An Expert acquiring method of Diagnosis and Senario based on maximum knowledge entropy

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ABSTRACT: *The objective of this study is to present an Improved REX-1 method, rationalize the essential difference of Knowledge and information in medical practice. It aims at fighting for the effective and efficient Expert-diagnosis process when various symptoms are to be distributed by the root knowledge mainbody in health care knowledge flow. The IREX-1 method can eliminate decision tree, creatively abstract knowledge entropy so as to improve the speed and accuracy of diagnosis-decision results. On this purpose, the authors use digestive diseases diagnosis prototype to justify the validity of this method, and do the comparison with renowned ID3,C4.5, ILA, ILA, 2 and original REX-1 algorithms when used in medical health care expert-diagnosis situation.*

Keywords: knowledge acquire, Medical knowledge flow, knowledge entropy, digestive diseases

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1. Introduction

Expert diagnosis is a significant part of medical knowledge management. Under the environment of collaborative diagnosing process, the knowledge accumulation level of experts should be directly interrelated with those methods when how rules or experience be picked up then distributed, and whether the using treating methods are rational, rapid and safe enough. On algorithms, classic expertise take Quinlan's ID3 (1986) and his further C4.5(Quinlan,1993), famous ILA(1998) **[5-6]** which generates IF-THEN rules and its improved ILA-2 (1999) **[3-4]** , inductive learning algorithms etc. However, all above methods create decision trees with diverse level analysis, and this brings some defects like wasting time and high cost, which is extremely fatal in competition of patient's diagnosis. As rejuvenation as the theory of knowledge reuse **[7-9]**, practitioner need to evaluate the effect of their use as much as tacit knowledge (1998)**[1]** after they have solved clinical activities. In this way, knowledge entropy is such a concept that can judge how about 'implicit assets' is being used in hospital knowledge flow, and the value of entropy distinctly shows the capacity of practitioners who solve clinical tasks best or not. Experiment result tells our method for Expert-diagnosis based on maximum knowledge entropy guarantees the effect and efficiency to make important decisions.

This paper firstly introduce the theory of knowledge flow and entropy, then describe the Improved REX-1(IREX-1) method, thirdly we take attributes sample set of Digestive diseases diagnosis prototype to testify this algorithm, finally we compare other rules-picking up methods on rules numbers, constraint conditions and accuracy, then give out our verification.

2. Medical Knowledge flow and knowledge entropy theory

2.1 Medical Knowledge flow

Knowledge has become a very precious property in modern society. There are more and more medical knowledge being or to be discovered, used and stored in hospital. On one hand, practitioner has succeeded in managing formalized knowledge as static information **[10]**, like knowledge base, data mining system or pattern identification etc. On the other hand, under the current collaborative environment, the question that how to dynamically research the representation, model function, evaluating method and optimization index of 'fluid' medical knowledge plays a great important role of health-care knowledge management area**[25].**

Obviously, Knowledge is not equal to information, the difference lies in knowledge owns deeper relation or extension about concept and its attributes than information, in addition, knowledge has been a sort of cognition to natural discipline. On the contrary, information is just the semantic explanation of data, which belongs to a lower level. Concept of Expert diagnosis, under the cooperative working condition, is a vigorous application on knowledge rather information, then mutual behaviors between practitioners embody a form of medical knowledge flow **[14]**. Knowledge Flow (KF) concepts systematic characteristics of practitioner's cognitive evolution**[12-13]**. In addition, literatures **[12, 15]** have advanced to use KFC (knowledge flow component) to construct a KF Network **[11, 24]**. Therefore, it is urgent and necessary to study dynamic Expert diagnosis problem based on KF theory under collaborative working process.

2.2 Knowledge entropy

Knowledge entropy derives from concept of information entropy and theory of KF **[24]**. Because knowledge has such an intense relationship and discipline that comes from information, it is believed to be practically feasible on knowledge entropy based on information entropy theory, such as famous Shannon and Hartley's information value. This paper assumes readers have known some basic concepts about information theory, if necessary please review literatures **[16, 17]**.

