ISSN: 0975-766X
CODEN: IJPTFI
Available Online through **Research Article**
www.ijptonline.com

IDENTIFICATION OF CHIEF CHARACTERISTICS OF ALCOHOL CONSUMPTION TRAITS IN SCHOOLS USING ROUGH SET AND FORMAL CONCEPT ANALYSIS

Saurabh Thakur*[1], Rahul Chowdhury[1]
[1]School of Computing Science and Engineering, VIT University, Vellore, India.
Email: saurabh.chandrakantthakur2013@vit.ac.in

Received on 06-08-2016 *Accepted on 10-09-2016*

Abstract

Abstract Youth and substance abuse has been on its epitome and is today seen as a global concern. While there is much awareness on adult drinking habits and alcohol abuse, most of such habits inseminate at a very early age. Psychological studies indicate that alcohol addiction not only affects teenager's health but is also known to affect their academic and social life. In this paper we try to extract the major attributes that correlates most to a teenager's drinking habits from the Portuguese high school alcohol consumption dataset. We make use of rough set theory as well as formal concept analysis over traditional probabilistic and fuzzy models as rough set exclude the various assumptions made in the later models. The result clearly provides some important insights about the factors that are most important for an alcohol free teenage which clearly match with numerous psychological studies conducted on the similar cases.

Keywords: Rough set; in-discernibility; approximation space; implication relation; extent and intent; decision rules.

Introduction

One of the delusions that exist in today's world is that alcohol is not as harmful as other drugs. Drinking alcohol excessively can cause damage to vital organs of the human body such as the brain, heart, liver and pancreas. Furthermore, over consumption of alcohol can lead to weakening of the immune system and thus allow diseases like tuberculosis and anemia to easily infect the body. However, drinking alcohol is more dangerous to adolescents than adults as during adolescence, the human body is going through the most crucial development stage. This danger is increased by the fact that alcohol is the most frequently used drug among adolescents. As a child matures from an adolescent to being an adult, he faces extreme physical and emotional changes. Extreme ingestion of alcohol during adolescence leads to future susceptibility to memory impairment [1]. Adolescents addicted to alcohol have shown signs of increased liver enzymes causing liver damage [2]. Also, alcohol consumption can lead to imbalance in critical sex hormones such as testosterone (in males) and estrogen (in females) which are further responsible for the secretion of other growth hormones for development of normal vital organs [3].

Although law enforcements state alcohol consumption to be illegal till a certain age in most of the countries, there are many factors due to which adolescents start consuming alcohol. Firstly, children around the age of 9 have a dislike towards alcohol but by the age of 13, children's expectancies towards alcohol take a positive shift [4]. Also, drinking at an early stage is considered more of a social activity performed in the absence of parental attention which at a later stage is quantifiable by the number adolescent's outing with his or her friends [5]. Another governing reason of teenage alcohol addiction is access to today's open media. Since most of the teenagers today have an open and an easy access to the internet they are exposed to various advertisements on the sites they most often visit like social networks which mislead the young minds to see alcohol positively [6].

Parental attitudes and family support also control teenagers drinking habits to a large extent. The kind of culture offered inside the house affects the adolescent's thoughts and attitudes towards all the things. Various research points to fact that there is a high probability that a child might be an alcoholic given his parent are alcoholics too [7]. Huge improvement in computational resources and the ease of implementation have allowed us to apply computational analysis to various fields including psychological and social problems such as youth and substance abuse, internet addiction leading to depression and suicidal tendency [8] and much more. Some research has been done in alcohol consumption and its effects on high school individuals with help of data mining as a major tool [9]. On similar lines various drinking patterns and important factors leading to alcohol consumption and addiction among high school students is also studied. The study was carried out at eastern Ethiopia and analysis was carried out over data sample of 1721 students. The research identified the correlation between various affecting attributes and its effects in student's academics [10]. Our study will consider data collected during the 2005- 2006 school year from two public schools, from the Alentejo region of Portugal [11]. Authors also have carried out an exhaustive comparative study on this data by applying various data mining algorithms to achieve accuracy [12]. But, objective of the problem is to identify chief characteristics that effects the school children to become alcoholic are missing. Authors simply identify the correlation between alcohol consumption and various attributes like age, gender and study time attributes. But, while studying the dataset, it is observed that the dataset contains uncertainties and inconsistencies. In addition to that there may be presence of many superfluous attributes. Although much work is done on mining and prediction of various attributes on the datasets there is a paucity on dimensionality reduction research on the same. By eliminating the superfluous attributes enables a highly efficient decision making models. There are many methods available in the literature to achieve dimensionality reduction like, principle component analysis [13], random forests [14], ensemble trees [15], and rough sets [16]. Among all such methods rough set is more applicable because of its simplicity [17]. Additionally, rough set generates effective decision rules and helps in prediction whereas formal concept analysis [18] helps in description. Therefore, efforts have been made to hybridize rough set and formal concept analysis.

