On limitations of using rough set approach to analyse non-trivial medical information systems

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Abstract

The rough set theory has been used to analyse medical experience with urolithiasis patients treated by extracorporeal shock wave lithotripsy (ESWL). The aim of this analysis was to evaluate the significance of attributes for two classifications expressing the patients' condition after the ESWL treatment and to discover strong decision rules representing classification patterns interesting for practitioners. The ESWL information system is an example of non-trivial medical data set where the use of a simple rough set model gives a high number of possible reducts which are impossible to interpret. Two heuristic strategies based on the rough set theory are proposed. They lead to the selection of the most significant attributes having a good clinical interpretation. Inducing only discriminating decision rules do not give good interpretation results - rules are weak and too specific. Discovery of partly discriminating rules allows to extract strong classification patterns.

1 Introduction

Medicine in last decades of this century is characterized by an enormous development and expansion of measurement and laboratory techniques. It creates an increasing stream of data which must be analyzed by the physicians. These data contain usually different information about patients: e.g. information coming from interviewing and investigating patients by specialists, measurement parameters characterizing the patients' condition, and data describing the course of the treatment. A large part of this data is now being stored in databases.

Such records have, however, different practical importance for the physicians. So, they are analysed in order to find and select the most important and valuable data elements for the medical interpretation. Typical tasks in the analysis of the medical data, in particular concerning the problems of diagnosing and/or treatment of a given disease, are the following:

- to identify the most important attributes (i.e. characteristic features describing patients) for the patients' classification (resulting from the diagnostic point of view),
- to determine the relationships between values of the important attributes and the patients' classification.

One of the possible data analysis methods which are used to solve the above tasks is the *rough set theory* introduced by Z.Pawlak (Pawlak 1991). In last years, the authors successfully applied it to several medical problems (see e.g. (K.Slowinski 1992), (K. Slowinski *et al* 1989), (K. Slowinski and Shariff 1994)). Other medical applications described in (R.Slowinski 1992) or (Ziarko 1994) also confirm its usefulness. Such elements of the rough set theory as the *approximations of objects' classification*, the *quality of these approximations* and notions of *reducts* could help in evaluating the attributes. Moreover, combination of the rough set theory with *rule induction techniques* gives the representation of the important relationships in the form of *decision rules*. They are easy to interpret and produce a qualitative characterization and explanation of regularities in data.

It must be noticed, however, that in practical applications one can also meet more 'difficult' data sets where the use of the rough set theory, and other data analysis techniques, is not so obvious. Such data sets are characterized by many properties which make them *non-trivial* to analyse, e.g.

- the number of attributes is too large comparing to the number of patients,
- some attributes may be highly dependent on others,
- classes of the patients' classification are non-balanced taking into account the number of individuals; one class is often a strong majority class,
- observations describing patients may have individual character and be difficult to generalize.

The application of the rough set theory to such data sets usually leads to finding a high number of possible reducts, makes it very difficult to evaluate the significance of attributes, produces too many decision rules which are too specific and refer to single cases.

As practitioners usually want to avoid the above ambiguity in interpreting results, it seems to be necessary to consider some extensions of rough set theory approach devoted to the analysis of such non-trivial data set.

In the following paper, we discuss on a practical example such an attempt still based on the rough set theory principles.

First, we propose to use two different heuristic approaches which should evaluate the attribute significance in a more convincing way than by the analysis of the high number of reducts only. Then, we show that for different data set it may be useful to look for *strong* but *partly discriminating* decision rules instead of producing only *strictly discriminating* rules from the lower approximations.

Problems of the analysis non-trivial medical information systems and usefulness of the proposed approach is illustrated on a practical medical example. This medical problem consists in the analysis of a clinical experience with *urolithiasis* treated by *extracorporeal shock wave lithotripsy* (**ESWL**). Urolithiasis is one of the most common diseases of urinary tract. The current progress in the urinary stones treatment is based on a development of a non - invasive method of disintegration of calculi by extracorporeally induced shock waves, i.e. the extracorporeal shock waves lithotripsy (**ESWL**) (cf. (Chaussy *et al* 1979), (Wilbert *et al* 1987)).

Although the collected data set is characterized by some of mentioned limitations, the medical problem itself is very important for urological practice. The ESWL method of treatment of the urolithiasis patients is a quite new technique while the diagnostic knowledge and indications are not still precisely defined. So, all attempts to study recommendations for the ESWL treatment are very interesting from the medical point of view.

