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AN EFFICIENT ALGORITHM FOR DISEASE DIAGNOSIS USING HYBRID FUZZY-ROUGH SET MODEL

[1]**C.Ashwini,** [2]**S.A.Ramesh Kumar,** [3]**V.K.Rathina Bharathy**
[1,2,3]Assistant Professor,
CSE, Karpaga Vinayaga College of Engineering & Technology
Email: sarkphd@gmail.com, ashwinichakravarthi@gmail.com

ABSTRACT

The model presented herein is an information system which guarantees avoidance of redundancy besides minimizing complexities in computing data. This could be used in creating rules which may serve as an aid in elucidation of our knowledge in fields such as medicine. In situations when the information system possesses redundancy, it is necessary to treat data in any one of the ways using the concept of reduction without altering the indiscernible relations. Data reduction concept aims to determine a minimal data subset from a problem domain while retaining suitable original data. In this context fuzzy set and rough set (RST) theories are being used as a mathematical tool to perform data reduction and framing decision rules as a pre-processing with little success. In the existing system, some of the attributes may be lost and not providing required accuracy of attributes. Hence, in the present work, by employing a hybrid variant of fuzzy set and rough set, a new reduction technique called ad Fuzzy-Rough set model is proposed. This would be use as an efficient algorithm for the reduction of information set without any loss and framing the decision rule to be employed successfully efficiently for disease diagnosis in medical field.

Keywords: Rough set, Fuzzy set, Rough-Fuzzy Sets, Indiscernibility

I. INTRODUCTION

Generally speaking, a database always contains a lot of attributes that are redundant and not necessary for rule discovery. Reduction of pattern dimensionality via attribute extraction and attribute selection belongs to the most fundamental steps in data pre-processing. Attribute selection is often isolated as a separate step in processing sequence. But the attribute should be deleted is very difficult to decide for non-experts and even for experts. The problem of attribute subset selection is that of finding an optimal subset of attributes of a database according to some criterion, and generating the highest possible accuracy classifier by an inductive learning algorithm that is run on data containing only the subset of attributes. There are various theories and methods to deal with incomplete and uncertain information in classification. For examples, fuzzy sets, rough sets, decision tree, and so on. The focus of this paper is on Rough set theory was originated by Pawlak in 1982 as a formal mathematical theory, modelling knowledge about the domain of interest in terms of a collection of equivalence relations. The main advantage of rough sets is that it does not need any preliminary or additional information about data like probability in probability theory, grade of membership in fuzzy set theory. Nowadays many rough sets based-approaches have been successfully applied in data mining. Rough set theory has been applied to many fields successfully, such as machine learning, data mining, pattern recognition, process control, knowledge discovery and so on. Equivalence relations and partition are the basic concepts in rough set theory, lower and upper approximations of a set can be defined by using the equivalence relation, and then through the upper and lower approximations the decision rules which are manifestation of knowledge can be exacted from the database. Apart from exacting decision rules, another application of rough sets is to find attribute reduction. However, traditional rough sets can be only applied to the databases which can induce equivalence relations; this limits the scope of application of the classical rough sets. To address this issue, some scholars generalized the equivalence relation to a similarity relationship or tolerance relationship.

II. BACKGROUND

A. *Basic Concepts and Definitions*

In this section we will introduce the basic notion of rough set theory .We assume that data are represented by an information system where a finite set of objects are described by a finite set of attributes.

Definition 1

Let

U - Be a finite set of objects called the universe,

A - Be a finite set of attributes,

V - Be a set of attribute values, where

$V = \cup V_a$, Va is called the domain V of a.

$a \in A$

f - Be an information function f: U× A → V, where for every $x \in U$ and $a \in A$ $f(x, a) \in V_a$

By the information system we will understand a quadruple S = < U, A, V, f >.A decision information system is also defined as S = < U, A, D, V, f >, where A is the set of condition attributes, D is the set of decision attributes, and $A \cap D = \emptyset$.

