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Application of rough sets in the presumptive diagnosis of urinary system diseases

JACEK CZERNIAK, HUBERT ZARZYCKI

Technical University of Szczecin, Faculty of Computer Science & Information Systems

Institute of Artificial Intelligence & Mathematical Methods

address: ul. Żołnierska 49, 71-210 Szczecin, e-mail: jczerniak@wi.ps.pl, hzarzycki@wi.ps.pl

Abstract: The main idea of this article is to prepare the model of the expert system, which will perform the presumptive diagnosis of two diseases of urinary system. This is an example of the rough sets theory application to generate the set of decision rules in order to solve a medical problem. The lower and upper approximations of decision concepts and their boundary regions have been formulated here. The quality and accuracy control for approximations of decision concepts family has been provided as well. Also, the absolute reducts of the condition attributes set have been separated. Moreover, the certainty, support and strength factors for all of the rules have been precisely calculated. At the end of the article, the author has also shown the reverse decision algorithm.

Key words: rough sets, decision rules, concept, attribute reduct set, region, certainty factor, support factor, strength factor, decision algorithm.

1. DESCRIPTION OF THE PROBLEM

1.1 Introduction

The main idea of this article is to prepare the algorithm of the expert system, which will perform the presumptive diagnosis of two diseases of urinary system. It will be the example of diagnosing of the acute inflammations of urinary bladder and acute nephritises. For better understanding of the problem let us consider definitions of both diseases given by Manitius.

„Acute inflammation of urinary bladder is characterised by sudden occurrence of pains in the abdomen region and the urination in form of constant urine pushing, micturition pains and sometimes lack of urine keeping. Temperature of the body is

rising, however most often not above 38°C. The excreted urine is turbid and sometimes bloody. At proper treatment, symptoms decay usually within several days. However, there is inclination to returns. At persons with acute inflammation of urinary bladder, we should expect that the illness will turn into protracted form." [1]

„Acute nephritis of renal pelvis origin occurs considerably more often at women than at men. It begins with sudden fever, which reaches, and sometimes exceeds 40°C. The fever is accompanied by shivers and one- or both-side lumbar pains, which are sometimes very strong. Symptoms of acute inflammation of urinary bladder appear very often. Quite not infrequently there are nausea and vomiting and spread pains of whole abdomen." [1]

1.2 General decisive diagram

In order to better visualise the research problem let us accept as start point to further considerations, the diagram of expert system with six inputs for data and two decision outputs, which was showed on the picture Fig.1.

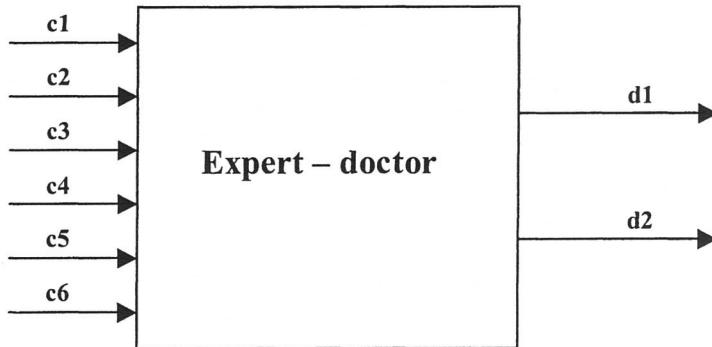


Fig. 1 General decisive diagram of expert system.

1.3 Original database of information

Below there is the full set of experimental data, which in further sections of this article will be processed using the method of rough sets in order to obtain optimum set of decisive equations.[2][6]

Patient	Temperature	Nausea	Lumbar pain	Urine pushing	Micturition pains	Burning of urethra	Inflammation of urinary bladder	Nephritis
Obj.	c1	c2	c3	c4	c5	c6	d1	d2
p1	p	no	no	yes	yes	no	yes	no
p2	w	yes	yes	yes	yes	yes	yes	yes
p3	g	no	yes	yes	no	yes	no	yes
p4	p	no	yes	no	no	no	no	no
p5	w	yes	yes	yes	yes	no	yes	yes
p6	p	no	no	yes	yes	yes	yes	no
p7	w	no	no	no	no	no	no	no
p8	p	no	no	yes	no	no	yes	no
p9	n	no	no	yes	yes	yes	yes	no
p10	n	no	yes	no	no	no	no	no
p11	w	yes	yes	no	yes	no	no	yes
p12	w	no	yes	yes	no	yes	no	yes

Tab. 1 Original information database.

