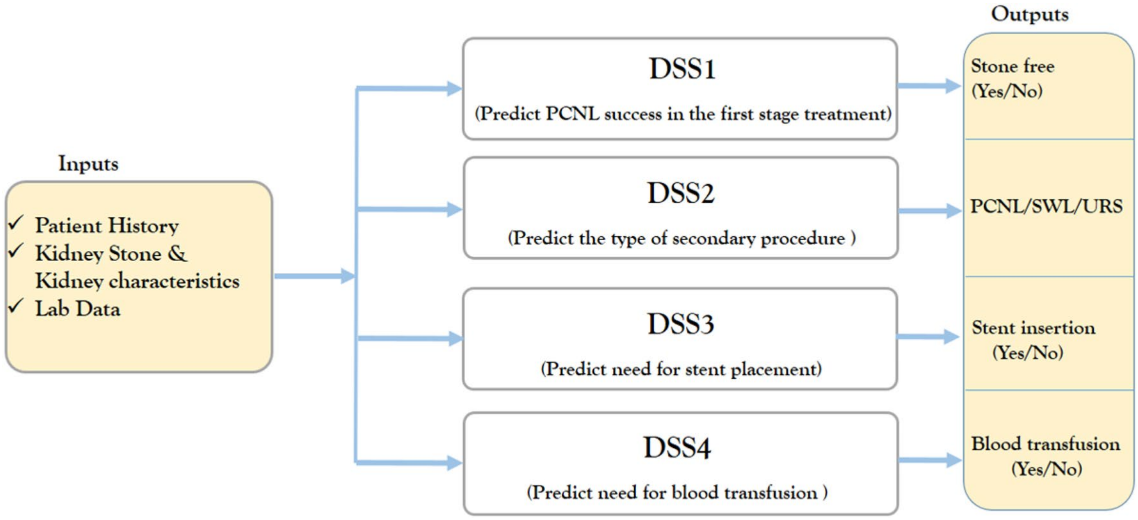

Fig. 1 An overview of decision support systems (DSSs) developed to assist urologists in the treatment of large kidney stones. DSS1 predicts the success of PCNL at the first step of the treatment; DSS2 recommends the proper treatment method for the second stage of treatment (if needed). DSS3 predicts whether the patient needs stent placement after the removal of the stone or not. DSS4 estimates whether the patient might require a blood transfusion during the surgery or not

Table 3 Performance of the developed decision support systems in predicting the stone-free status of a kidney after the first stage of treatment, conducted by PCNL method

Methods	Parameters	Sensitivity (%)	Specificity (%)	Accuracy (%)
QDA_SFS	–	71.1	69.5	70.3
QDA_SFSFDA	–	72.3	84.7	78.0
KNN_SFS	$K=3$	80.7	65.3	73.5
KNN_SFSFDA	$K=5$	85.6	72.3	79.4
MLP_SFS	Number of hidden neuron: 85	71.1	55.6	63.9
MLP_SFSFDA		81.9	68.1	75.5
SVM_SFS	Kernel function: RBF	92.7	91.6	92.3
SVM_SFSFDA	Kernel function: sigmoid	100.0	88.9	94.8

Table 4 presents the performance of the DSSs developed to accurately predict postoperative ancillary procedures. Based on the results, the combination of FDA and SFS for finding the best feature subset was effective, particularly in improving system sensitivity. According to this table and considering sensitivity, specificity, and accuracy, the best methods for predicting postoperative secondary surgery are the systems that were developed, using the SVM classifier and SFSFDA approach (SVM_SFSFDA). Although some of the examined systems provided higher accuracy than the SVM_SFSFDA, this system provided the highest sensitivity value.

Table 5 presents the performance of the DSSs in °predicting if a patient will have prolonged urine leakage after surgery, which was managed by inserting a Double-J stent (Ureteric Stent) inside the ureter. These cases are referred to as "Need for Stent Insertion" here. According to the results, considering all three indices sensitivity, specificity and accuracy, the SVM_SFSFDA system is recommended for this application. The QDA_SFSFDA method yielded the highest sensitivity, but its specificity was much lower than the SVM_SFSFDA system.

