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Healthy Diet Food Decision Using Rough-Chi-Squared Goodness

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Abstract

Rough sets approximations have been implemented to handle categorical attributes from various domain problems. However, few studies investigate the combination between dependency degree of rough sets and chi-square test in decision support of the categorical data analysis. In this paper, we are interested to decide the healthy status based on healthy diet foods based on rough sets and chi-square test. To improve the decision accuracy, the data reduction of rough sets is also considered. The gathering data was taken from 20 adult persons using question list form. Results showed that dependency degree and chi-square test after data reduction is better than before. Therefore, the final healthy status (Good) is determined by combination food type, level and dependency degree = {(Food A; High; 50%), (Food; Less; 50%), (Food C; Normal; 44.4%) and (Food F; Less; 27.8%). In this case, the accuracy on decision making is really influenced by inconsistent information from the conditional attributes and objects in the data set, thus both can be solved by data reduction strategy. Additionally, the dependency degree is very helpful to support chi-square test for investigating relationship between conditional and decision attributes, especially limited or small data sizes.

Keywords: Rough sets; dependency degree, chi-square test; data reduction; healthy diet food; decision making.

1. Introduction

Rough set is commonly used in conjunction with other techniques connected to discretization on the data set. The main advantage of rough set data analysis is both non-invasive and notable ability to handle non-numerical data. This fits into most real-life applications effectively [1]. Rough set theory has been widely applied to solve complex problems by researchers in recent years. For example, pattern recognition, emergency room diagnostic medical, acoustical analysis, power system security analysis, spatial-metrological pattern classification, intelligent control systems and measure the quality of a single subset [1]. In medical diagnostic applications, the rough set approaches can be used to assist such inexperienced doctors in diagnosing based on clinical decision support model of disease symptoms [1-5]. The decision support model can be used to determine whether a patient can be discharged, requires further investigation, or consultation.

Some decision support model have the potential to provide accuracy recommendation as good as medical experts [1]. There are existing rough set applications in medical diagnostic procedure to detect diseases [4, 5], such as, dengue [2], diabetes mellitus [2, 3], chikungunya [2], and other. However, the step-by-step procedure in determining suitable rules for the medical diagnostic applications remains an interesting issue since the ultimate goal is to achieve accurate prediction results.

Based on RST, application research mainly focuses on attribute reduction, rule acquisition, intelligent algorithm, etc. Attribute reduction as a NP-Hard problem has been carried out a systematic research. Based on rough set model, the development of reduction theory provides a lot of new methods for data mining. For example, in the different information systems (coordinated or uncoordinated, complete or incomplete), with information entropy theory, concept lattice and swarm intelligence algorithm, the rough set theory has gained the corresponding achievements. At present, the research is mainly concentrated on three aspects, such as theory, application and algorithm. RST is useful in analysing database attributes and controlling process. In application research, RST is widely used for fault diagnosis, image processing, massive data processing, etc [18]. Moreover, some integration studies between rough sets and statistical approaches are also implemented to fault diagnosis and attribute selection such as, medical diagnosis [1- 5, 11-13], purchase decision [14], financial wellbeing [15], e-learning [16, 17]

The aim of this paper is to present the contribution data reduction strategy of RST for improving the dependency degree and chi-square approaches in decision support system. Furthermore, application both approaches is implemented to investigate the relationship between food groups and healthy status. Additionally, developing rules are also provided to predict healthy diet decision. This paper is organized as follows. In section 2, the fundamental theories are presented. In sections 3 and 4, the proposed decision rules and implementation are discussed. The summary is concluded in section 5.

2. Fundamental Theories and Methodology

2.1. Rough Sets Theory (RST)

The methodology of RST is related to classification and analysis of inconsistent, imprecise, knowledge, incomplete information and it is considered one of the first non-statistical approaches in data analysis [6, 7]. Information system can also be name as information. Within the table there are objects and attributes. By using this system, knowledge representation in rough sets is done which can show the relationship between object and attribute value in tabular form as presented in Figure 1.