In this paper our model building approach involves two phases namely pre-phase and post-phase. Pre-phase mostly deals with data reduction and mining various rules with the help of rough set theory. On the other hand post-phase involves using of formal concept analysis to extract most important characteristics that govern a teenager's drinking habits. The remainder of the paper is organized as follows: Section 2 presents the basics of rough set theory and information system. Section 3 provides the basic idea of formal concept analysis. The proposed data mining model and numerical illustrations are given in Section 4. Section 5 presents a comparative empirical study on teenage drinking habits and extraction of most important parameters from the available data. Finally, conclusion is stated in section 6.

Information System

An information system is representing a data set as a table in such a way that each row represents an object of the universe and every column represents an attribute of all these objects. The attribute may be also supplied by a human expert. Mathematically, an information system can be defined as a pair $I = (U, A, V, f)$, where U is a non empty finite set of objects called the universe and A is a non empty finite set of attributes, $V = \cup V_a$, $a \in A$, and $f : (U \times A) \rightarrow V$ is an information function such that $f(x,a) \in V_a$, where V_a is the domain of the attribute $a \in A$. If $A = (C \cup D)$, where C is the set of conditional attributes and D is the set of decisions, we call the information system as decision system. The information system may be of qualitative, quantitative or hybridized [19].

For example, consider a shopping mall dataset of 10 objects with 3 attributes such as price, popularity, brand-power, purchasing decision. The Table 1 shown below is a sample qualitative information system. The attribute price is the price range of objects which is categorized as either low, or average or high. Similarly, the other attributes are also categorized. The decision is the consumer buying decision which is either yes or no. The presented example is a qualitative information system. If the attribute values are numerical, we call the information system as quantitative.

Table: 1. Sample information system.

Objects	Price	Popularity	Brand Reputation	Purchasing Decision
x_1	Low	Popular	High Reputed	Yes
x_2	Low	Popular	Less Reputed	Yes
x_3	High	Less Popular	Less Reputed	Yes
x_4	High	Popular	Less Reputed	Yes
x_5	Low	Popular	High Reputed	Yes
x_6	Average	Popular	Medium Reputed	No
x_7	Low	Popular	Less Reputed	No
x_8	High	More Popular	Less Reputed	Yes
x_9	High	Popular	Less Reputed	No

2.1. Indiscernibility relation

Universe can be considered as a large collection of objects. Each object is associated with some information (data, knowledge) within it. In order to find knowledge about the universe we need to process these attribute values. Therefore, we require sufficient amount of information to uniquely identify, classify these objects into classes and to extract knowledge about the universe. The classification of the objects of the universe is done based on in-discernibility relation among these objects. It indicates that objects of a class cannot discern from one another based on available set of attributes of the objects [20, 21]. The in-discernibility relation generated in this way is the mathematical basis of rough set theory. Any set of all indiscernible objects is called an elementary concept, and form a basic granule (atom) of knowledge about the universe. Any union of the elementary sets is referred to be either crisp (precise) set or rough (imprecise) set. Let $P \subseteq A$ and $x, y \in U$. Then we say that two objects x and y are indiscernible by the set of attributes P in A if and only if the following equation (1) holds.

$$f(x,a) = f(y,a) \quad \forall \quad a \in P \tag{1}$$

For example consider Table 1, given the attributes price, popularity, and brand reputation the objects x_1 and x_5 are indiscernible. Similarly, the other indiscernible classes can also be obtained. In general, each object x_i, i = 1, 2, $\cdots$, 9 is compared with each other cell wise to find the indiscernibility in the attribute value. From the data set Table-1, on considering the attributes A = {Price, Popularity, Brand reputation}, we get the family of equivalence classes of A, i.e., the partition determined by set of attributes A, denoted by U / A or $I(A)$. Therefore,

$$U / A = \{\{x_1, x_5\}, \{x_2, x_7\}, \{x_3\}, \{x_4, x_9\}, \{x_6\}, \{x_8\}\}$$