Definition 2

Fuzzy set, initialized by Zadeh, is an important concept to deal with problems with ambiguity caused by indeterminate boundary. Let *U* be a nonempty set, called a universe of discourse, a fuzzy set on *U* means a mapping *A* from *U* to [0,1]. $A(x)$ is called the membership function of *A*. It is also called the membership degree of *x* belonging to *A*. Thereby every fuzzy concept can be characterized by a fuzzy set. For two fuzzy sets *A* and *B* on *U*,*A* is referred to be a subset of *B* if $A \leq B$, i.e. $A(x) \leq B(x)$ for all $x \in U$. The degree of certainty of a fuzzy set can be evaluated by some measure *M*. Area, centroid and mean-value of membership degree are typical measures of fuzzy set.

Area: $M(A) = \sum_{i=1}^{N} A(x_i)$

Centroid: $M(A) = \frac{\sum_{i=1}^{N} x_i A(x_i)}{\sum_{i=1}^{N} A(x_i)}$

Mean-value: $M(A) = \frac{\sum_{i=1}^{N} A(X)}{N}$

Definition 3

For a *decision table* S, every attribute subset $R \subseteq \neg C \cup D$ determines a binary indiscernibility relation IND(R) as follows: $IND(R) = \{(x, y) \in U \times U \mid a \in R, f(x, a) = f(y, a)\}$. IND(R) determines a partition of U, which is denotedby U/IND(R) (in short U/R). Any element $[x]_R = \{y \mid \forall a \in R, f(x, a) = f(y, a)\}$ in U/R is called equivalence class.

Definition 4

For a decision table S, let U/D = {D1, D2...*Dk}* be the partition of D to U, and

U/C= { $C_1, C_2, \ldots, C_r$} be the partition of C to U, where *i C* is basic block, then $POS_c(D) = \cup_{D_i \in U/D} \underline{C}(D_i)$ is called positiveregion of C on D.

Definition 5

Indiscernibility Relation is a central concept in Rough Set Theory, and is considered as a relation between two objects or more, where all the values are identical in relation to a subset of considered attributes. Indiscernibility relation is an equivalence relation, where all identical objects of set are considered as elementary.

III. PRELIMINARIES

A. Feature Selection

Feature selection is common in machine learning, where it may also be termed *feature subset selection*, *variable selection*, or *attribute reduction*. Fundamentally, it can be considered as the process of selecting the input attributes of a dataset that most closely define a particular outcome. FS attempts to focus selectively on relevant features, whilst simultaneously attempting to ignore the (possibly misleading) contribution of irrelevant features. From a computational complexity point of view, it is beneficial to have a minimal set of features involved in the classification phase, and as noted previously, many learning algorithms scale up rapidly with the inclusion of additional features. In addition to the improvement in classifier performance, the costs associated with collecting large amounts of (feature) measurements can also be reduced by ensuring a minimal feature set. It should be noted that it is not possible for even the most advanced learning algorithms to compensate for poor FS techniques which select irrelevant or redundant features. This highlights the importance of performing efficient and robust FS in the first instance. Feature selection is often employed in areas where the dimensionality of the original data is such that it is impossible for humans to comprehend, but where it is imperative for the reduced data to retain the underlying meaning of the reduced features (e.g. rule induction).

B. Dimensionality Reduction

The inclusion of a dimensionality reduction (DR) step in a variety of problem-solving systems may be proposed for a number of different reasons. For many Dimensionality Reduction real-world application problems, data is processed in the form of a collection of real-valued object vectors e.g. text classification, bookmark categorisation, mining of medical data, mammographic image analysis, etc. If such data is of high dimensionality, it can be beneficial to employ a DR step. Indeed, it is often necessary where the dimensionality of the data prior to reduction may be prohibitively large. The central idea behind DR therefore is the reduction of the data to a size which is computationally tractable, without information loss. Hence, a DR step is usually included as an integral part of a data pre-processing system. There are often cases where high-dimensional phenomena are governed by significantly fewer, simple features. Here, the process of dimensionality reduction acts as a tool for modelling these phenomena, thus improving clarity. Additionally, a significant amount of redundant or misleading information is also present; this requires removal prior to any further processing. For instance, the problem of deriving classification rules from large datasets often benefits from a data reduction pre-processing step. Not only does this reduce the time required to perform induction, but the resulting rules are more comprehensible and this can potentially improve the classification accuracy. Many DR techniques destroy the underlying meaning (the semantics) behind the features present in a dataset - this is an undesirable property for many applications. This is particularly true where the understanding of the data processing method and that of the resulting processed data is as important as the accuracy of the resultant lower dimensional dataset in use. For example, in medical imaging it may be important to be able to identify particular areas of the image or data which are of greatest interest both prior to, and following reduction. It is important at this point to emphasise that DR can be divided into two categories; transformation-based approaches, and selection-based approaches. The former, is a set of approaches which perform dimensionality reduction but in doing-so irreversibly transform the descriptive dataset features. The latter approaches however, preserve the original meaning or semantics of the data through the removal of redundant, noisy, or irrelevant features - i.e. the set of survival features is a subset of the original unreduced features.