In a broad sense, entropy is defined as the disorder of a given system **[23]**. Many areas use diverse entropy functions to depict systematic state, such as thermodynamic entropy, information entropy and topological entropy etc. As long as disorder of given system increases, we can calculate it out by using counterpartial rising entropy function, that is, gain of medical knowledge can also be calculated with respect to each entropy value.

The definition of **knowledge entropy**: a kind of status function used to judge the fluidity of KF and weigh effects of how knowledge has been applied into tasks. Let an practitioner has knowledge set $P=\{X_1,X_2,\cdots X_m\}$, $X_i,(i=1,2,\cdots m)$ symbols knowledge elements; then the entropy of P is $H(k)=-K\bullet\sum_{i=1}^{m}P(X_i)\log_2 P(X_i)$, 1) K is 'knowledge' constant that is the simplest measure when doing 'one of half' dilemma, namely K=1/2; 2) $P(X_i)=\frac{|X_i|}{|U|}, i=1,2,\cdots m$, if P is limited then $|X_i|$ symbols its potential index. 3) The minus sign means the opposite relationship between knowledge order and knowledge entropy.

Therefore, we can draw the conclusion that the more entropy value gets, the more disorder a KF system becomes and the less effect how knowledge has been used throughout KF, vice versa. S. Haykin [19] argues that knowledge measurement I(X) is inversely proportional with being applied probability P(X), that is $I(X)=f(1/P(X))$, to m elements owned knowledge set P: $H(k)=K\bullet\sum_{i=1}^{m}P_i\bullet I_i=K\bullet\sum_{i=1}^{m}P_i\log_2(\frac{1}{P_i})=-K\bullet\sum_{i=1}^{m}P_i\bullet\log_2(P_i)$.

3. Improved REX-1 method for medical use

3.1 The necessity of medical knowledge acquisition

In collaborative diagnosing working process, doctors generally have three ways to acquire knowledge: 1) to ask for expert; 2) to learn by literature, textbook or papers; 3) to do reliable experiments. However—Firstly, expertise is often reasonable, but experts are always busy in doing affairs or attending various conventions outsides. it also takes much time to systematically absorb medical knowledge; Secondly, it is easy to deviate from right health-care knowledge by checking sketch personally, in addition, lack of enough clinical experiences makes it difficult to get solutions as expected; Thirdly, supervisors will not permit initiating any experiment unless cost gets controlled and patient gets cured. Hence, to shake off the defects of knowledge acquisition in medical field, it is indispensable to develop an automatic algorithm to absorb right or expertise knowledge.

3.2 Reasons to improve original algorithm

Feigenbaum**[18]** remarks that Knowledge Management(KM) should primarily solve three troubles: knowledge representation, knowledge acquisition and knowledge application. Nevertheless, knowledge acquisition has been a bottleneck for many years, if we can get expert diagnosis rules from disease attributes database using IREX-1 method, then this bottleneck in medical knowledge acquisition will be properly conquered.

We believe that medical knowledge acquisition stems from mature expertise knowledge repository. At good aspect, original REX-**1[21]** algorithm allows deriving some rules out of the set of attributes database directly and firstly using entropy value to sort attribute list, whereas it still does not eradicate the pitfalls of decision tree. Some REX-1 algorithm is much easier in natural knowledge reasoning but not in medical Knowledge flow. Therefore, we have to improve REX-1 algorithm, following detail stepwise show as figure 1.

3.3 Description of IREX-1 algorithm

IREX-1 is a new task-oriented, multi-'IF-THEN' rules driven and picking-up algorithm, it uses the value knowledge entropy of attributes database. The IREX-1 simplifies original REX-1 stepwises and does not reply on decision tree to generate appropriate ED rules. Here, IREX-1 performs ED rules induction by firstly calculating knowledge entropy values of each attributes in samples, and giving top priority to the attributes with the least disorder one. That is, we descendly sort by importance of each attribute with practical entropy values from sections of samples, even ignoring least significant one. At step 4, IREX-1 selects zero entropy for mono-number as a rule, and marks it with 1-level. Then we go to check whether it has any overlaps. The following steps will go through the figure 1.