The paper is organised as follows. Section 2 gives the brief description of the ESWL data set. Then, basic information about chosen methodology are given in section 3. Section 4 describes the performed analysis. Discussion of obtained results and final remarks are presented in Section 5.

2 Description of the ESWL data set

We analyse the clinical experience with extracorporeal shock wave lithotripsy (ESWL) in urolithiasis patients. Data were collected at the Urology Clinic of K.Marcinkowski University of Medical Science in Poznań (Kwias *et al* 1992). In order to qualify patients for the ESWL treatment different data, i.e. attributes, characterizing patients, are taken into account. The source of these data is usually: anamnesis (i.e. information coming from investigating patients by the physician), laboratory and imaging tests.

The ESWL treatment of urinary stones has been performed at the Urology Clinic of University of Medical Science in Poznań since 1990. Although the current experience includes over 1000 patients per year, we could choose to the analysis only part of it, i.e. data about patients with completely defined pre-operation attributes and with known and verified long term results of treatment.

The patients are described by 33 pre-operation attributes currently considered in an urological practice. These are the following attributes: 1 - age, 2 - sex, 3 - duration of disease, 4 - type of urolithiasis, 5 - lithuresis, 6 - operations in the past, 7 - nephrectomy, 8 - PNCL, 9 - number of the ESWL treatment previously done, 10 - evacuation of calculi by zeiss cather, 11 - lumbar region pains, 12 - dyspectic symptoms, 13 - basic dysuric symptoms, 14 - other dysuric symptoms, 15 - temperature, 16 - general uriscopy, 17 - urine reaction, 18 - erythrocyturia, 19 - leucocyturia, 20 - bacteriuria, 21 - crystaluria, 22 - proteinuria, 23 - urea, 24 - creatinine, 25 - bacteriological test, 26 - kidney location, 27 - kidney size, 28 - kidney defect, 29 - status of urinary system, 30 - secretation of urinary contrast, 31 - location of the concrement, 32 - calixcalculus, 33 - stone size. Let us notice that nearly all of these attributes have a qualitative character. Their domains usually consist of a limited number of values which are qualitative and linguistic terms. In addition, the domains of many attributes cannot be ordered.

The post-operation conditions of the patients were described by two attributes having the following clinical meaning:
1. A patient's physical condition after the lithotripsy, i.e.:
- treatment without complications,
- treatment with complications.
2. Long term results of the treatment:
- recovery (good results),
- no recovery,
- lack of effects.

The both post-operation attributes define two classifications of patients, denoted as $\mathcal{Y}_1$ and $\mathcal{Y}_2$ respectively. Values of these classifications will be further called *decision classes*. These classifications are typical standards used to evaluate the medical treatment.

The representation of the ESWL experience for a set of 343 patients has been preliminary examined by the authors in the study (K.Slowinski *et al.* 1995). This study was focused on using the rough set theory to identify a group of the most significant attributes for both classifications. Reducts of attributes (i.e. subset of attributes ensuring the same approximation of patients classification as a set of all attributes) were tried to be found. However, the authors and medical experts met difficulties with interpretation of obtained reducts because of their too high number.

To avoid this ambiguity in interpreting results we have decided to:
- extend the number of considered patients,
- use additional heuristic strategies which should identify the most significant attributes in a less subjective way than previously.

Additionally, in the current study we decided to look for relationships between values of attributes and the patients' classification represented in the form of decision rules. Such rules should be meaningful and interesting for the practitioners.

Taking into account the number of patients, first we have managed to extend it to 435 ones and performed the analysis of the significance of attributes using the strategies discussed in the next sections. Moreover, for the last phase of the rule discovery we get information about additional patients what finally increased their number up to 500 ones.