Emergence of Rough Set Theory

The emergence of new technologies in the field of data science has led to a vast increase in the assemblage of data. However, these data are of no use unless some useful information is derived from it. Additionally, these available data may be of structured or unstructured. Analysis of unstructured data is another issue in data analysis. On the other hand, structured data may contain uncertainties and may be imprecise in nature. Analyzing such data is of great challenge and requires some intelligence techniques like fuzzy sets. But, there are certain difficulties in designing membership functions. This requires expertise and failing to do so may lead to wrong conclusion. Therefore, it is a major issue in the field of artificial intelligence while extracting knowledge from this voluminous data. Later in 1982, Pawlak gave his theory of rough sets [16] for data analysis. It requires no membership function to analyze data. The basic concept is based on an equivalence relation. In recent years it is gaining popularity while applying to various real life problems. Also, it has been extended in many directions to handle variety of problems. Though it has extended in many directions, still it is useful for solving many real world problems and to handle imperfect knowledge. The main advantages of the rough set approach are as follows:

- It helps in reducing original data, i.e. to find minimal sets of data with the same knowledge as in the original data.
- It does not need any additional information about data such as membership function in the fuzzy set theory.
- Widely used in the fields of machine learning, data mining, and pattern recognition.
- It is very easy to comprehend and easily generates if-then rules from the given data.

3.1. Rough set

In this section, we recall the basic definitions of basic rough set theory developed by Z. Pawlak [16]. Let U be a finite nonempty set called the universe. Suppose $R \subseteq (U \times U)$ is an equivalence relation on U. The equivalence relation R partitions the set U into disjoint subsets. Elements of same equivalence class are said to be indistinguishable. Equivalence classes induced by R are called elementary concepts. Every union of elementary concepts is called a definable set. The empty set is considered to be a definable set, thus all the definable sets form a Boolean algebra and (U, R) is called an approximation space. Given a target set X, we can characterize X by a pair of lower and upper approximations. We associate two subsets R_* and R^* called the R – lower and R–upper approximations of X respectively and are given by

$$R_*(X) = \{x \in U : [x] \subseteq X\} \quad (2)$$

And $$R^*(X) = \{x \in U : ([x] \cap X) \neq \phi\} \quad (3)$$

The R–boundary of X, $BN_R(X)$ is given by $BN_R(X) = R^*(X) - R_*(X)$. We say X is rough with respect to R if and only if $R^*(X) \neq R_*(X)$, equivalently $BN_R(X) \neq \phi$. The target set X is said to be R – definable if and only if $R^*(X) = R_*(X)$ or $BN_R(X) = \phi$. Therefore, a set is rough with respect to R if and only if it is not R – definable. The lower approximation of a set is union of all granules which are entirely included in the set whereas the upper approximation is the union of all granules which have non-empty intersection with the set. The boundary region of a set is the difference between the upper and the lower approximation of the set.

Let $P, Q \subseteq A$ be two indiscernibility relations defined over the universe U.The P-positive region of Q is defined as below. It denotes the set of objects that can be properly classified to the Q- elementary sets generated by the classification U/Q employing the knowledge expressed by the classification U/P.

$$POS_P(Q) = \bigcup_{X \in U/Q} P_*(X) \quad (4)$$

Similarly, the P - negative region of Q and P - boundary region of Q is defined as below.

$$NEG_P(Q) = U - \bigcup_{X \in U/Q} P^*(X) \quad (5)$$

$$BN_P(Q) = \bigcup_{X \in U/Q} P^*(X) - \bigcup_{X \in U/Q} P_*(X) \quad (6)$$

3.2. Attribute reduction and rule generation

In an information system, some attributes may not play a vital role in classification and decision making process. Such attributes are known as superfluous attributes. Therefore, it is essential to remove such attributes before making further analysis. This leads to the concept of attribute reduction. Let $I = (U, A, V, f)$ be an information system and $B \subseteq A$. An attribute $a \in B$ is said to be dispensable in B if $U/B = U/(B - \{a\})$; otherwise a is said to be indispensable in B. The set of attributes B is said to be independent if all its attributes are indispensable.

According to rough set theory of Pawlak [16], a decision rule S in an information system is expressed as $\phi \to \psi$, where ϕ and ψ are conditions and decisions of the decision rule S respectively. The measurements associated with decision rule are accuracy of the decision rule, support of a rule, and strength of the decision rule. The support of a rule is defined as $Supps(\phi, \psi) = Card \quad (\| \phi \wedge \psi \|_S)$, whereas the strength of the decision rule $\phi \to \psi$ is defined as:

$$\sigma(\phi,\psi)=\frac{Supps(\phi,\psi)}{Card(\|U\|_{\psi})} \quad (7)$$

It implies that stronger rules cover more number of supporting objects and its strength can be calculated by using relation (7). In general, the dataset is divided into two parts such as training (55%) and testing (45%). The training dataset is processed to obtain rules whereas the testing dataset is used to validate the rules. For better understanding of these concepts, consider the information system presented in Table 2 containing 19 objects. The objects refer to various companies.