No	Description of attribute	Symbol	Domain
1	Temperature of patient	c1	{ n, p, g, w } n – normal temp. 36^0 - 37^0 C p – subfebrile state 37^0 - 38^0 C g – febrile state 38^0 - 40^0 C w – high fever above 40^0 C
2	Occurrence of nausea	c2	{ yes, no }
3	Lumbar pain	c3	{ yes, no }
4	Urine pushing (continuous need for urination)	c4	{ yes, no }
5	Micturition pains	c5	{ yes, no }
6	Burning of urethra, itch, swelling of urethra outlet	c6	{ yes, no }
7	Inflammation of urinary bladder	d1	{ yes, no }
8	Nephritis of renal pelvis origin	d2	{ yes, no }

Tab. 2 The breakdown of input attributes and their values.

2. DETERMINATION OF THE EXPERT MODEL

2.1 Elementary conditional sets

Process of determination of decisive equations set of characteristic for expert should be started from separation of elementary conditional sets. All these sets are shown in the table below.

Obj.	c1	c2	c3	c4	c5	c6	d1	d2	E _i	X _i
p1	p	no	no	yes	yes	no	yes	no	E1	X1
p2	w	yes	E2	X2						
p3	g	no	yes	yes	no	yes	no	yes	E3	X3
p4	p	no	yes	no	no	no	no	no	E4	X4
p5	w	yes	yes	yes	yes	no	yes	yes	E5	X2
p6	p	no	no	yes	yes	yes	yes	no	E6	X1
p7	w	no	E7	X4						
p8	p	no	no	yes	no	no	yes	no	E8	X1
p9	n	no	no	yes	yes	yes	yes	no	E9	X1
p10	n	no	yes	no	no	no	no	no	E10	X4
p11	w	yes	yes	no	yes	no	no	yes	E11	X3
p12	w	no	yes	yes	no	yes	no	yes	E12	X3

Tab. 3 Elementary conditional sets.

Let us assume, that U is universe of p_i examples. So, we obtain as follows:

$$U = \{p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, p12\} \quad \text{card}(U) = 12$$

Set of conditional C attributes. $C = \{c1, c2, c3, c4, c5, c6\}$

Family of C^* attribute sets, which is C-elementary E_i . $C^* = \{E1, E2, E3, E4, \dots, E12\}$

Attribute C-elementary E_i sets.

$$E1 = \{p1\}, E2 = \{p2\}, E3 = \{p3\}, E4 = \{p4\}, E5 = \{p5\}, E6 = \{p6\}, E7 = \{p7\},$$

$$E8 = \{p8\}, E9 = \{p9\}, E10 = \{p10\}, E11 = \{p11\}, E12 = \{p12\}$$

As it can be seen from above calculations, all elementary E_i sets are singletons.

2.2 Elementary decisive sets (concepts)

The next step to determine the expert model should be concepts fixing, i.e. elementary decisive sets. All these sets are contained in the Tab.3 table. [4][2]

Let us assume, that F is family of decisive concepts X_i .

$$F = \{X1, X2, X3, X4\} \text{ where;}$$

$$X1 = \{p1, p6, p8, p9\}, X2 = \{p2, p5\}, X3 = \{p3, p11, p12\}, X4 = \{p4, p7, p10\}$$

Let us make an attempt to present decisive concepts X_i in form of logical elementary sums, of attribute sets E_i .

$$\text{Concept } X1 : X1 = \{p1, p6, p8, p9\} = \{p1\} \cup \{p6\} \cup \{p8\} \cup \{p9\} = \{E1\} \cup \{E6\} \cup \{E8\} \cup \{E9\}$$

Concept X2: $X2 = \{p2, p5\} = \{p2\} \cup \{p5\} = \{E2\} \cup \{E5\}$

Concept X3: $X3 = \{p3, p11, p12\} = \{p3\} \cup \{p11\} \cup \{p12\} = \{E3\} \cup \{E11\} \cup \{E12\}$

Concept X4: $X4 = \{p4, p7, p10\} = \{p4\} \cup \{p7\} \cup \{p10\} = \{E4\} \cup \{E7\} \cup \{E10\}$

In the next step one should try to restrict the solution, if of course such possibility will exist. One should check it by calculating lower and upper approximations of concepts.