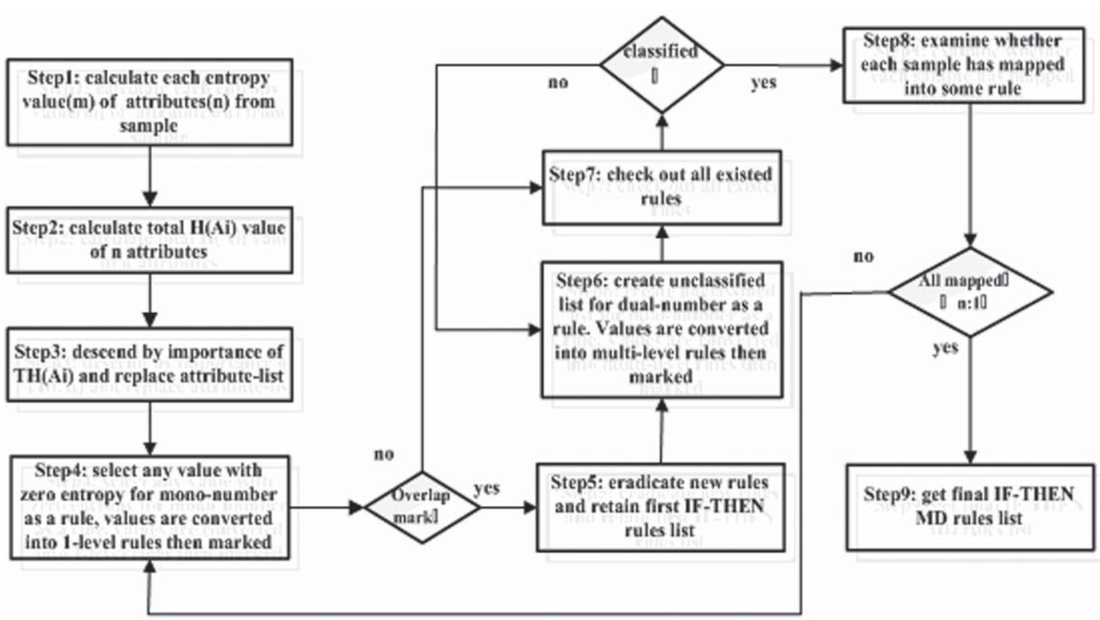

Figure 1. Stepwise of IREX-1 algorithm

Note: in step2, the total entropy $TH(A_i) = n_i \bullet H(A_i)$, A_i is ith attribute of disease and n_i is the number of ith attribute in sample set.

4. Digestive diseases diagnosis prototype

Digestive disease is common in clinical diagnosis, plus there are sufficient quantity and quality medical activities to be distributed into knowledge with the form of IF-THEN rules, especially in auto, rapid attributes' picking up method. Therefore, we give out our sample set (table1). We use following stepwise fashion of IREX-1 algorithm (see fig.1) to pick up ED task rules quickly and attribute them to A-D diagnosis.

Number	Test(T)	Observation(O)	Feeling(F)	Duration(D)	ED Class
1	Mesocaval excessive gas	Repeated heating	like chewing gum	At least 12 weeks (not necessarily consecutive)	A- it's aerophagia
2	Mesocaval gas	exhaust increased probability	excessive soda habit	With 15 weeks	A- it's aerophagia
3	Paving stones kind of performance	The whole wall inflammatory lesions	Continuous lesions	1 week	C—it's Crohn's Diseases
4	Edema, ascites	Neurological l symptoms frequent changes	High fever, sleepiness	Within 2 weeks	D—it's fulminant hepatitis
5	excessive gas	exhaust increased	Like drinking	With 12 weeks	A- it's aerophagia
6	renal dysfunction	psychological symptoms frequent changes	sometimes disturbing Mania	1 week	D—it's fulminant hepatitis
7	Mesocaval excessive gas	exhaust increased probability	Love soda habit	With 20 weeks	A- it's aerophagia
8	Umbilical more persistent	Accompanied by nausea and other symptoms of early satiety	No appetite, diarrhea or dysphagia	At least 12 weeks (not necessarily consecutive)	B—it's dyspepsia
9	recurrent pain or discomfort	exhaust increased	Like Exhaled	With 13 weeks	A- it's aerophagia
10	renal dysfunction	psychological not stable	extreme weakness,	1.5 week	D—it's fulminant hepatitis
11	excessive gas	Repeatedly Exhaust	Love Chewing snacks	15 weeks	A- it's aerophagia
12	longitudinal ulcer	The whole wall inflammatory lesions	non-segmental lesions	2 weeks	C—it's Crohn's Diseases
13	Mesocaval excessive gas	exhaust increased probability	Like drinking	With 20 weeks	A- it's aerophagia
14	excessive gas	exhaust increased probability	Like Exhaled	With 17 weeks	A- it's aerophagia