Table 6 summarizes the performance of the developed systems for predicting whether or not a patient will require a blood transfusion, due to significant blood loss during surgery. Based on the results and considering sensitivity, specificity, and accuracy, the SVM_SFSFDA system is suggested. Once again, augmented dimension reduction algorithm via combining FDA and SFS improved system sensitivity.

Discussions

Kidney stone disease puts a huge burden of cost on individuals and society; hence, its precise treatment is vital. The success rate of existing surgical approaches is multifactorial; thus, a model to predict the treatment success is required to assist physicians in choosing a proper treatment method. Selecting and applying an appropriate method can result in high stone-free rate, low associated morbidity, high survival probability, quick recovery times, and low treatment cost [1]. Applications of machine learning in medicine have gained

Table 4 Performance of the developed decision support systems in predicting correct postoperative ancillary procedure

Surgery	Methods	Parameters	Sensitivity (%)	Specificity (%)	Accuracy (%)
rePCNL	QDA_SFS	–	60.0	100	99.2
	QDA_SFSFDA	–	80.0	87.6	87.4
	KNN_SFS	$K=1$	40.0	100	98.8
	KNN_ SFSFDA	$K=1$	40.0	100	98.8
	MLP_SFS	Number of neuron in hidden layer: 85	20.0	100	98.0
	MLP_ SFSFDA	Number of neuron in hidden layer: 85	60.0	88.0	87.0
	SVM_SFS	Kernel function: Sigmoid	0	100	98.0
	SVM_ SFSFDA	Kernel function: MLP	80.0	98.0	97.6
URS	QDA_SFS	–	72.7	86.1	85.1
	QDA_ SFSFDA	–	90.9	88.9	89.0
	KNN_SFS	$K=3$	54.5	99.3	96.1
	KNN_ SFSFDA	$K=5$	63.6	97.9	95.5
	MLP_SFS	Number of neuron in hidden layer: 85	18.2	98.6	92.9
	MLP_SFSFDA	Number of neuron in hidden layer: 85	54.5	99.3	96.1
	SVM_SFS	Kernel function: Sigmoid	100	36.4	95.5
	SVM_SFSFDA	Kernel function: MLP	90.9	93.0	92.9
SWL	QDA_SFS	–	77.8	84.9	84.5
	QDA_SFSFDA	–	100	81.5	82.6
	KNN_SFS	$K=3$	33.0	99.0	95.5
	KNN_SFSFDA	$K=3$	44.5	99.3	94.8
	MLP_SFS	Number of neuron in hidden layer: 85	22.3	100	95.5
	MLP_SFSFDA		33.4	100	96.1
	SVM_SFS	Kernel function: polynomial	22.3	99.3	94.8
	SVM_SFSFDA	Kernel function: MLP	88.9	91.8	91.6

Table 5 Performance of the developed systems in correctly predicting need for stent insertion

Methods	Parameters	Sensitivity (%)	Specificity (%)	Accuracy (%)
QDA_SFS	–	13.2	98.3	76.8
QDA_SFSFDA	–	89.5	53.8	62.6
KNN_SFS	$K=3$	44.7	91.5	80.0
KNN_SFSFDA	$K=1$	55.3	86.3	78.7
MLP_SFS	Number of neurons in hidden layer: 85	10.5	99.1	77.5
MLP_SFSFDA		39.0	93.0	80.0
SVM_SFS	Kernel function: sigmoid	42.1	93.1	80.6
SVM_SFSFDA	Kernel function: MLP	71.1	89.7	85.2

Table 6 Performance of the systems developed for predicting need for blood transfusion