3 Brief information about the method

The ESWL information system is analysed using the rough set theory (Pawlak 1991). From the rough set theory point of view, the analysis is connected with examining *dependencies between attributes* in the defined data set (called further an *ESWL information system*). More precisely, similarly to previous medical applications (K.Slowinski *et al* 1989, 1992, 1995), the following elements of rough set theory are used:

- creating classes of *indiscernibility relations* (atoms) and building *approximations* of the objects' classification,
- evaluating the ability of attributes to approximate the objects' classification; the measure of the *quality of approximation of the classification* defined as the ratio of the number of objects in the lower approximations to the total number of objects is used to for this aim,
- discovering *cores* and *reducts* of attributes (a reduct is the minimal subset of attributes ensuring the same quality of the classification as the entire set of attributes; a core is an intersection of all reducts in the information system),
- examining the *significance* of attributes by observing changes in the quality of approximation of the classification caused by removing or adding given attributes.

All necessary definitions could be found in (Pawlak 1991), (R. Slowinski 1992) or (Ziarko 1994).

Results obtained in (K.Slowinski *et al* 1995) and for the increased here ESWL information system show that using only these elements to identify the most significant attributes for the two patients' classifications may be insufficient. It results from the fact that although the quality of approximation of objects' classification is maximal, equal to 1, the number of possible reducts is extremely high, the core is empty and there are no direct indications which reduct should be treated as the best one.

So, to get results confirmed in a more convincing way, we decided to use independently two additional heuristic approaches directly oriented to determine the most significant attributes.

The heuristics are the following:

- The strategy based on adding to the core, the attributes of the highest increase of discriminatory power,
- The strategy based on dividing the set of attributes into disjoint subsets and analysing the significance inside subsets,

In the first strategy, the core of attributes is chosen as a starting reduced subset of attributes. It usually ensures lower quality of approximation of the objects' classification than all attributes. A single remaining attribute is temporarily added to the core and the influence of this adding on the change of the quality is examined. Such an examination is repeated for all remaining attributes. The attribute with the highest increase of the quality of classification is chosen to add to the reduced subset of attributes. Then, the procedure is repeated for remaining attributes. It is finished when an acceptable quality of the classification is obtained. If there are ties in choosing attributes several possible ways of adding are checked. This strategy has been introduced in (Slowinski *et al* 1989) and successfully used to analyse the considered medical problem.

The aim of the second strategy is to reduce the number of interchangeable and independent attributes in the considered information system. If the system contains too many of such attributes, one usually gets as a result an empty core, high number of equivalent reducts and atoms supported by single objects. We suggest to divide the set of all attributes into disjoint subsets. Each subset should contain attributes which are dependent each other in a certain degree and have a common characteristic for a domain expert. Such a division could be done either nearly automatically as in (Ziarko and Shan 1995) or depending on the background domain knowledge.

The above strategies can be used to select the most important attributes. In the current study, *discovery of decision rules* is also considered. Decision rules are logical statements expressed in the following form:

$$IF\ (a_1,v_1)\&(a_2,v_2)\&\ \ldots\&(a_n,v_n)\ THEN\ class_j$$

where a_i is the ith attribute, v_i is its value and $class_j$ is one of the decision classes in objects' classification.

To discover the decision rules in the ESWL data set we use our implementation of LEM2 algorithm introduced by Grzymala (1992). This algorithm induces from lower approximations of decision classes, so called, *discriminating rules* (also called certain rules). These rules distinguish positive examples, i.e. objects belonging to the lower approximation of the decision class, from other objects.

To interpret the discovered rules we use the measure of their *strength*. It is the number of objects in the information system whose description satisfy the condition part of the rule. Generally, one is interested in discovering the strongest rules. Discovery of such rules may be impossible for data sets like ESWL one where rules are weak and too specific.

We think that one of the possible solution to avoid these limitations is to induce *partly discriminating decision rules* instead of discriminating only. These are rules that besides positive examples belonging to the given decision class could cover a limited number of objects not belonging to it. The partly discriminating rules are characterized by a coefficient called *level of discrimination* defined as:

$$d = \frac{p}{n}$$

where p is a number of positive examples and n is a total number of examples covered by the rule.

We argue that establishing a proper threshold for the minimum value of the level of discrimination will result in discovering stronger rules having *good interpretation characteristics.* In this study we induce partly discriminating rules using a modified version of LEM2 algorithm.

The above motivation is somehow similar to the concept of so called *Variable Precision Rough Set Model* introduced by Ziarko (1993).

4 Analysis of the ESWL information system

4.1 Looking for reducts

Let us consider the ESWL information system extended to 435 patients described by 33 attributes and classified by two classifications $\mathcal{Y}_1$ and $\mathcal{Y}_2$.