Table 1. Attributes sample 1

Table 1 consists of 14 sets of samples (row), 4 attributes (Test, Observation, Feeling and Duration), and 4(A-D) Expert diagnosis classes, namely A—it's aerophagia; B—it's dyspepsia; C—it's Crohn's Diseases; D—it's fulminant hepatitis. The relationship among A-D decisions goes as depicted in fig.2 (left). Hence, using the example set based on digestive disease above, the improved REX-1 algorithm has been implemented as follows:

Knowledge entropies are calculated for every attribute. For example, each T= 'Mesocaval excessive gas' attribute corresponds to class A diagnosis, this entropy is computed like $H_{T-ED}(M.e.g) = -\frac{1}{2}\times(\frac{3}{3}\log_2\frac{3}{3}) = 0$, other Test entropy values are $H_{T-ED}(\mathrm{P}.s.p) = -\frac{1}{2}(3\times\frac{2}{6}\log_2\frac{2}{6}) = 0.793$, $H_{T-ED}(\text{excessive gas}) = -\frac{1}{2}(\frac{1}{2}\log_2\frac{1}{2}+\frac{1}{2}\log_2\frac{1}{2}) = 0.5$

$H_{T-ED}(\text{dysfunction}) = -\frac{1}{2}(\frac{3}{3}\log_2\frac{3}{3}) = 0$, then we compute Test's total knowledge entropy

TH(k): $TH_k(T) = \frac{3}{14}\times H_{T-ED}(M.e.g)+\frac{6}{14}\times H_{T-ED}(P.s.p)+\frac{2}{14}\times H_{T-ED}(ex.g)+\frac{3}{14}\times H_{T-ED}(dysf.) = 0.340$

similarly other attributes' TH values are: $TH_k(O) = 0.625$, $TH_k(F) = 0.558$, $TH_k(D) = 0.527$. Hence, we get table 2 (the overview of entropy values of attributes).

Attributes (A)	value of TH bit	Value of attributes(V)	Diagnosis-Making distribution	Value of H(bit)
Test(T)	0.340	Paving stones kind of performance	3-0-0-0	0
		Mesocaval excessive gas	2-2-2-0	0.793
		Umbilical more persistent or	2-0-0-0	0
		longitudinal ulcer	0-0-0-3	0
Observation(O)	0.625	exhaust increased probability	4-0-0-0	0
		Repeatedly Exhaust	1-1-2-2	0.959
		exhaust increased probability	2-0-1-1	0.750
Feeling(F)	0.558	Love soda habit	2-0-2-1	0.761
		Continuous lesions	1-1-0-1	0.793
		No appetite, diarrhea or dysphagia	3-0-0-1	0.406
		High fever, sleepiness	2-0-0-0	0
Duration(D)	0.527	With 20 weeks	3-0-0-0	0
		With 15 weeks	2-0-0-1	0.459
		Within 2 weeks	1-0-2-1	0.750
		1 week	2-1-0-1	0.750

Table 2. Entropy values of attributes collection 2

After table2, four digestive TH values are: $TH(T) = 4 \times 0.340 = 1.36$, $TH(O) = 3 \times 0.625 = 1.875$, $TH(F) = 4 \times 0.558 = 2.232$, $TH(D) = 4 \times 0.527 = 2.108$ respectively, in according with the sort of ***'TH(T)<TH(O)<TH(D)<TH(F)'***, we relocate the importance of each attribute as table 3 goes.