2.3 Lower and upper approximations of concepts and their boundary regions

Lower CX1 approximation of X1 concept in the area of conditional attributes looks like below.

$$C = \{c1, c2, c3, c4, c5, c6\}. \quad \underline{CX1} = E1 \cup E6 \cup E8 \cup E9$$

Upper approximation of X1 concept.

$$\overline{CX1} = E1 \cup E6 \cup E8 \cup E9 \quad \overline{CX1} = \underline{CX1}$$

Conclusion:

Concept $X1 \in F$ is C-distinguishable, which means, that it is distinguishable in relation to set of attributes $C = \{c1, c2, c3, c4, c5, c6\}$.

Lower approximation of X2 concept. $\underline{CX2} = E2 \cup E5$

Upper approximation of X2 concept.

$$\overline{CX2} = E2 \cup E5 \quad \overline{CX2} = \underline{CX2}$$

Conclusion:

Concept $X2 \in F$ is C-distinguishable.

Lower approximation of X3 concept. $\underline{CX3} = E3 \cup E11 \cup E12$

Upper approximation of X3 concept.

$$\overline{CX3} = E3 \cup E11 \cup E12 \quad \overline{CX3} = \underline{CX3}$$

Conclusion:

Concept $X3 \in F$ is C-distinguishable.

Lower approximation of X4 concept. $\underline{CX4} = E4 \cup E7 \cup E10$

Upper approximation of X4 concept.

$$\overline{CX4} = E4 \cup E7 \cup E10 \quad \overline{CX4} = \underline{CX4}$$

Conclusion:

Concept $X4 \in F$ is C-distinguishable.

Boundary region $GR(X_i)$ of rough set X_i .

$$GR(X_i) = GP(X_i) - DP(X_i)$$

$$GR(X_1) = GP(X_1) - DP(X_1) = \{\phi\} \quad GR(X_2) = GP(X_2) - DP(X_2) = \{\phi\}$$

$$GR(X_3) = GP(X_3) - DP(X_3) = \{\phi\} \quad GR(X_4) = GP(X_4) - DP(X_4) = \{\phi\}$$

Conclusion :

Due to the fact that for every concept, the boundary region is an empty set, there are no such ranges in the area of attributes, in which deduction is not certain.

2.4 Quality and accuracy of approximation of decisive concepts family in the area of conditional attributes

Continuing the discussion on concepts, let us move to calculations of quality and accuracy of their approximations. The table below contains the breakdown of concepts and their upper and lower approximations.

X_i	$\text{card}(\underline{C}X_i)$	$\text{card}(\overline{C}X_i)$
$X_1 = \{p1, p6, p8, p9\}$	4	4
$X_2 = \{p2, p5\}$	2	2
$X_3 = \{p3, p11, p12\}$	3	3
$X_4 = \{p4, p7, p10\}$	3	3
Suma	12	12

Tab. 4 List of decisive concepts.

Thus assuming, that $\text{Pos}_c(F)$ is C-positive area of F concepts family, we obtain as follows:

$$\begin{aligned}\text{card}(\text{Pos}_c(F)) &= \text{card}(\underline{C}X_1 + \underline{C}X_2 + \underline{C}X_3 + \underline{C}X_4) = \\ \text{card}(\{p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, p12\}) &= 12 \\ \text{card}(U) &= 12\end{aligned}$$

$$\sum_{X_i \in F} \text{card}(\underline{C}X_i) = \text{card}(\underline{C}X_1) + \text{card}(\underline{C}X_2) + \text{card}(\underline{C}X_3) + \text{card}(\underline{C}X_4) = 4+2+3+3 = 12$$

Now we can calculate C-quality of concepts family approximations from the formula below.

$$\gamma_c(F) = \frac{\text{card}(\text{Pos}_c(F))}{\text{card}(U)} = \frac{12}{12} = 1$$

Whereas C-accuracy of concepts family approximations, using the following equation.

$$\beta_c(F) = \frac{\text{card}(\text{Pos}_c(F))}{\sum_{X_i} \text{card}(\overline{C}X_i)} = \frac{12}{12} = 1$$

As results from calculations, all X_i concepts of F family are C-distinguishable. D set of decisive attributes depends completely on set of conditional C attributes ($k = \gamma_c(F) = 1$). It means, that expert, who gave data related to presumptive diagnosis performed an unambiguous classification.