C. Reducts

The reduction of attributes is achieved by comparing equivalence relations generated by sets of attributes. Attributes are removed so that the reduced set provides the same quality of classification as the original. A reduct is defined as a subset R of the conditional attribute set C such that R (D) = C (D). A given dataset may have many attribute reduct sets, so the set R of all reducts is defined as: $R = \{X: X \subseteq C, X (D) = C (D)\}$. The intersection of all the sets in R is called the core, the elements of which are those attributes that cannot be eliminated without introducing more contradictions to the dataset. In RSAR, a reduct with minimum cardinality is searched for; in other words an attempt is made to locate a single element of the minimal reduct set $R_{min} \subseteq R : R_{min} = \{X : X \in R, \forall Y \in R, |X| \leq |Y|\}$ A basic way of achieving this is to calculate the dependencies of all possible subsets of C. Any subset X with X (D) = 1 is a reduct; the smallest subset with this property is a minimal reduct. However, for large datasets this method is impractical and an alternative strategy is required.

D. Fuzzy-Rough Hybrids

Fuzzy Equivalence Classes

The way that crisp equivalence classes are central to rough sets, fuzzy equivalence classes are central to the hybrid approaches. Rough set theory can be extended by the inclusion of a similarity relation on the universe, a fuzzy set S which determines the extent to which two elements are similar in S. The usual properties of reflexivity ($\mu S(x, x) = 1$), symmetry ($\mu S(x, y) = \mu S(y, x)$) and transitivity ($\mu S(x, z) \geq \mu S(x, y) \wedge \mu S(y, z)$) hold. Using the fuzzy similarity relation, it is now possible to define the fuzzy equivalence class [x] S for objects close to x:

$\mu[x]S (y) = \mu S(x, y) \ \forall y \in X$

This definition degenerates to the normal definition of equivalence classes when S is non-fuzzy. The following axioms should hold for a fuzzy equivalence class.

1. μFi is normalized, $\exists x, \mu Fi (x) = 1$
2. $\mu Fi (x) \wedge \mu S(x, y) \leq \mu Fi (y)$
3. $\mu Fi (x) \wedge \mu Fi(y) \leq \mu S(x, y)$

The first axiom corresponds to the requirement that an equivalence class is non-empty. The second axiom states that elements in y's neighbourhood are in the equivalence class of y. The final axiom states that any two elements in Fi are related via S. With these definitions, the concepts of rough-fuzzy and fuzzy-rough sets may be introduced.

Rough-Fuzzy Sets

A rough-fuzzy set is a generalisation of a rough set, derived from the approximation of a fuzzy set in a crisp approximation space. In RSAR, this corresponds to the case when the decision attribute(s) values are fuzzy. The lower and upper approximations incorporate the extent to which objects belong to these sets, and are defined as:

$\mu RX ([x]R) = \inf \{\mu X(x) | x \in [x]R\}$

$\mu RX ([x]R) = \sup \{\mu X(x) | x \in [x]R\}$

Where $\mu X(x)$ is the degree to which x belongs to fuzzy equivalence class X, and each [x] R is crisp. The tuple $< RX,RX >$ is called a rough-fuzzy set. It can be seen that in the crisp case (where $\mu X(x)$ is 1 or 0), the above definitions become identical to that of the traditional lower and upper approximations.