Methods	Parameters	Sensitivity (%)	Specificity (%)	Accuracy (%)
QDA_SFS	–	74.0	100	95.5
QDA_SFSFDA	–	88.9	71.0	74.2
KNN_SFS	$K=3$	44.5	92.9	84.5
KNN_SFSFDA	$K=1$	59.3	89.8	84.5
MLP_SFS	Number of neurons in hidden layer: 85	7.4	100	83.2
MLP_SFSFDA		29.6	94.5	83.2
SVM_SFS	Kernel function: sigmoid	40.7	94.5	85.1
SVM_SFSFDA	Kernel function: MLP	85.2	85.2	85.2

a greater interest due to flexibility, promising accuracy, and higher accuracy in comparison with statistical models [24]. In urology, pattern recognition-based systems were utilized to diagnose kidney disease, predict the existence of a kidney stone, spontaneous disposal, recurrent stone formation after treatment, and the outcome of the SWL approach [9, 17, 24–30]. In this study, the objective was to investigate the possibility of developing a machine learning-based system to assist urologists in managing large renal calculi. As shown in Tables 3, 4, 5, and 6, the developed DSSs provided promising results, mainly in terms of sensitivity.

The models presented in this paper have several advantages over the existing methods: (1) it can be adjusted over time by exposing it to new dataset, whereas the models presented in [1, 12, 14] do not have this ability; (2) it considers both stone factors and patient characteristics as input to the model, while others just included stone parameters [1]; (3) it provides not only stone-free status, but also postoperative complications and the need for ancillary surgical procedure, and (4) it provides higher accuracy compared to the model presented in [9].

The variables (features) selected for each DSS, are shown in Table 7. The obtained results are consistent with those reported in previous studies [1, 9, 12, 17]. In general, it was reported that preoperative variables, such as size and location of the stones, single or multiple stones, kidney disorders, treatment history, and being a stag-horn stone are the most important factors that affect stone-free outcome of a treatment procedure. In this study, we found that stone characteristics play an important role in the outcome of PCNL procedure as six features out of eight are from these categories.

We hypothesized that the dimensionality reduction step might not be required at all; hence, we developed four systems using the four examined classifiers (QDA, KNN, MLP, and SVM) without any dimension reduction. The best accuracy in predicting the stone-free status of a kidney after the first treatment was 60.0%, provided by the SVM classifier. Comparing this value to those presented for the SVM-based systems in Table 3, it revealed that feature selection and dimensionality reduction methods were effective and necessary.

The main reason why our systems outperformed the previous ones is that we used multiple system strategy to both design the classifier and find the best subset of features. As described above, instead of designing a single classifier with five outputs for the whole system, we built a separate system for each outcome. The features that were chosen for each outcome, as listed in Table 7 support this strategy. In fact, a group of features that is best for an output might necessarily not work for other postoperative events. Several biomedical engineering works have revealed that multiple classifier systems could perform better than single classifier systems [31–33]. Likewise, multiple feature extraction approach was shown to be effective in improving the classification accuracy [34].

Finally, the results of this study should be considered as a preliminary exercise, but a promising one in the applications of machine learning in treating large kidney stone. We

Table 7 Variables (features) selected for predicting each postoperative outcome

Category	Preoperative/intraoperative feature	Stone-free status	re-PCNL	TUL	SWL	Stenting insertion	Blood transfusion
Patient history	Age		✓	✓			
	Hx of SWL	✓					
	Hx of dialyses				✓		✓
	Hx of diabetes					✓	
	Hx of hypertension					✓	
	Another problems					✓	
Kidney stone/characteristics	Stone location						
	Upper calyx			✓	✓		
	Mid calyx			✓			
	Renal pelvis	✓			✓		✓
	Ureter	✓	✓	✓			
	Stone property						
	Side	✓					
	Size						
	Volume	✓	✓				✓
	Staghorn	✓					
	Multiple	✓		✓			✓
	Renal anomy	✓					✓
	Skeleton anomy	✓				✓	
Lab features	Preoperative hemoglobin						✓

omitted several features, such as the surgeon's experience and PCNL operation factors, since competent surgeons with almost the same level of skill and using the same equipment and instrument completed the procedures. We used the leave-one-patient-out approach in estimating numerical values for each performance index used, since the dataset was small. Therefore, we relayed on only the mean values in comparing the eight classification schemes studied here. We are fully aware that in carefully assessing the performance of a classifier, the variability of its performance should be considered, too. A large dataset to confirm the predictability of the developed systems and its reliability is essential.