To keep the order and systematic of deduction, let us check C-boundary area F family of X_i sets yet.

$$\begin{aligned}B_{n\tilde{c}}(F) &= U_{X_i \in F} B_{n\tilde{c}} X_i & B_{n\tilde{c}}(X_i) &= \overline{C}X_i - \underline{C}X_i \\ B_{n\tilde{c}}(X_1) &= \overline{C}X_1 - \underline{C}X_1 = \{\emptyset\} & B_{n\tilde{c}}(X_2) &= \overline{C}X_2 - \underline{C}X_2 = \{\emptyset\} \\ B_{n\tilde{c}}(X_3) &= \overline{C}X_3 - \underline{C}X_3 = \{\emptyset\} & B_{n\tilde{c}}(X_4) &= \overline{C}X_4 - \underline{C}X_4 = \{\emptyset\} \\ B_{n\tilde{c}}(F) &= B_{n\tilde{c}}(X_1) \cup B_{n\tilde{c}}(X_2) \cup B_{n\tilde{c}}(X_3) \cup B_{n\tilde{c}}(X_4) = \{\emptyset\}\end{aligned}$$

We can officially express two final rules about relative possibility to remove attributes [7]. If the following equality is valid;

$$\text{Pos}_{\tilde{C}-\{c_i\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*) \text{ to } \gamma_{\tilde{C}-\{c_i\}}(D^*) = \gamma_{\tilde{P}}(D^*)$$

then we say, that c_i attribute is removable (D – removable).

However If;

$$\text{Pos}_{\tilde{C}-\{c_i\}}(D^*) \neq \text{Pos}_{\tilde{P}}(D^*) \text{ to } \gamma_{\tilde{C}-\{c_i\}}(D^*) < \gamma_{\tilde{P}}(D^*)$$

Then we say, that c_i attribute is irremovable (D – irremovable).

So because the following equalities are valid;

$$\text{Pos}_{\tilde{C}-\{c_1\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*) \quad \text{Pos}_{\tilde{C}-\{c_2\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*)$$

$$\text{Pos}_{\tilde{C}-\{c_3\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*) \quad \text{Pos}_{\tilde{C}-\{c_5\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*)$$

$$\text{Pos}_{\tilde{C}-\{c_4\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*)$$

It means, that attributes c_1, c_2, c_3, c_5, c_6 are D-removable from set of conditional attributes. Whereas due to the following equality;

$$\text{Pos}_{\tilde{C}-\{c_6\}}(D^*) = \text{Pos}_{\tilde{P}}(D^*)$$

2.7 Relative significance of conditional attributes

On this stage of considerations we can try to list calculated relative significance of conditional attributes. Those calculations are based on the following formula [2]:

$$\delta_{(C,D)}(C_i) = \frac{\gamma_c(D^*) - \gamma_{\tilde{C}-\{c_i\}}(D^*)}{\gamma_c(D^*)} = 1 - \frac{k'}{k}$$

As a consequence, we can find results in Tab.7 table, which shows $\delta_{(C,D)}$ values for each attribute.

Decision		Removed C_i conditional attribute					
d_1	d_2	c_1	c_2	c_3	c_4	c_5	c_6
no	no	0	0	0	0	0	0
no	yes	0	0	0	0.33	0	0
yes	no	0	0	0	0	0	0
yes	yes	0	0	0	0.5	0	0

Tab. 7 Breakdown of relative significance values of conditional attributes.

Further comments on this list does not seem purposeful.

2.8 Decisive algorithm of the problem and its partition on the well and badly defined part

So, there is full set of decisive rules, which due to previous considerations could be considerably limited.