Fuzzy-Rough Sets

Rough-fuzzy sets can be generalised to fuzzy-rough sets, where all equivalence classes may be fuzzy. In RSAR, this means that the decision values and the conditional values may all be fuzzy. The lower and upper approximations are now:

μX (Fi) = infxmax{1 − μFi (x), μX(x)} ∀i

μX (Fi) = supxmin{μFi(x), μX(x)} ∀i

where Fi denotes a single fuzzy equivalence class. The tuple < X,X > is called a fuzzy-rough set. Again, it can be seen that these definitions degenerate to traditional rough sets when all equivalence classes are crisp. Additionally, if all F is are crisp, the result is a rough-fuzzy set. Fuzzy-rough sets have been used before but not in the field of dimensionality reduction.

IV. PROPOSED METHODOLOGY

For many application problems, it is often necessary to maintain a concise form of the information system, but there exist a noisy data that can be removed, without altering the basic properties and more importantly the consistency of the system. The process of reducing an information system, such that the set of attributes of the reduced information system is independent and no attribute can be eliminated further without losing. In existing system, the dataset is taken and reduction is performed on the dataset without altering the indiscernibility relation, using the hybrid technique called the fuzzy-rough set approach. After reduction is being performed the necessary decision rule is framed for the reduced data set. In RST, a reduct is defined as a subset R of the attributes which have the same information content as the full attribute set A. In terms of dependency function this means that the values $\gamma(R)$ and $\gamma(A)$ are identical and equal to 1 if the dataset is consistent. However, in the fuzzy-rough approach this is not necessarily the case as the uncertainty encountered when objects belong to many fuzzy equivalence classes results in a reduced total dependency. One solution could be to stop the QUICK REDUCT algorithm if there is no gain in dependency with any of the attributes added to the potential reduct (i.e. a deal end" has been reached by the search). This may well fail in larger datasets as it may be the case that the algorithm will not stop until all attributes are added; each addition may produce a small increase in the overall dependency. The introduction of some threshold value to terminate the algorithm if the change in dependency is not significant enough could alleviate this problem. However, it is not known at the present whether this is a suitable solution as it requires information outside the given dataset. In this system there exist some disadvantage like information may be lost as a result of quantization when reliant upon a crisp dataset and System may not react with the dynamically changing data when used in the information system to overcome this in the proposed system. In our proposed methodology we use the attribute reduction method where the data set is taken and the reduct is performed on the dynamic information system using the proposed algorithm. After the reduction is performed on the data set decision rule is framed on the reduced data for the disease diagnosis which is useful for medical community.

V. SYSTEM ARCHITECTURE

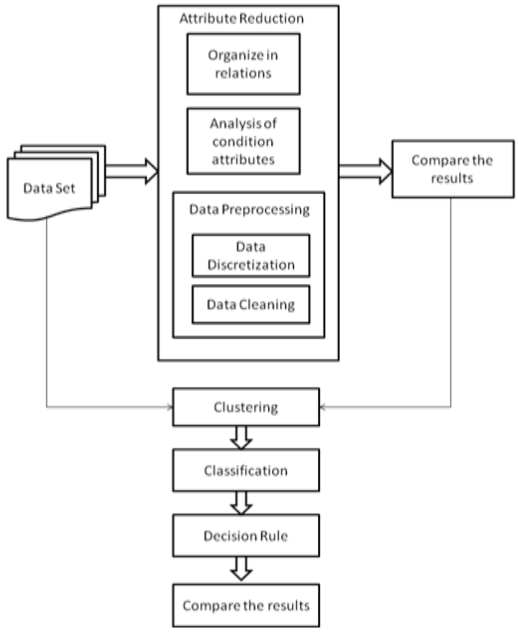

Fig 1 Architecture diagram for reduction

The data set used is, several patients data set with possible dengue symptoms is given as the input. It consists of the conditional attributes and decision attribute. The conditional attribute consist of the attributes like blotched_red_skin, muscular_pain_articulations, temperature and nominal values like yes, no and normal, high, very high and decision attribute is whether the patient is suffering from dengue or not. Then the given data set is organised into the conditional attributes and the analysis of each condition attributes is done in order to reduce the data sets. Then the data pre-processing stage understands the functions related to the reception, the organization and to the treatment of data, this stage has as its objective the preparation of the data for the mining stage. And then clustering is done on the analysed attributes and from that point classification is done using the IF-THEN rule classification.