The attributes are expenditure in marketing (a_1), expenditure in distribution (a_2), expenditure in advertisement (a_3), miscellaneous expenditure (a_4), expenditure on research and development (a_5), and total sales (d). The attribute total sale is considered as the decision variable. The expenditure on various factors is categorized five different classes such as very high (1), high (2), average (3), low (4), very low (5). However, these values do not affect our analysis. The first 10 objects are considered as training object whereas the rest 9 objects are considered as testing objects. The following algorithm is used for generating rules.

Algorithm: (Rule Generation)

Input: Target information system

Output: Validated decision rules

1. Set object number $i=1$
2. Choose object i from the training data set and compute a set of reducts for all the condition attributes.
3. Replace $i=i+1$
4. If all objects have been chosen, then go to step 5; else go to step 2.
5. Compute the number of supporting objects for each reduct after combining the identical reducts.
6. Obtain the decision rules from the selected reducts.

The decision rules obtained using above algorithm is tested with the testing data set. Each decision rule obtained is compared with each new object from the testing data set. Find the number of supporting objects and non-supporting objects. Calculate the accuracy by using equation (8),

where $|S_{obj}|$, $|NS_{obj}|$ represents the number of supporting and non-supporting objects. Discard the rules those falling less than the predefined threshold values.

$$\text{Accuracy} = \frac{|S_{obj}|}{|S_{obj} + NS_{obj}|} \tag{8}$$

Table: 2. Sample information system

Objects	Marketing	Distribution	Advertisement	Miscellaneous	Research and Development	Decision (d)
x_1	1	2	2	3	3	2
x_2	1	3	2	1	4	1
x_3	1	4	2	2	2	1
x_4	2	4	2	3	1	3
x_5	1	1	3	1	4	1
x_6	2	4	3	1	4	1
x_7	2	2	1	1	4	2
x_8	1	2	1	2	3	2
x_9	1	5	1	3	1	4
x_{10}	2	3	1	3	2	3
x_{11}	2	3	2	2	2	1
x_{12}	1	2	2	2	3	2
x_{13}	2	1	1	3	3	3
x_{14}	2	2	1	2	2	2
x_{15}	1	3	3	2	4	1
x_{16}	2	5	1	3	3	4
x_{17}	2	5	1	2	1	4
x_{18}	2	1	3	2	2	1
x_{19}	1	3	1	3	4	2

The rules generated from first 10 objects, its support, strength, and accuracy is presented Table 3. The notation $R_{i,d}$ represents the i^{th} rule for the decision d. The support, strength and accuracy of each rule are computed on considering the testing objects.

Table: 3. Support, strength and accuracy of decision rules.

Rule Number	Notation	Decision	Meaning	Support	Strength	Accuracy
1	$R_{1,1}$	1	If $(a_3 = 3)$, then $d = 1$	2	66.67	100 %
2	$R_{2,1}$	1	If $(a_1 = 1)$ & $(a_2 = 3)$, then $d = 1$	1	33.33	50 %
3	$R_{3,1}$	1	If $(a_4 = 2)$ & $(a_5 = 2)$, then $d = 1$	2	66.67	66.67
4	$R_{4,2}$	2	If $(a_2 = 2)$, then $d = 2$	2	66.67	100
5	$R_{5,3}$	3	If $(a_1 = 2)$ & $(a_4 = 3)$, then $d = 3$	1	100	50
6	$R_{6,4}$	4	If $(a_2 = 5)$, then $d = 4$	2	100	100

Rudiments of Formal Concept Analysis

Formal concept analysis (FCA) is a subfield of applied mathematics that mathematizes concept and concept hierarchy. This in turn provides tools to conceptually understand and gain plethora of insights from data. Moreover, it is a way to express a unit of a thought that is a concept and its hierarchy in a mathematical form [22]. It has applied to many practical applications such as data mining, knowledge extraction, chemistry, physics, semantic web, software development. The development of lattice theory by Garrett Birkhoff [23] gave formal concept analysis a new look of building a hierarchy.