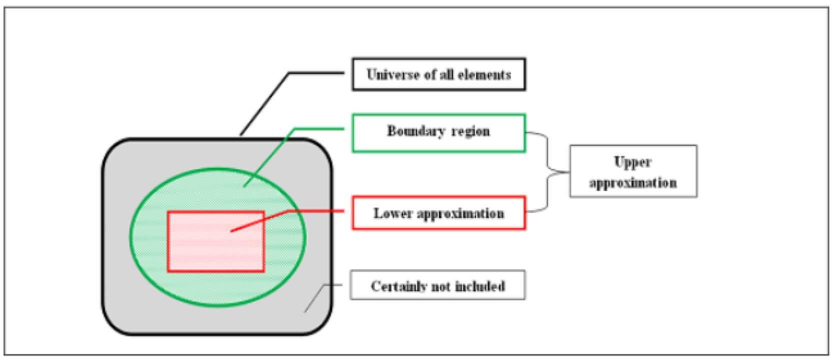


Fig. 1. RST and its information system

Indiscernibility relation is the main concept in rough set theory that may identifies a group of data. Indiscernibility relation is considered as a relation between multiple objects where all the values are identical in relation to a subset of considered attributes. The idea behind rough sets is to construct approximations of sets. The area of approximation consists of ordered pair U and R, where U is the universe that define as a finite and non-empty set of elements. R represents as indiscernibility relation which is an equivalence relation for U [1].

- Lower Approximation (B_*): The lower approximation (B_*) is the collection of objects which able to be classified surely as the members of the set A, by using the attribute of set B [1, 6, 7]
- Upper Approximation (B^*): The upper approximation (B^*) is the collection of objects that may possibly to be classified as the members of set A [1, 6, 7]

- Boundary Region (BR): The boundary region is the difference between the upper approximation and lower approximation. BR of X is written as [1, 6, 7]:

$$\mathrm{BND}(X) = B^*(X) - B_*(X). \tag{1}$$

- Decision Tables and Decision algorithms: The decision table consists of two types attributes which is condition attribute and decision attribute. Every row of the table determines a decision rule which specifies the decisions that should be taken when conditions are point out by condition attributes. The decision rules are always shown as implications in the form of **"If ... Then ..."** [1]
- Dependency of Attributes: Intuitively, the set of attribute D depends entirely on the attribute set C, denoted by, if the attribute value of C uniquely determines the attribute value of D. In other words, D depends entirely on C, if there is a functional dependence between the values of C and D. Hence, if and only if rule is true in A for every $x \in U$. D can depend partly on C. Formally such dependence can be defined in the following way. It is said that D depends on C to degree k ($0 \leq k \leq 1$) and denoted as [8, 9]:

$$l = \gamma(D, C) = \frac{\sum_{x \in U/D} |\underline{C}(X)|}{|U|}; C, D \subseteq A \wedge C \cap D = \emptyset. \tag{2}$$

Note that:
If $l = 1$, D (Decision attribute) depends totally on C (Conditional attribute).
If $l < 1$, D (Decision attribute) depends partially (in a degree l) on C (Conditional attribute).

- Reduction of Attributes: The process of reducing an information system as the set of attributes of the reduced information system is independent and none of the attribute can be eliminated further. Some of the information from the system might be lose if the elimination continues [1].

2.2. Chi-Square Test

Chi-square test is one type of non-parametric comparative test which is carried out on two variables, where the data scale of the two variables is nominal. Chi-square test is one of the most widely performed non-parametric tests. The chi-square test is used to test the variance homogeneity of several populations. There are several other problems that can be solved by taking the benefits of the chi-square test, including: testing the proportion for multinomial data, the mean similarity of the Poisson data, independent between two factors in contingency, conformity. between the observed data with the distribution model from which the data was thought to be taken, and the distribution model based on the observed data. The chi-square test can be formulated as follows [10]:

$$x^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}. \tag{3}$$

Based on Eq. (3), x^2 is denoted as chi-square test, O_i is the i-th observation value and E_i is the i –th expected value. The computational steps of chi-square test are:

Step 1: State the hypotheses.
H_0: There is no significant relationship between the two variables.
H_a: There is a significant relationship between the two variables.
Step 2: Calculate chi-square (x^2) using Eq. (3).
Step 3: Determine the level of significance.
Step 4: Make a decision based on criteria:
If Sig. > 0.05 then H_0 is accepted
Step 5: Write a conclusion.

3. Association Healthy Diet Food and Healthy Status

In this case study, the daily food consumed by a group of people is recorded. Table 1 shows the quantity based on group of food consumed by our experimental subject within a month. The columns of the table represent the attributes, which is conditional attribute and decision attribute. The rows represent our experimental subject. The entries in the table are the attribute values. From Table 1, where P are all of the objects or patients of the system, given set P = {p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, p12, p13, p14, p15, p16, p17, p18, p19, p20}, the set conditional attributes is represented by F = {Food A, Food B, Food C, Food D, Food E, Food F} for Vegetable Group, Fruit Group, Carbohydrate Group, Dairy Group , Protein Group, Fat Group and the set G represented the decision attribute, where H ={Healthy Status}. For example, the patient p5 is characterized by the value set (Food A, Less), (Food B, Normal), (Food C, High), (Food D, Normal), (Food E, High), (Food F, Less) and (Healthy Status, Bad), which gives information about subject p5.