VI. RESULTS AND DISCUSSIONS

This paper explains how the attribute reduction is performed. Here, the data set is taken which consists of conditional attribute and decision attribute, then the information system is reduced and the decision rule is framed from the reduced information. Further the discussions can be made on how the system reacts to dynamically changing information system and how it reacts to larger data set. Here the data set taken as the 20 records and the reduction is performed on the attribute. Finally we have only 3 records and for the three records decision rule is framed. The table 1 shows the Information system or information table with the respective patient symptoms in which the reduct is being performed. From table 1, Where, B are all of the objects or registrations of the system, given set B={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 C={blotched_red_skin, muscular_pain_articulations, Temperature} and the set D represented the decision attribute, where D={dengue}. Similarly like table 2, all the conditional attributes of table 1 can be organized into the relations with their nominal values. From table 2, Lower approximations, upper approximations and Boundary regions are calculated. Observation: Boundary Region (BR), the set constituted by elements P9 and P11, which cannot be classified, since they possess the same characteristics, but with differing conclusions differ in the decision attribute. Analysis of each condition attributes with the attributes set is performed, which is shown in table 3. Table 4. shows Analysis of Attributes blotched_red_skin and muscular_pain_articulations in Table 3. Table 6, shows Analysis of Attributes attributes blotched_red_skin and temperature. After the analysis is being performed Verification of equivalent (intersection) data in the Tables 5,7 and 9 correspond where data is the element of reduct information in relation to Table 3.

Table 1. Patients with respective symptoms

Patient	Conditional Attributes			Decision Attribute
	blotched_red_skin	muscular_pain_artic u lations	Temperature	Dengue
P1	No	No	Normal	No
P2	No	No	High	No
P3	No	No	Very High	Yes
P4	No	Yes	High	Yes
P5	No	Yes	Very High	Yes
P6	Yes	Yes	High	Yes
P7	Yes	Yes	Very High	Yes
P8	No	No	High	No
P9	Yes	No	Very High	Yes
P10	Yes	No	High	No
P11	Yes	No	Very High	No
P12	No	Yes	Normal	No
P13	No	Yes	High	Yes
P14	No	Yes	Normal	No
P15	Yes	Yes	Normal	No
P16	Yes	No	Normal	No
P17	Yes	No	High	No
P18	Yes	Yes	Very High	Yes
P19	Yes	No	Normal	No
P20	No	Yes	Normal	No

Table 2. Table 1 organize in relations blotched_red_skin attribute

Patient	**Conditional Attributes**			**Decision Attribute**
	blotched_red_skin	muscular_pain_articu Lations	Temperature	Dengue
P1	No	No	Normal	No
P12	No	Yes	Normal	No
P13	No	Yes	High	Yes
P14	No	Yes	Normal	No
P2	No	Yes	High	No
P20	No	Yes	Normal	No
P3	No	No	Very High	Yes
P4	No	Yes	High	Yes
P5	No	Yes	Very High	Yes
P8	No	No	High	No
P10	Yes	No	High	No
P11	Yes	No	Very High	No
P15	Yes	Yes	Normal	No
P16	Yes	No	Normal	No
P17	Yes	No	High	No
P18	Yes	Yes	Very High	Yes
P19	Yes	No	Normal	No
P6	Yes	Yes	High	Yes
P7	Yes	Yes	Very High	Yes
P9	Yes	No	Very High	Yes

Table 3. Reduct of Information of Table 1

Patient	**Conditional Attributes**			**Decision Attribute**
	blotched_red_skin	muscular_pain_articu lations	Temperature	Dengue
P1	No	No	Normal	No
P2	No	No	High	No
P3	No	No	Very High	Yes
P4	No	Yes	High	Yes
P5	No	Yes	Very High	Yes
P6	Yes	Yes	High	Yes
P7	Yes	Yes	Very High	Yes
P8	No	No	High	No
P10	Yes	No	High	No
P12	No	Yes	Normal	No
P15	Yes	Yes	Normal	No
P16	Yes	No	Normal	No
P19	Yes	No	Normal	No

Table 4. Analysis of Attributes blotched_red_skin and muscular_pain_articulations in Table 3