Conclusions

A large number of parameters should be considered when treating and managing kidney stone diseases. The accomplishment of an employed treatment procedure is multifactorial. Hence, developing a system that can assist surgeons in predicting the outcome of a treatment might be effective in reducing the risks and expenses. In this paper, we developed a decision support system to assist surgeons in treating large kidney stones. Among the methods investigated here, the systems developed using SVM classifier and integration of the SFS algorithm and FDA approach for dimensionality reduction were the best candidates. The relatively high accuracy of the developed systems is promising to provide counseling and operational support and to predict the surgical outcomes.

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Compliance with ethical standards

Conflicts of interest The authors declare that they have no relevant conflict of interest.

Ethical Approval For the part of this study that we used data of patients, all the procedures performed in this work involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Research involving human participants and/or animals This study was conducted according to the Ethics Committee of Human Experimentation (ECHE) of Shiraz University of Medical Sciences. Owing to this type of this study that patients were not directly involved, the requirement for obtaining written informed consent from each patient was waived by the ECHE of the Shiraz University of Medical Sciences.

Appendix 1: Preoperative, intraoperative, and postoperative data for all patients

See Tables 8 and 9.

Table 8 Preoperative and intraoperative variables for 254 patients included in this work

Variables	Value
Age (years) (mean ± SD)	46.64 ± 12.16
Gender (male/female)	155/99
Stone volume (mean ± SD) (mm^3)	6702.86 ± 381.6
Stone size (mean ± SD) (mm)	21.587 ± 9.09
Stone side (right to left)	123–131
Previous surgery in target kidney, *n* (%)	88 (34.6)
Hx of diabetes, *n* (%)	48 (18.9)
Hx of hypertension, *n* (%)	72 (28.3)
Preoperative hemoglobin (g/dL) (mean ± SD)	13.40 ± 1.77
Preoperative creatinine (mg/dL) (mean ± SD)	1.15 ± 0.48
Body mass index (kg/m^2) (mean ± SD)	26.5 ± 3.52
Renal anomaly, *n* (%)	14 (5.5)
Skeletal anomaly, *n* (%)	2 (0.78)
Stone location, *n* (%)	
Upper calix	13 (5.1)
Mid calix	25 (9.8)
Lower calix	63 (24.8)
Renal pelvis	72 (28.3)
Staghorn	52 (20.4)
Multiple	29(11.4)
Stone lucency, *n* (%)	
Opaque	171 (67.3)
Semiopaque	64 (25.2)
Lucent	19 (7.5)
Degree of hydronephrosis, *n* (%)	
Mild	112 (44.1)
Moderate	90 (35.4)
Severe	52 (20.5)
Radiation exposure during access (s) (mean ± SD)	103.17 ± 49.74
Operative time (min) (mean ± SD)	40.5 ± 10.5

For stone size, the largest diameter is considered. Radiation exposure during access is defined as the duration of X-ray exposure from the insertion of the access needle to the start of nephroscopy

Table 9 Postoperative outcomes for 254 patients studied

Variable	Value
Stone free, *n* (%)	194 (76.4)
Postoperative stone volume (mm^3)	193.4–87.7
Postoperative hemoglobin (g/dL)	11.3–1.17
Postoperative creatinine (mg/dL)	1.16–0.23
Postoperative urine leakage (double-J insertion), *n* (%)	67 (26.4)
Need for blood transfusion, *n* (%)	58 (22.8)
Postoperative ancillary procedures, *n* (%)	
SWL	15 (5.9)
URS	15 (5.9)
PCNL	12 (4.7)

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