Table 1. Patient profile and food consuming

Patient Code	Food A	Food B	Food C	Food D	Food E	Food F	Healthy Status
p1	L	H	N	N	H	L	N
p2	H	L	H	N	N	L	G
p3	L	L	L	H	N	H	B
…	…	…	…	…	…	…	…
p20	L	N	N	L	H	H	B

From Table 1, the conditional attributes can be organized into the relations with their nominal values. In the Table 2, nominal values of attributes is shown as:

Table 2. Healthy diet attribute and its nominal values

Attributes	Healthy diet attributes	Nominal values of attribute
Conditional Attributes	Food A, B, C, D, E, F	(L: Less: 1), (N: Normal: 2), (H: High: 3)
Decision Attribute	Healthy Status	(B: Bad: 1), (N: Normal: 2), (G: Good: 3)

From Tables 1 and 2, the indiscernibility (IND) elementary sets can be grouped for each attribute in Table 3. Each attribute is divided into 3 categories.

Table 3. Indiscernibility elementary sets for food group and healthy status

Conditional and decision attributes	Indiscernibility elementary sets
Food A	INDA ({Food A}) = {(Less), (Normal), (High). = {{p1, p3, p5, p8, p12, p13, p14, p20}, {p7, p10, p11, p16, p17, p18}, {p2, p4, p6, p9, p15, p19}}.
…	…
Food F	INDA ({Food F}) = {(Less), (Normal), (High). = {{p1, p2, p5, p6, p11, p16, p19}, {p4, p9, p13, p15, p19}, {p3, p7, p8, p10, p12, p14, p18, p20}}.
Healthy status	INDA ({Healthy status}) = {(Bad), (Normal), (Good). = {{p3, …, p20}, {p1, …, p18}, {p2, …, p19}}.

Table 3 shows the registration object or element for each attribute based on set and sub-sets by following criteria given in Table 2.

3.1. Association Based on Chi-Square Test

Based on Sub-section 2.2, the association between attributes before data reduction using Chi-square test can be presented in Table 4.

Table 4. Chi-square test before data reduction

Attributes/Variables	Value	df	Significance ($p < 0.05$)
Food A	6.000^a	4	0.199 (Not significant)
Food B	4.578^a	4	0.333 (Not significant)
Food C	4.095^a	4	0.393 (Not significant)
Food D	5.333^a	4	0.255 (Not significant)
Food E	5.333^a	4	0.255 (Not significant)
Food F	18.032^a	4	0.001* (Significant)

Table 4 shows the Food F (Fat Group) is very significant attribute if compared with other food groups. This indicates there is a strong association between Food F and Healthy status of patients. In this case, there is no elimination object and attribute, respectively. Moreover, the further association is also measured after data reduction as presented in Table 5.

Table 5. Chi-square test after data reduction

Attributes/Variables	Value	df	Significance ($p < 0.05$)
Food A	4.082^a	4	0.395 (Not significant)
Food B	5.569^a	4	0.234 (Not significant)
Food C	5.247^a	4	0.263 (Not significant)
Food F	13.454^a	4	0.009* (Significant)

From Table 5, the most significant variable is also Food F if compared with Food A, B and C. In this Table, Food D, E attributes and also (p7, p18) patients already removed using data reduction of rough sets. Therefore, we are really confident to claim that Food F has a strong relationship with healthy status based on both tables given. Theoretically, Fat food groups are an essential part of our diet and important for good health. There are different types of fats, with some fats being healthier than others. To help make sure you stay healthy, it is important to eat unsaturated fats in small amounts as part of a balanced diet. When eaten in large amounts, all fats, including healthy fats, can contribute to weight gain. Fat is higher in energy (kilojoules) than any other nutrient and so eating less fat overall is likely to help with weight loss [20].

3.2. Association Based on Dependency Degree

By using Sub-section 2.1 and data reduction results, the dependency degree between conditional and decision attributes can be shown in Table 6.