The major objective of FCA is to assist the user to activate mathematical thinking about data and its attributes. Additionally, it helps in analyzing and structuring the data based on the user's interest. It makes the fundamental process of data analysis mathematically based on formal understanding that can be regarded as a unit of thought. From the perceptions of philosophy, concepts can always be understood as basis of the though process within each and every environmental aspect. As stated philosophically a concept is basically described by two terms that are correlative namely extension, intension. All objects to which a concept applies makes up the extension and all the attributes describing those objects is called intension. For instance the intension for the substantive or concept car is a medium of road travel, has four wheels etc. On the other hand the extension of cars can be of its any type such as SUV's, sedans, hatchbacks etc. Collectively set of all such attributes, objects and relations between them together make up the basic conceptual structure of a data set called formal context. Concept can only be in relationship with other concepts which leads to a formation of sub concept-super concept relationship. Such relationships play a very crucial role in data analysis [24].

4.1. Basic notions of formal concept analysis

The section describes some of the concept and notions of FCA as introduced by R. Wille [22]. A formal context is a collection of all concepts and their relations with the attributes. A formal concept is defined as a triple $K=(U,A,R)$, where U is a non empty finite set of objects called the universe, A is the set of attributes associated with it, and R is binary relation from $U \to A$. It indicates that $R \subseteq (U \times A)$. Let us take $X \subseteq U$ and $Y \subseteq A$. The derivation operators X' and Y' are defined as follows:

$$X' = \{a \in A:\ xRa\ \ \forall\ \ x \in X\} \tag{9}$$

$$Y' = \{x \in U:\ xRa\ \ \forall\ \ a \in A\} \tag{10}$$

Using above information a formal concept can be defined as a pair (X,Y) such that $X' = Y$ and $Y' = X$, where X is called the extent and Y is called the intent. The characteristics of it are as follows. Objects in X share all the properties in Y, and all objects in X only possess properties in Y. Due to sub concept and super concept relation all formal concepts in formal context form a lattice structure called a concept lattice [22, 23]. Before, we construct the lattice diagram, we first construct the cross table from the decision rules. The cross table of the decision rules presented in Table 3 is shown in Table 4. The corresponding lattice diagram depicting the sub concept and super concept relation is presented in Figure 1. In such diagram the name of each object is attached to its respective concept and so are the attributes. It clearly describes the transitive nature of the sub-concept super-concept relation.

Table: 4. Cross table of decision rules.

Rule	a_{11}	a_{12}	a_{22}	a_{23}	a_{25}	a_{33}	a_{42}	a_{43}	a_{52}	D_1	D_2	D_3	D_4
R_1	--	--	--	--	--	×	--	--	--	×	--	--	--
R_2	×	--	--	×	--	--	--	--	--	×	--	--	--
R_3	--	--	--	--	--	--	×	--	×	×	--	--	--
R_4	--	--	×	--	--	--	--	--	--	--	×	--	--
R_5	--	×	--	--	--	--	--	×	--	--	--	×	--
R_6	--	--	--	--	×	--	--	--	--	--	--	--	×

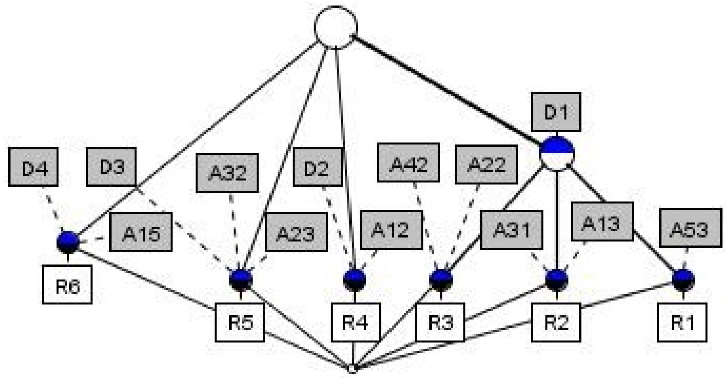

Fig: 1. Lattice diagram of decision rules.