For both classifications $\mathcal{Y}_1$ and $\mathcal{Y}_2$ lower and upper approximations of decision classes were calculated. The qualities of the approximations of classification by the set of all 33 attributes in both cases were equal to 1.0. However, the number of atoms was the nearly the same as the number of objects (patients), and was equal to 434 for both classifications. Although, the quality of the approximation of the classification was the maximal one, the number of atoms was too high. Nearly all of these atoms were represented by single patients. So, they could not be treated as a good basis for expressing strong classification patterns. One can check, that similar results were also obtained for the smaller number patients in the previous study (K.Slowinski *et al* 1995).

Then, we looked for cores and reducts of attributes. Using the microcomputer program Rough-DAS (R. Slowinski and Stefanowski 1992) we were able to conclude, that the core of the first classification $\mathcal{Y}_1$ was empty and the core of the second one $\mathcal{Y}_2$ consisted of two attributes only (i.e. 20 and 21). For both classifications, we found out that the number of the reducts was very high. We could not precisely determine it within reasonable time because of the limited capacity of the used computer equipment. We could suspect, considering these results, that the attributes used to construct the data set are interchangeable. One can remove few of them and others will take their role and still give the highest classification ability. As a result, the number of reducts is very high and even finding all of them would not lead to any reasonably solution from the medical point of view.

To help the urologists in determining the significance of attributes, we decided to use two heuristic approaches to select the most significant attribute.

4.2 Heuristic strategies to select attributes

Proceeding in the way described in section 3, for both classifications we obtained the most acceptable reduced subset of attributes by adding the most discriminating ones to the core. The obtained subsets are presented in Table 1. Here, due to the limited size of the paper, we give summarized results only. Details are presented in (Stefanowski and K.Slowinski 1995).

Table 1: Acceptable subsets of attributes for both classifications obtained as a result of adding the most discriminatory attributes to a core

Classification	Selected attributes
$\mathcal{Y}_1$	1 3 6 11 14 21 22 25 28 29 30 31 33
$\mathcal{Y}_2$	1 2 6 11 14 16 20 21 31 33

The obtained reduced subsets of attributes are nearly the same as the ones found in the study (K.Slowinski *et al* 1995). On the other hand, it should be noticed that this strategy starts from adding attributes to the core here characterized by a very low quality of approximation of the classification and first additions does not lead to the fast increase of this quality (around 0.1). The final results partly depends on the first choices. This is the additional motivation to check other strategies.

So, we used the second strategy to solve the difficulties with existing in the ESWL information system too many interchangeable and independent attributes. According to it, we divided the set of all attributes into disjoint subsets. Each subset should contain attributes which are dependent each other in a certain degree and have common characteristics for a domain expert. In this study we performed a division according to the medical experts' background knowledge and chose two disjoint subsets which have a different medical source and interpretation:

- attributes coming from the physician's investigation of the patient - anamnesis; i.e. these are attributes 1 - 14 and they create *information system A*,

- attributes obtained as a result of laboratory tests and examinations; i.e. these are attributes 15 - 33 and they create *information system B*.

Then, for both classifications $\mathcal{Y}_1$ and $\mathcal{Y}_2$ and each information system A and B we examined the significance of attributes using "traditional rough set approach" (e.g. as in (K. Slowinski 1992)), i.e. we removed temporarily single attributes and observed the decrease of quality of classification. Results are presented in Table 2.

Table 2: Subsets of attributes resulting from examining the significance of attributes in subdivided systems A and B

Classification	Type of attributes	Selected attributes
$\mathcal{Y}_1$	the most significant	1 3 6 11 21 25 29 30 32
$\mathcal{Y}_1$	the less significant	7 8 10 13 17 23 26 27 28
$\mathcal{Y}_2$	the most significant	1 6 11 21 25 30 32 33
$\mathcal{Y}_2$	the less significant	7 10 13 15 16 26 27 28

4.3 Determining the most significant attributes

One can notice that results obtained using these two strategies, i.e. chosen subsets of attributes, are quite similar. These results were carefully interpreted by urologists. They confirmed that among the selected attributes they can find these that are assumed to be very important for clinical practice. Moreover some of the redundant attributes are also suspected by them to be unnecessary for qualifying patients to the ESWL.