We pick up simple rules from zero entropy value in table2, by mono-number fashion, we can get Rules (1-4).They are:
Rule-1: IF T=Mesocaval excessive gas or T= recurrent pain or discomfort THEN ED= A- it's aerophagia;

Number	Test(T)	Observation(O)	Duration(D)	Feeling(F)	ED Class
1	Mesocaval excessive gas	Repeated heating	At least 12 weeks (not necessarily consecutive)	like chewing gum	A- it's aerophagia
2	Mesocaval gas	exhaust increased probability	With 15 weeks	excessive soda habit	A- it's aerophagia
3	Paving stones kind of performance	The whole wall inflammatory lesions	1 week	Continuous lesions	C—it's Crohn's Diseases
4	Edema, ascites	Neurological l symptoms frequent changes	Within 2 weeks	High fever, sleepiness	D—it's fulminant hepatitis
5	excessive gas	exhaust increased	With 12 weeks	Like drinking	A- it's aerophagia
6	renal dysfunction	psychological symptoms frequent changes	1 week	sometimes disturbing Mania	D—it's fulminant hepatitis
7	Mesocaval excessive gas	exhaust increased probability	With 20 weeks	Love soda habit	A- it's aerophagia
8	Umbilical more persistent	Accompanied by nausea and other symptoms of early satiety	At least 12 weeks (not necessarily consecutive)	No appetite, diarrhea or dysphagia	B—it's dyspepsia
9	recurrent pain or discomfort	exhaust increased	With 13 weeks	Like Exhaled	A- it's aerophagia
10	renal dysfunction	psychological not stable	1.5 week	extreme weakness,	D—it's fulminant hepatitis
11	excessive gas	Repeatedly Exhaust	15 weeks	Love Chewing snacks	A- it's aerophagia
12	longitudinal ulcer	The whole wall inflammatory lesions	2 weeks	non-segmental lesions	C—it's Crohn's Diseases
13	Mesocaval excessive gas	exhaust increased probability	With 20 weeks	Like drinking	A- it's aerophagia
14	excessive gas	exhaust increased probability	With 17 weeks	Like Exhaled	A- it's aerophagia

Table 3. Attributes sample 3

Rule-2: IF T= Edema, ascites THEN ED= D—it's fulminant hepatitis;

Rule-3: IF T= excessive gas THEN ED= A- it's aerophagia;

Because N=1 sample has been picked up by rule-1, there is no need for rule-3 to redistill it at all, and the repeated sample set {1, 13} is not considered here. Next, we will see:

Rule-4: IF F= Like drinking THEN ED= A- it's aerophagia;

Rule-5: IF D=more than 10 weeks THEN ED= A- it's aerophagia;

By now, the rests are unclassified samples like set {3, 8, 9, 12} and table 4 collects them.
Calculate next step 6 as fig.1 shows, we start the dual-number operation to sample set {3, 12}, for instance, let dual combination sets {O= The whole wall inflammatory lesions, D=1 week}, { O= The whole wall inflammatory lesions, D=2 week }, {F= Continuous lesions, T= longitudinal ulcer } match each other by following IREX-1 algorithm, we have:

Rule-6: IF O= The whole wall inflammatory lesions and {F= Continuous lesions, T= longitudinal ulcer } THEN ED= C-it's Crohn's Diseases.;

Number	Test(T)	Observation(O)	Duration(D)	Feeling(F)	ED Class
3	Paving stones kind of performance	The whole wall inflammatory lesions	1 week	Continuous lesions	C—it's Crohn's Diseases
8	Umbilical more persistent	Accompanied by nausea and other symptoms of early satiety	At least 12 weeks (not necessarily consecutive)	No appetite, diarrhea or dysphagia	B—it's dyspepsia
9	recurrent pain or discom-fort	exhaust increased	With 13 weeks	Like Exhaled	A- it's aerophagia
12	longitudinal ulcer	The whole wall inflammatory lesions	2 weeks	non-segmental lesions	C—it's Crohn's Diseases

Table 4. Rest sample set 4

Rule-7: IF {T= Umbilical more persistent, D=at least 12 weeks} and {F= No appetite, diarrhea or dysphagia, O= Accompanied by nausea and other symptoms of early satiety } THEN ED= B—it's dyspepsia;

Rule-8: IF {T= recurrent pain or discomfort, D= With 13 weeks } and {F= Like Exhaled, O= exhaust increased } THEN ED= A- it's aerophagia;

Till all available rules are picked up, there is no more unclassified samples N. Hence, on one side, rules list as table 5 demonstrates. On the other side, we comprehensively fill out each trail's probability of diagnosis-distribution in a medical knowledge flow process (see fig.2 (right)).