Proposed Model for Finding Alcoholic Traits

In this section we primarily lays down a flow of what we intend to do with our data. All the steps taken in order as follows data preparation, data cleaning, data processing i.e. is making it suitable for application of our model, discovery of decision rules using rough set and last is formal concept analysis to extract chief attributes for alcoholic traits. Usually the importance of a data varies from individual to individual. One might dump some of the attributes while other might treasure it. It is because of the uncertainty present in the dataset. Since there is huge vagueness present in data, reasoning makes it very difficult to find useful patterns and information. One thumb rule might be to first have hypothesis or questions to ask for instance: If a student drinks alcohol on every weekend there is a chance of him being an addict, hence here the problem definition is to find a correlation between drinking frequency and addiction. But the problem arises when there is incomplete data or element of vagueness. To solve this problem our work flow is divided into two processes one is pre-process and another is post process. Pre-process handles major part of data preparation and processing for ease of rule extraction, for instance classification of objects, identification of reducts and boundary regions. Finding of decision rules after multiple iterations and its validation is the primary objective of pre-process. Post-process simply uses formal concept analysis to mine relevant attribute characteristics to gain important insights of the problem. The major objective of hybridizing rough set and formal concept analysis is that rough set helps in obtaining decision rules whereas formal concept analysis helps in description. This helps in analyzing, identifying, and interpreting the results in a more specific way. Additionally, it could help the school and society to take necessary action in reducing alcohol consumption. An abstract view of the proposed model is depicted in Figure 2.

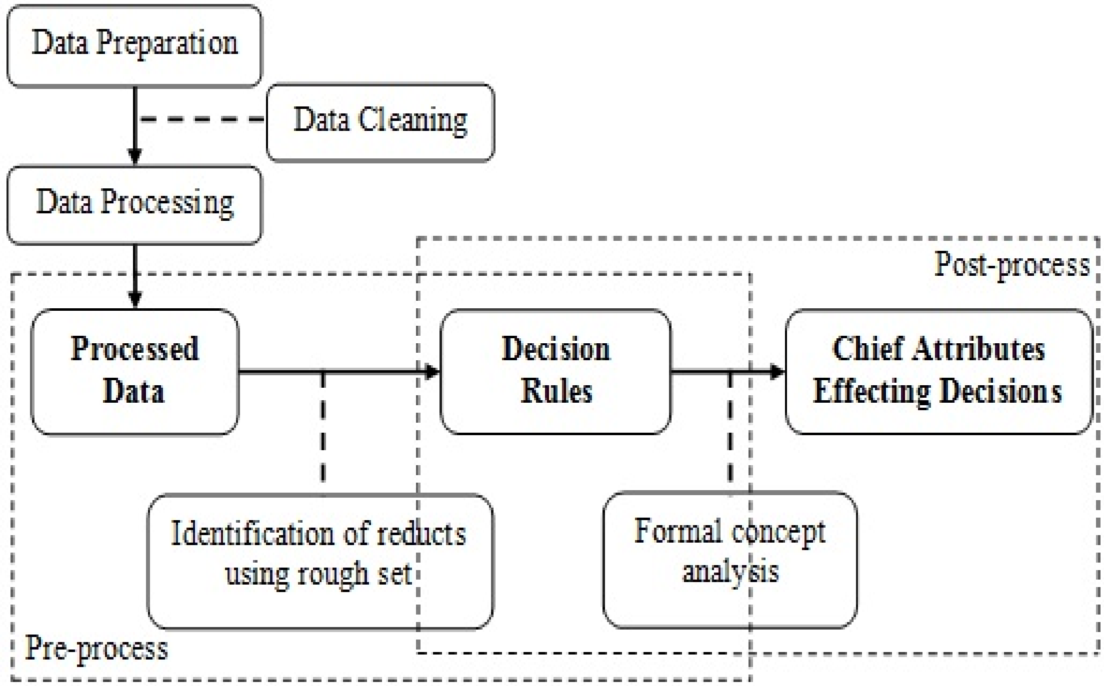

Fig: 2. An abstract view of proposed model.

5.1. Pre-process of proposed model

In this section we discuss pre-process design of the proposed model. The flow of operations carried out on dataset in order to ensure systematic and standard results is analyzed in this section. The flow chart shown in Figure 3 lucidly depicts the workflow of the pre-process design. As discussed in the previous section, pre-process includes problem description i.e., identifying the problem or state the questions that need to be answered using the dataset; data cleaning i.e., removal of incomplete data; and outlier analysis. The outlier detection helps us to get rid of any human error or noisy data. Secondly, we develop a structured information system that helps us to perform mining operations. Thirdly, we process the data to make it suitable for the algorithm as discussed in Section 3.2. A numerical representation for the algorithm is illustrated in Section 3. For each attribute, we compute the indiscernibility classes based on equivalence relation. The equivalence relation identifies the indiscernibility among the objects and induces equivalence classes. After obtaining the equivalence classes, we apply rough set data reduction (horizontal reduction) technique to reduce the number of attributes that do not effect the decisions. Furthermore, we divide the dataset into two partitions such as training dataset of 55% and testing dataset of 45%. The rule generation algorithm is employed on training dataset to obtain decision rules whereas the decision rules are validated over the testing dataset. Finally, the rules having accuracy more than the pre defined threshold value is selected as candidacy rules. These candidacy rules are the input to the post-phase of the proposed model which we will discuss in the next subsection.