In conclusion, they agreed to redefine the ESWL information system. They decided:
- to remove from the information system the following attributes: 7,10,17,20,26,27
- to create a new attribute referring to dysuric symptoms on the basis of previous attributes 13 and 14 (both also referring to different dysuric symptoms).

Moreover, after this discussion they managed to provide information about additional patients. So, finally the number of analysed patients was equal to 500.

The ESWL information system was reduced to 26 attributes. In the following parts of the paper, we stay with the same number codes of attributes for the reduced system as for the original one to be more consistent.

The rough set approach was applied to the reduced ESWL information system. The results are presented in Table 3. Let us notice that the quality of the classification slightly decreased as a result of redefining attributes. However, now we can obtain cores of attributes characterizing by more elements and the higher quality value.

Table 3: Results of approximations of patients' classification for the reduced ESWL information system - 26 attributes

Classification	Quality of approx. of classification	Core of attributes	Quality of classification for the core
$\mathcal{Y}_1$	0.996	11 29 31	0.174
$\mathcal{Y}_2$	0.992	1 11 21 29 31	0.448

As the number of possible reducts was still high we repeated the strategy of adding the most discriminating attributes to cores. It was noticed that now the choice of joined attributes was more supported by higher difference in the increase of the quality of classification approximation than for 33 attributes case. This procedure led us to first reduced subsets of attributes characterized by the fastest increase of the quality of the classification - these are subsets 1 and 3 presented in Table 4. This procedure indicates that sometimes more than one attribute could be chosen (the difference between increase of the quality for possible attributes was smaller than 5%). So, few other reducts could be found. We summed up attributes occurring in the additional reducts and get subsets 2 and 4, showed in Table 4.

Table 4: The most significant attributes for the reduced ESWL information system

Classification	Number of subset	Selected attributes
$\mathcal{Y}_1$	1	1 2 6 11 13 22 29 31 33
$\mathcal{Y}_1$	2	1 2 3 6 11 13 21 22 25 29 30 31 32 33
$\mathcal{Y}_2$	3	1 2 11 13 21 29 31
$\mathcal{Y}_2$	4	1 2 3 6 11 21 25 29 30 31 32 33

It should be noticed that the selected attributes are quite similar to results obtained for 33 attribute version of the ESWL information system (compare Tables 2 vs 4).

4.4 Looking for decision rules

The authors' implementation of LEM2 algorithm was used to induce discriminating (certain) decision rules. The rules were induced both from the ESWL information system describing 500 patients by the selected 26 attributes and the information system built using reduced subset of attributes (subsets 2 and 4 from Table 4) - as they were preferred by the urologists. The results are presented in Table 5.

Table 5: The discriminating decision rules induced from the ESWL information system for 26 attributes and reduced subsets of attributes. Numbers in brackets refer to decision classes in both classifications. The first classifications consists of two values and the second consists of 3 ones

Classification	Number of attributes	No. of rules: total and in classes	Average strength of the rule [objects]	the strongest rule [objects]
$\mathcal{Y}_1$	26	119 (65/64)	(9.42/3.37)	23
$\mathcal{Y}_1$	subset 2	151 (79/72)	(6.81/2.5)	22
$\mathcal{Y}_2$	26	123 (55/51/17)	(9.15/4.24/1.71)	24
$\mathcal{Y}_2$	subset 4	160 (74/68/18)	(7.55/3.25/1.56)	18

One can notice that the number of discriminating rules is quite large. Most of them also refer to a small number of patients or even single ones. According to the medical experts' interpretation these sets are too large and specific. The experts expect up to 20 stronger rules for each classification.

For these reasons we decided to induce partly discriminating rules (as it has been described in section 3). Let us notice that the majority decision class, coded by 1, is equal to 68.8% and 60.4% patients for classifications $\mathcal{Y}_1$ and $\mathcal{Y}_2$, respectively. Taking it into account and experts' preferences to the possible level of discrimination we decided to check the following possible values of this level: 0.75, 0.8, 0.85. Similarly as before we considered the sets of 26 and reduced attributes. The information about obtained rule sets are presented in Table 6.

Let us notice that for the level of discriminating equal to 0.8 it was possible to discover smaller number of rules which are also stronger at least three times than strictly discriminating rules. Moving the level of discrimination up to 0.75 resulted in obtaining even stronger rules. Moreover, among them there are rules which are (according to urologists) very interesting, have simple and general condition parts and refer to high number of patients (see Table 6). For example, for class 1 in classification $\mathcal{Y}_1$ there are rules covering 144 or 102 patients (41.87% and 20% of all patients from this class).