R1: IF (c1=p) & (c2=n) & (c3=t) & (c4=n) & (c5=n) & (c6=n) THEN (d1=n) & (d2=n)
R2: IF (c1=w) & (c2=n) & (c3=n) & (c4=n) & (c5=n) & (c6=n) THEN (d1=n) & (d2=n)
R3: IF (c1=n) & (c2=n) & (c3=t) & (c4=n) & (c5=n) & (c6=n) THEN (d1=n) & (d2=n)
R4: IF (c1=g) & (c2=n) & (c3=t) & (c4=t) & (c5=n) & (c6=t) THEN (d1=n) & (d2=t)
R5: IF (c1=w) & (c2=t) & (c3=t) & (c4=n) & (c5=t) & (c6=n) THEN (d1=n) & (d2=t)
R6: IF (c1=w) & (c2=n) & (c3=t) & (c4=t) & (c5=n) & (c6=t) THEN (d1=n) & (d2=t)
R7: IF (c1=p) & (c2=n) & (c3=n) & (c4=t) & (c5=t) & (c6=n) THEN (d1=t) & (d2=n)
R8: IF (c1=p) & (c2=n) & (c3=n) & (c4=t) & (c5=t) & (c6=t) THEN (d1=t) & (d2=n)
R9: IF (c1=p) & (c2=n) & (c3=n) & (c4=t) & (c5=n) & (c6=n) THEN (d1=t) & (d2=n)
R10: IF (c1=n) & (c2=n) & (c3=n) & (c4=t) & (c5=t) & (c6=t) THEN (d1=t) & (d2=n)
R11: IF (c1=w) & (c2=t) & (c3=t) & (c4=t) & (c5=t) & (c6=t) THEN (d1=t) & (d2=t)
R12: IF (c1=w) & (c2=t) & (c3=t) & (c4=t) & (c5=t) & (c6=n) THEN (d1=t) & (d2=t)

As it seems to be purposeful to explain the meaning of the decisive algorithm recorded in this manner, let us do this with the one of decisive rule as an example. So, the Rule R4 has the following meaning:

IF
Temperature - 380-400 AND
Nausea - not present AND
Lumbar pain - present AND
Urine pushing - present AND
Micturition pains - not present AND
Burning of urethra - present
THEN
It Is NOT Inflammation of urinary bladder
It Is Nephritis of renal pelvis origin

Remaining rules should be unfolded in analogous manner.

At the end of this of section, let us consider also the lower approximations of possible decisions:

$$\begin{aligned}\tilde{CD}_1 &= E_4 \cup E_7 \cup E_{10} = \{p_4, p_7, p_{10}\}; \tilde{CD}_2 = E_3 \cup E_{11} \cup E_{12} = \{p_3, p_{11}, p_{12}\} \\ \tilde{CD}_3 &= E_1 \cup E_6 \cup E_8 \cup E_9 = \{p_1, p_6, p_8, p_9\}; \tilde{CD}_4 = E_2 \cup E_5 = \{p_2, p_5\} \\ \text{Pos}_{\tilde{C}}(D^*) &= \tilde{CD}_1 \cup \tilde{CD}_2 \cup \tilde{CD}_3 \cup \tilde{CD}_4 = \{p_1, p_2, \dots, p_{12}\}\end{aligned}$$

$$\gamma_{\tilde{C}}(D^*) = \frac{\text{card}(\text{Pos}_{\tilde{C}}(D^*))}{\text{card}(U)} = \frac{12}{12} = 1$$

Due to the fact, that all rules are determinative, the decisive algorithm has been defined well. Because there were no not-determinative rules, so there is no badly defined part as well.

2.9 Support, certainty and strength of each rule

In order to calculate the support of $\Phi \rightarrow \Psi$ rules in S, let us begin, as usual, from recalling full set of rules.

Reduced table of rules looks like below. Empty places mean, that value of attribute in this place does not influence the output [5].

Rule	c1	c2	c3	c4	c5	c6	d1	d2	Support
Rn1		no		no	no	no	no	no	3
Rn2	g	no	yes	yes	no	yes	no	yes	1
Rn3	w		yes				no	yes	2
Rn4	p	no	no	yes			yes	no	3
Rn5	n	no	no	yes	yes	yes	yes	no	1
Rn6	w	yes	yes	yes	yes		yes	yes	2

Tab. 8 Reduced table of rules.

Before we begin considerations included in this section, the following explanations are worth to be done:

- premise of rule,
- conclusion of rule,
- $\Phi \rightarrow \Psi$ - decisive rule,
- $\|\Phi\|_S$ - meaning of Φ premise in the S information system.