Table 6. Dependency degree between food type and healthy status

Conditional attribute		Decision attribute	Intersection between conditional and decision attributes	Dependency degree
Food type	Category	Healthy status		
Food A	Less	Bad	$\{p3, p5, p11, p13, p18\}$	0.5 (50%)
	Normal	Normal	$\{p16\}$	
	High	High	$\{p2, p6, p17\}$	
Food B	Less	Bad	$\{p3, p8, p9\}$	0.5 (50%)
	Normal	Normal	$\{p4, p12, p14\}$	
	High	High	$\{p6, p10, p15\}$	
Food C	Less	Bad	$\{p3, p8, p9\}$	0.44 (44.4%)
	Normal	Normal	$\{p1\}$	
	High	High	$\{p2, p6, p7, p10\}$	

	Less	Bad	$\{p5\}$	
Food F	Normal	Normal	$\{p4, p12, p16\}$	0.278 (27.8%)
	High	High	$\{p7\}$	

Table 6 shows the healthiest status (level) depends partially 0.5 (50%) to the Food A (vegetable group) and B (fruit group). Otherwise, (Food C, Food F) contribute (44.4%, 27.8%) to the healthy status. These percentages indicate that the patient's healthy level is very much influenced by food composition such as, vegetables, fruits, carbohydrates and fats. This result is also supported previous work that the adequate intake of carbohydrate and fats have a relationship to the nutritional status of employees [19].

3.3. Evaluation of Associations

In this section, both associations have been obtained from two different approaches (Sub-sections 3.1.and 3.2). The intersection is Food F attribute between Chi-square and dependency degree. However, the healthy status is also partially influenced by Food A, B and C, respectively. In this case, we consider dependency degree of rough sets to measure the relationship among attribute, while chi-square test is not fully appropriate to approximate this association because small data size issue.

4. Generating Rules for Healthy Diet Food Decision

4.1. Generated Rules before Data Reduction (without removing inconsistent attributes)

Based on Sub-Section 2.1, the object boundary region (BR) is p7, p9, p15 and p18. Hence, the patients p7, p9, p15 and p18 cannot be uniquely classified with available knowledge. Because they possess the same characteristics, but with differing conclusions differ in the decision attribute. After removing these patients, then equivalent information can be arranged in Table 7.

Table 7. The equivalent information after removing of the inconsistent information

Patient code	Food A	Food B	Food C	Food D	Food E	Food F	Healthy status
p3	L	L	L	H	N	H	B
p5	L	N	H	N	H	L	B
p10	N	L	L	L	H	H	B
…	…	…	…	…	…	…	…
p11	N	H	H	N	L	L	G
p16	N	H	N	N	N	L	G

Based on Table 7, the necessary decision rules that help to the determine healthy status can be generated by reduction of information shown as above. The rules are presented in Table 8:

Rule No.	Proposed rule without attribute reduction
Rule 1	**If** patient consumed **Food E with level H (High)** and **Food F with level also H (High)**, **then** his/her **Healthy status is B (Bad)**.
Rule 2	**If** patient consumed **Food E with level H (High), Food F with level N (Normal) or Food E with level N (Normal)**, and **Food F with level H (High)**, then **his/her Healthy status is B (Bad).**
Rule 3	**If** patient consumed **Food A with level H (High) and Food B with level H (High)**, then **his/her Healthy status is G (Good).**
Rule 4	**If** patient consumed **Food A with level H (High), Food B with level N (Normal)** or **Food A with level N (Normal), Food B with level H (High)**, then **his/her Healthy status is G (Good)**.
Rule 5	**If** patient consumed **Food C with level H (High), Food D with level H (High)**, then **his/her Healthy status is N (Normal).**
Rule 6	**If** do not match with rules **R1, R2, R3, R4**, or match with multiple rules in contradiction result **except R5**, then **Healthy status**

is N (Normal).

From Table 8, there are six generated rules for healthy diet food decision. In this table, we assumed that each criterion has two proposed rules such as, R3 and R4 can be used to decide the healthy criteria "Good".

4.2. Generated Rules after Data Reduction (with removing inconsistent attributes and elements)

Food E and F are removed from data set, while p7 and p18 are also eliminated from data set. In this section, we are interested to investigate the effect of removing conditional attributes and elements in rule development. The generated rules are presented in Table 9.

Table 9. Proposed rules with removing attributes and elements

Rule No.	Proposed rule with attribute reduction and elements
Rule 1	**IF** Food A = L AND Food B = H AND Food C = N AND Food F = L **THEN** Healthy status → N.
Rule 2	**IF** Food A = H AND Food B = L AND Food C = H AND Food F = L **THEN** Healthy status → G.
Rule 3	**IF** Food A = L AND Food B = L AND Food C = L AND Food F = H **THEN** Healthy status → B.
Rule 4	**IF** Food A = H AND Food B = N AND Food C = L AND Food F = N **THEN** Healthy status → N.
…	…
Rule 15	**IF** Food A = N AND Food B = H AND Food C = N AND Food F = L **THEN** Healthy status → G.
Rule 16	**IF** Food A = N AND Food B = L AND Food C = H AND Food F = N **THEN** Healthy status → N.