Patient	Conditional Attributes		Decision Attribute
	blotched_red_skin	muscular_pain_articula Tions	Dengue
P1	No	No	No
P2	No	No	No
P3	No	No	Yes
P4	No	Yes	Yes
P5	No	Yes	Yes
P12	No	Yes	No
P6	Yes	Yes	Yes
P7	Yes	Yes	Yes
P8	No	No	No
P16	Yes	No	No
P19	Yes	No	No
P10	Yes	No	No
P15	Yes	Yes	No

Table 5. Result of Analysis of Attributes blotched_red_skin and muscular_pain_articulations in Table 3

Patient	Conditional Attributes		Decision Attribute
	blotched_red_skin	muscular_pain_articula Tions	Dengue
P1	No	No	No
P3	No	No	Yes
P4	No	Yes	Yes
P6	Yes	Yes	Yes
P10	Yes	No	No
P15	Yes	Yes	No

Table 6. Analysis of Attributes blotched_red_skin and temperature in Table 3 Result of analysis

Patient	Conditional Attributes		Decision Attribute
	blotched_red_skin	Temperature	Dengue
P1	No	Normal	No
P12	No	Normal	No
P2	No	High	No
P8	No	High	No

P3	No	Very High	Yes
P5	No	Very High	Yes
P7	Yes	Very High	Yes
P4	No	High	Yes
P6	Yes	High	Yes
P10	Yes	High	No
P15	Yes	Normal	No
P16	Yes	Normal	No
P19	Yes	Normal	No

Table 7. Result of it Analysis of Attributes blotched_red_skin and temperature in Table 3

Patient	Conditional Attributes		Decision Attribute
	blotched_red_skin	Temperature	Dengue
P1	No	Normal	No
P2	No	High	No
P3	No	Very High	Yes
P4	No	High	Yes
P6	Yes	High	Yes
P10	Yes	High	No
P15	Yes	Normal	No

Table 8. Analysis of Attributes muscular_pain_articulations and temperature in Table 3

Patient	Conditional Attributes		Decision Attribute
	muscular_pain_articulati Ons	Temperature	Dengue
P1	No	Normal	No
P16	No	Normal	No
P19	No	Normal	No
P2	No	High	No
P8	No	High	No
P10	No	High	No
P3	No	Very High	Yes
P4	Yes	High	Yes
P6	Yes	High	Yes
P5	Yes	Very High	Yes
P7	Yes	Very High	Yes
P12	Yes	Normal	No
P15	Yes	Normal	No

Table 9. Result of it analysis of Attributes muscular_pain_articulations and temperature in Table 3

Patient	Conditional Attributes		Decision Attribute
	muscular_pain_articulati ons	Temperature	Dengue
P1	No	Normal	No
P2	No	High	No
P3	No	Very High	Yes
P4	Yes	High	Yes
P5	Yes	Very High	Yes
P12	Yes	Normal	No

Table 10. Table with result of information reduct of Table 3

Patient	Conditional Attributes			Decision Attribute
	blotched_red_skin	muscular_pain_articulations	Temperature	Dengue
P1	No	No	Normal	No
P3	No	No	Very High	Yes
P4	No	Yes	High	Yes

With the information reduct shown above, it can be generated the necessary decision rules for aid to the dengue diagnosis. The rules are presented to proceed:

Rule-1

R1: If patient
blotched_red_skin = No and
muscular_pain_articulations = No and
temperature = Normal
Then dengue = No.

Rule-2

R2: If patient
blotched_red_skin = No and
muscular_pain_articulations = No and
temperature = Very High
Then dengue = Yes.

Rule-3

R3: If patient
blotched_red_skin = No and
muscular_pain_articulations = Yes and
temperature = High
Then dengue=yes.

VII. CONCLUSION AND FUTURE WORK

Data set is taken as input and the reduction is performed on the data set for the disease diagnosis by the hybrid technique called the fuzzy-rough set approach and the final decision is made on the reduced information system by framing the decision rule on the reduced system and from this we obtain to the final decision which is useful for the medical community for the diagnosis of the disease. In the future work the data set is taken and the new algorithm is framed for the reduction overcomes the disadvantage of the existing system, i.e. the system does not react with the dynamically changing information in the information set.

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