Rule-N	Description of each rule
Rule-1:	IF T=Mesocaval excessive gas or T= recurrent pain or discomfort THEN ED= A- it's aerophagia;
Rule-2:	IF T= Edema, ascites THEN ED= D—it's fulminant hepatitis;
Rule-3:	IF T= excessive gas THEN ED= A- it's aerophagia;
Rule-4:	IF F= Like drinking THEN ED= A- it's aerophagia;
Rule-5:	IF D=more than 10 weeks THEN ED= A- it's aerophagia;
Rule-6:	IF O= The whole wall inflammatory lesions and {F= Continuous lesions, T= longitudinal ulcer } THEN ED= C—it's Crohn's Diseases.;
Rule-7:	IF {T= Umbilical more persistent, D=at least 12 weeks} and {F= No appetite, diarrhea or dysphagia, O= Accompanied by nausea and other symptoms of early satiety } THEN ED= B—it's dyspepsia;
Rule-8:	IF {T= recurrent pain or discomfort, D= With 13 weeks } and {F= Like Exhaled, O= exhaust increased } THEN ED= A- it's aerophagia;

Table 5. Diagnosis-distribution rules picked up (sample set 5)

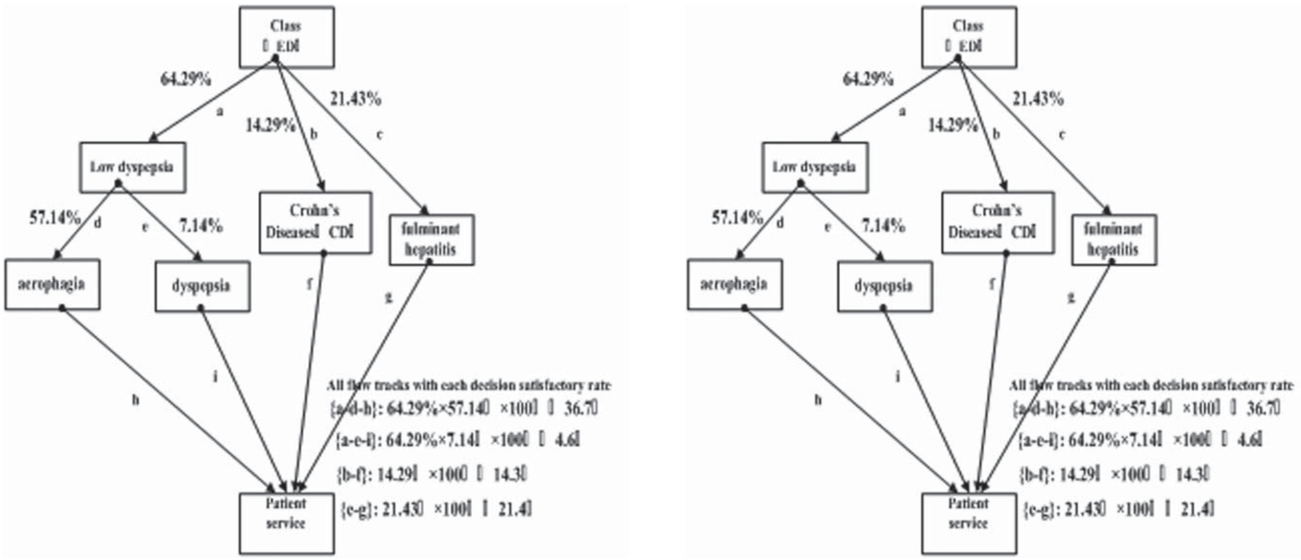

Figure 2. ED class analysis (left is before IREX-1 algorithm; right is after use of IREX-1 algorithm)

5. Results and Discussion

We compared our IREX-1 method with other common inductive learning algorithms and selected several renowned database sets (http://www.ailab.si/orange/doc/datasets/) to verify. From the result, it proved Improved REX-1 algorithm is effective and efficient in medical diagnosis.