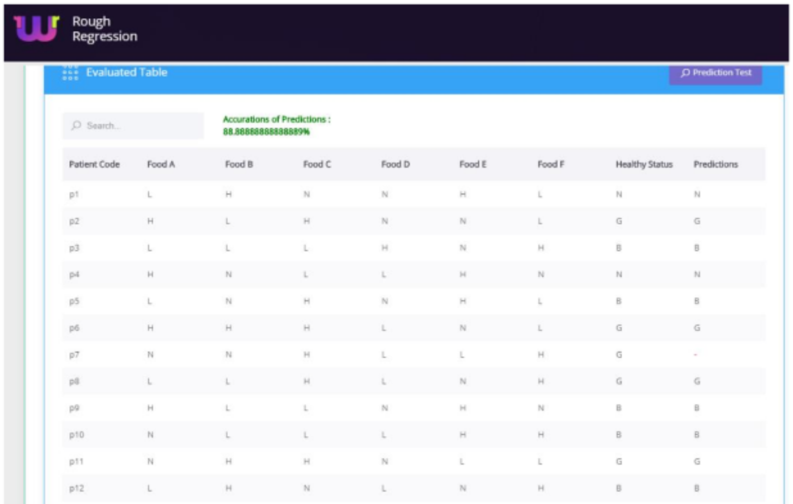
4.3. Evaluation of Accuracy Rules before-after Data Reduction

Generated rules from Section 4.1 and 4.2 are implemented to approximate the healthy status of patients. In Table 10, the predicted healthy status without removing the inconsistent attribute and with removing the inconsistent objects.

Table 10. Actual vs predicted decision without removing inconsistent attributes

Patient code	Actual healthy status	Predicted healthy status
p1	Normal	Normal
p2	Good	Normal
p3	Bad	Bad
p4	Normal	Normal
p5	Bad	Normal
…	…	…
p19	Good	Normal
p20	Bad	Bad
	Accuracy	65%

In this research, we also provide a special tool namely, RWR (Rough Wan Regression) application, this application is very useful to analyze categorical data based on rough-regression approach. Through this application, the inconsistent objects (p7, p18) and attributes (Food D and Food E) are removed from data set. The comparison between actual and predicted healthy status is illustrated in Fig. 2.



Patient Code	Food A	Food B	Food C	Food D	Food E	Food F	Healthy Status	Predictions
p1	L	H	N	N	H	L	N	N
p2	H	L	H	N	N	L	G	G
p3	L	L	L	H	N	H	B	B
p4	H	N	L	L	H	N	N	N
p5	L	N	H	N	H	L	B	B
p6	H	H	H	L	N	L	G	G
p7	N	N	H	L	L	H	G	-
p8	L	L	H	L	N	H	G	G
p9	H	L	L	N	H	N	B	B
p10	N	L	L	L	H	H	B	B
p11	N	H	H	N	L	L	G	G
p12	L	H	N	L	N	H	B	B

Fig. 2. Actual vs predicted healthy status based on RWR application

Fig. 2 shows the accuracy of prediction on healthy decision is 88.88%. This percentage indicates that proposed rules could predict the better decision if compared with generated rules in Table 10. It caused by removing the inconsistent information from conditional attributes and also elements. While, the attribute reduction is not considered in Table 10.

5. Conclusion

In this paper, we considered two different approaches in healthy diet decision. Firstly, Chi-square approach is the most frequently used to investigate the relationship between two categorical attributes/variables or more. Based on this approach, only Food F (Fat group) attribute has a strong association to the healthy status. This attribute always appears before and after data reduction. While, two conditional attributes are reduced using rough sets, namely Food D and E. Based on dependency degree, the rest of attributes partially contribute to the healthy decision included Food F. Therefore, there is a similarity food attribute between dependency degree and chi-square test which related to healthy status.

Through this paper, we adopted rough sets approximations, namely dependency degree to chi-square test. In the beginning stage, the removing the inconsistent information from elements or conditional attributes is considered. This type of information disturbed the decision attribute significantly. Statistically, chi-square approach is very significant to check the association between categorical variables, however it could not be used to measure the value of association. Thus, the dependency degree of rough sets is considered to measure the association above. In applications, both approaches support each other to provide the better decision. Our recommendation, the data size should be increased in terms of attribute and object numbers to show the performance both approaches for decision support system.

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