5.2. Post-process of proposed model

Candidacy rules obtained in the pre-phase is the input to the post-phase. Post-phase is generally used to identify the prime attribute and its values effecting the decisions. To begin with, we prepare the cross table for candidacy rules obtained in pre-phase. It is a two dimensional table in which the horizontal row represents the rules whereas the vertical dimension refers to various attribute values. Relation between the rules and attributes is represented by a cross. An example of cross table is depicted in the previous section. Based on the cross table, the lattice diagram, implication sets, and association rules are generated. Further, we have to find the sub-concept and super-concept relation from the implication set table and hence the attributes effecting decisions can be obtained. It is also observed that, a concept is the sub-concept of any concept that can be reached by traveling upwards from it and hence sub-concept, super-concept follows transitive relation. A pictorial view of the lattice diagram is shown in Figure 2, where the formal concepts are represented as nodes.

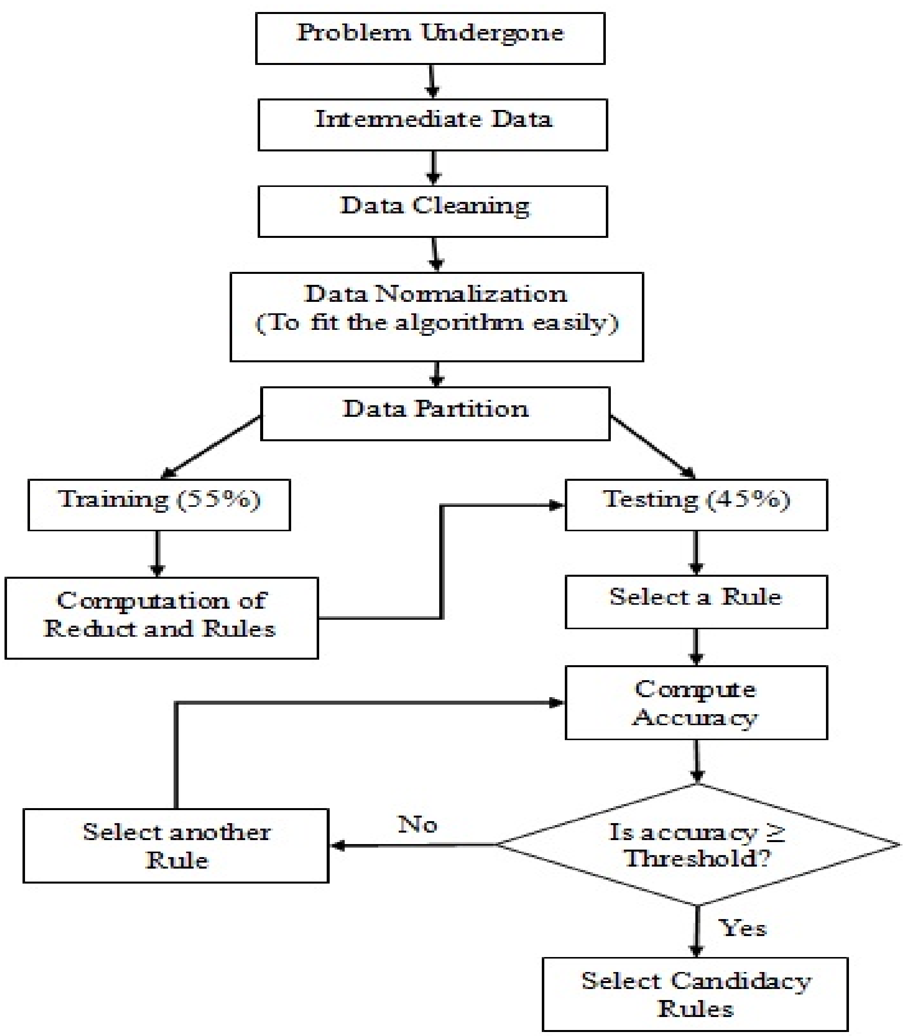

Fig: 3. A flow chart of pre-process design.