5.1 Balance-scale sample testing

'Balance Scale Weight & Distance Database' was generated to model psychological experiments reported by Siegler, R. S.(1976)**[20]**. It consists of 625 instances (49 balanced, 288 left, 288 right), 4 attributes (Left-Weight, Left-Distance, Right-Weight, Right-Distance) and 3 class names ED {L, B, R}, to some extent, considering validity and simplicity of IREX-1 rules reasoning, we divide into triple sample sets of {49, 288, 288}by 3*2 batch, that is, 1 training set and 2 testing sets, to calculate knowledge entropy values; finally, we use RULES-3,ID3,REX-1and IREX-1 to verify the average condition/rule index respectively based on balance-scale sample database, thus 4 algorithms above results are: {37, 19}, {44, 23}, {26, 14} and{17, 11}, so IREX-1 contains optimal average target value of condition/rule, namely 1.545.

5.2 Balloons and balance sample testing

We also use ID3, ILA, ILA, 2 and C4.5 algorithms respectively to verify balloons (1998) and balance**[21, 22]** sample sets of Orange database. The experiments results are clear: except for ID3, all others generate ballons testing set with the same number (3), while we find IREX-1 algorithm only get average 1.33 condition/rule value and 7.9% error rate. In contrast, the worst result is made by C4.5, generating total 26 rules that large and 16.8% error rate.

Database sets	**C4.5**	**ID3**	**ILA**	**ILA-2**	**REX-1**	**IREX-1**
Titanic	97.1	96.3	95.8	97.9	95.7	97.4
Servo	55.0	52.8	55.2	53.8	66.4	64.7
Monk1[**20**]_learn	93.5	80.0	100	100	97.9	97.2
Monk2_learn	62.2	69.9	68.5	69.7	65.8	72.4
Monk3_test	74.3	91.7	88.2	100	89.1	91.5
Yeast	87.3	99.1	91.2	98.2	93.6	99.1
Lenses	62.5	62.5	50.6	62.7	62.9	60.5
o-ring-erosion	100	80.9	99.1	84.1	93.3	92.3
Hayes-roth_test	92.7	89.4	87.9	73.4	79.8	83.7
Car	96.5	100	100	96.5	100	100
Mean	82.11	82.26	83.65	83.63	84.45	**85.88**

Table 6. The comparison of some relative algorithms on accuracy rate 6

5.3 The accuracy of main algorithms

From table 6 below Orange database sets, we use the index of Titanic, Servo, ***Monk***_learn (i) etc. for further verification and elaborate comparison. Because other listed algorithms universally adopt decision tree to pick up ED rules, and IREX-1 use knowledge Attributes entropy to resort their importance by descending fashion, IREX-1 can generate more practical method to distribute activities to practitioners—the use of privilege. With human-like thinking way, less condition/rule index and high accuracy rate, IREX-1 has proved the fact as follows:

The optimal accuracy algorithm is IREX-1, whose mean value is 85.88/100.

6. Main Research and Conclusion

This paper has analyzed the question about how to distribute health-care diagnosis activities under a collaborative environment. It discuss the medical knowledge acquisition method and related algorithms by advancing the concept of knowledge entropy and its formula. Based on this, we introduce our Improved REX-1 algorithm and stepwises in detail so as to solve clinical doctors' decision making strategy with a Digestive disease instance. The rules obtained by IREX-1 were produced using knowledge entropy and reformulated entropy values by importance. Therefore, those attributes with lower reformulated entropy were of higher precedence. From table 6, we get such a good comparison result between IREX-1 and the other algorithms, even better than original REX-1. Therefore, our IREX-1 does generate fewer number of rules and provide a higher rate of accuracy when diagnosing diseased people within a short and limited time, which is more suitable under the clinical diagnosis condition and collaborative working environment.

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