For discriminating rules, the use of reduced subsets of attributes did not give rules more interesting for urologists than rules obtained using all attributes. It is not a case for partly discriminating rules where we can get a limited number of strong enough rules.

Table 6: The partly discriminating decision rules induced from the ESWL information system for 26 attributes and reduced subsets of attributes

Classification	level of discri-mination	Number of attributes	No. of rules: total and in classes	Average strength of the rule [objects]	the stron-gest rule [objects]
$\mathcal{Y}_1$	0.85	26	97 (44/53)	(17.93/3.43)	63
$\mathcal{Y}_1$	0.80	26	82 (33/49)	(27.18/4.22)	105
$\mathcal{Y}_1$	0.75	26	59 (20/39)	(39.4/5.46)	144
$\mathcal{Y}_1$	0.85	subset 2	126 (54/72)	(14.59/2.68)	31
$\mathcal{Y}_1$	0.80	subset 2	111 (44/67)	(20.1/2.91)	79
$\mathcal{Y}_1$	0.75	subset 2	87 (29/58)	(34.1/3.48)	140
$\mathcal{Y}_2$	0.85	26	114 (46/51/17)	(12.83/4.96/1.71)	72
$\mathcal{Y}_2$	0.80	26	95 (34/44/17)	(21.35/5.18/1.88)	72
$\mathcal{Y}_2$	0.75	26	80 (23/44/13)	(26.91/5.41/2.23)	126
$\mathcal{Y}_2$	0.85	subset 2	140 (53/69/18)	(13.21/3.33/1.56)	54
$\mathcal{Y}_2$	0.80	subset 2	118 (44/56/18)	(18.25/4.57/1.56)	70
$\mathcal{Y}_2$	0.75	subset 2	99 (30/4.6/1.68)	(32.97/4.8/1.69)	124

The medical experts have chosen the strongest partly discriminating rules (they taken rules stronger than 25 patients for class 1, and over 8 patients for class 2) as the representation of indications for applying the ESWL treatment for uriolithiasis patients.

5 Final remarks

The ESWL information system has been analysed in this paper. The aim of this analysis was to evaluate the significance of attributes for two classifications expressing the patients' condition after the ESWL treatment of urolithiasis and to discover strong decision rules representing classification patterns interesting for practitioners.

The ESWL information system is an example of non-trivial medical data set where the use of the rough set based data analysis is not so obvious. Such data sets are quite often met in medical applications.

The performed analysis of the ESWL information system has led us to the following conclusions:

1. The use of the simple rough set model gives an enormous high number of possible reducts which are impossible to interpret. The core of attributes is empty. The urologists are unable to identify the most significant attributes for qualifying patients to the ESWL treatment.

2. Simple increasing the number of patients (over 33 %) and even attempts of reducing set of attributes from 33 to 26 ones did not help in the analysis. The number of reducts is still high. Previous experience with applying the rough set theory to medical data sets indicates that such a definition of the information systems which gives one or few reducts, leads also to good results and is the most preferred by practitioners (see e.g. K.Slowinski 1988, 1992).

3. The use of proposed strategies, first based on adding the most discriminating attributes to the initial set and the other one based on dividing the set of attributes into disjoint subsets, helped in selecting the significant attributes. Both strategies give the similar results. The chosen subsets of attributes are also consistent with the current urological experience.

4. Inducing only discriminating decision rules did not give good interpretation results - rules were weak and too specific. Discovery of partly discriminating rules allowed to extract strong and interesting classification patterns.

Proceeding in the described way, we were able to satisfy the urologists' expectations. They want to get a limited number of simple and general decision rules which are supported by high number of the cases. These results somehow confirm the general expert's clinical experience. However, additional experience and insight into the ESWL problem is also represented by weaker rules supported by single or few clinical cases. They refer to anomalies, exceptions and untypical cases which are also interesting for practitioners.

In spite of noticed limitations of the ESWL information systems, in the future we are going to create a medical decision support system based on strong decision rules, the selected attributes and representations of single exception cases. The aim of this system is to help the practitioners in qualifying urolithiasis patients for the ESWL treatment.

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