Support of rules calculated from the following equation, (it is quantity of its meaning in S) amounts to:

$$\text{supp}(\|\Phi \wedge \Psi\|_S) = \text{card}(\|\Phi \wedge \Psi\|_S)$$

Certainty (confidence) factor of $\Phi \rightarrow \Psi$ rule defines the frequency of occurrence of objects in S, that have Y conclusion in set of objects having Φ premise.

$$\pi_S(\Psi | \Phi) = p_u(\|\Psi\|_S | \|\Phi\|_S) = \frac{\text{card}(\|\Phi \wedge \Psi\|_S)}{\text{card}(\|\Phi\|_S)}$$

$$Rn1 : \pi_S(\Psi | \Phi) = \frac{3}{3} = 1 \quad Rn2 : \pi_S(\Psi | \Phi) = \frac{1}{1} = 1$$

$$Rn3 : \pi_S(\Psi | \Phi) = \frac{2}{4} = 0.5 \quad Rn4 : \pi_S(\Psi | \Phi) = \frac{3}{3} = 1$$

$$Rn5 : \pi_S(\Psi | \Phi) = \frac{1}{1} = 1 \quad Rn6 : \pi_S(\Psi | \Phi) = \frac{2}{2} = 1$$

It is necessary to remember, that certainty factor of the rule equals "1" then and only then, when $\Phi \rightarrow \Psi$ is true in S, so when quantity of examples $\Phi \rightarrow \Psi$ in S is equal to the quantity of examples with F premise in S.

The last one from the considered features is strength of $\Phi \rightarrow \Psi$ rule. Strength of rule is calculated from the formula below;

$$\delta_S(\Phi, \Psi) = \frac{\text{supp}(\Phi, \Psi)}{\text{card}(U)} = \frac{\text{card}(\|\Phi \wedge \Psi\|_S)}{\text{card}(U)} = \pi_S(\Phi | \Psi) \cdot \pi_S(\Phi)$$

$$Rn1 : \delta_s(\Phi, \Psi) = \frac{3}{12} = 0.25; Rn2 : \delta_s(\Phi, \Psi) = \frac{1}{12} = 0.08$$

$$Rn3 : \delta_s(\Phi, \Psi) = \frac{2}{12} = 0.16; Rn4 : \delta_s(\Phi, \Psi) = \frac{3}{12} = 0.25$$

$$Rn5 : \delta_s(\Phi, \Psi) = \frac{1}{12} = 0.08; Rn6 : \delta_s(\Phi, \Psi) = \frac{2}{12} = 0.16$$

2.10 Limited decisive algorithm and inverse decisive algorithm

So we can finally formulate the decisive algorithm. It is set of acceptable rules in S, which are independent, covering U-universe and they keep logical cohesion of information system. Limited set of decisive rules Dec(S):

Rn1:	IF (c2=n) & (c4=n) & (c5=n) & (c6=n)	THEN (d1=n) & (d2=n)
Rn2:	IF (c1=g) & (c2=n) & (c3=t) & (c4=t) & (c5=n) & (c6=t)	THEN (d1=n) & (d2=t)
Rn3:	IF (c1=w) & (c3=t)	THEN (d1=n) & (d2=t)
Rn4:	IF (c1=p) & (c2=n) & (c3=n) & (c4=t)	THEN (d1=t) & (d2=n)
Rn5:	IF (c1=n) & (c2=n) & (c3=n) & (c4=t) & (c5=t) & (c6=t)	THEN (d1=t) & (d2=n)
Rn6:	IF (c1=w) & (c2=t) & (c3=t) & (c4=t) & (c5=t)	THEN (d1=t) & (d2=t)

Due to the fact, that $\Psi \rightarrow \Phi$ rule is called the inverse decisive rule in relation to $\Phi \rightarrow \Psi$ rule, so set of all rules inversions of algorithm Dec(S) is called the inverse algorithm and marked Dec*(S). Set of inverse rules Dec*(S):

Rn1*:	IF (d1=n) & (d2=n) THEN (c2=n) & (c4=n) & (c5=n) & (c6=n)
Rn2*:	IF (d1=n) & (d2=t) THEN (c1=g) & (c2=n) & (c3=t) & (c4=t) & (c5=n) & (c6=t)
Rn3*:	IF (d1=n) & (d2=t) THEN (c1=w) & (c3=t)
Rn4*:	IF (d1=t) & (d2=n) THEN (c1=p) & (c2=n) & (c3=n) & (c4=t)
Rn5*:	IF (d1=t) & (d2=n) THEN (c1=n) & (c2=n) & (c3=n) & (c4=t) & (c5=t) & (c6=t)
Rn6*:	IF (d1=t) & (d2=t) THEN (c1=w) & (c2=t) & (c3=t) & (c4=t) & (c5=t)

In this manner, we obtained decisive algorithm seen from two points of view, showing expert model, which carries out presumptive diagnosis of acute inflammations of urinary bladder and acute nephritis of renal pelvis origin.

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