Empirical Study of Alcohol Consumption in Secondary School

The education competency at secondary level of any country can be measured by the number of students passing out successfully from secondary schools. Alcohol consumption has been one of the factors that have negatively influenced this number. The Portuguese alcohol consumption dataset, as provided by Paulo Cortez and Alice Silva, University of Minho, Portugal, provide real time collected dataset from 2 Portuguese schools for the time period of 2005-2006 [11]. They analyzed the data but, fail to find out the chief measures of alcohol traits. We will be analyzing the proposed model on alcohol consumption dataset was obtained from the UCI machine learning repository to extract prime factor effecting the decisions. These important features help the secondary school to think over it so as to reduce the alcohol consumption among students. The first source of the dataset was schools reports which were filled by questionnaires asked on sheet paper for some attributes such as number of school absences, etc. The rest of the attributes which seemed to be personal, such as family income, number of past failures, etc., were asked by closed question method. All the above responses were reviewed by school professionals and were also tested on 25 to 30 students for full proofing.

A total of 788 student's information was collected, out of which the information of 111 students was discarded due to lack of identification details. The final dataset of 677 students is divided into two partitions, one having training dataset of 372 students and the other having testing dataset of 305 students. The various attributes in the dataset and their description have been given in the Table 5 below.

Table: 5. Attribute description and its notation and classification

Attribute	Notation	Classification	Attribute	Notation	Classification
Student's Sex	a_1	Male (1) Female (0)	Student's Age	a_2	14 – 16 (1) 17 – 19 (2) 20 – 23 (3)
Home Address	a_3	Urban (1) Rural (0)	Family Size	a_4	≤ 3 (1) > 3 (0)
Parent's Cohabitation Status	a_5	Living together (1) Living apart (0)	Mother's Education	a_6	None (0) Till 4th Grade (1) 5th – 9th Grade (2) Secondary (3) Higher (4)
Father's	a_7	None (0)	Mother's	a_8	Teacher (1)

Education		Till 4th Grade (1) 5th – 9th Grade (2) Secondary (3) Higher (4)	Job		Health Care (2) Administration (3) At Home (4) None (5)
Father's Job	a_9	Teacher (1) Health Care (2) Administration (3) At Home (4) None (5)	Guardian	a_{10}	Mother (1) Father (2) Other (3)
Travel Time to School (Minutes)	a_{11}	Time < 15 (1) 15 < Time ≤ 30 (2) 30 < Time ≤ 60 (3) Time > 60 (4)	Weekly Study Time (Hours)	a_{12}	Time < 2 (1) 2 < Time ≤ 5 (2) 5 < Time ≤ 10 (3) Time > 10 (4)
Past Class Failures	a_{13}	n if $1 \le n \le 3$ Else 4	Educational Support	a_{14}	Yes (1) No (0)
Family Educational Support	a_{15}	Yes (1) No (0)	Extra Paid Classes	a_{16}	Yes (1) No (0)
Extra Curricular Activities	a_{17}	Yes (1) No (0)	Attended Nursery School	a_{18}	Yes (1) No (0)
Interested for Higher Education	a_{19}	Yes (1) No (0)	Internet Access at Home	a_{20}	Yes (1) No (0)
Romantic Relationship	a_{21}	Yes (1) No (0)	Family Relationship	a_{22}	Very Bad (1) Bad (2) Fair (3) Good (4) Excellent (5)
Free Time After School	a_{23}	Very Low (1) Low (2) Average (3) High (4)	Going Out with Friends	a_{24}	Very Low (1) Low (2) Average (3) High (4)

		Very High (5)			Very High (5)
Current Health Status	a_{25}	Very Bad (1) Bad (2) Average (3) Good (4) Very Good (5)	Number of School Absences (Yearly)	a_{26}	More than 20 Days (1) Less than 20 Days (0)
Final Grade	a_{27}	Above Average (2) Below Average (1)	Weekend Alcohol Consumption	d	Very Low (1) Low (2) Average (3) High (4) Very High (5)

The attribute final grade is taken from school reports. In order to use the dataset for classification of alcoholics we made some changes. We computed the weekend alcoholic based on weekday alcoholic and weekend alcoholic by using the following equation. These two attributes take values from 1 to 5 where 1 represents very low and 5 represent very high.

$$\text{Weekend Alcohol consumption } (d) = \frac{5 \times \text{Weekday consumption} + 2 \times \text{Weekend consumption}}{7} \tag{11}$$

Equation (11) presented above is a simple week weighted formula and it results value in between 1 and 5. Further, to fix our objective of finding chief attributes of alcoholic traits, we assume values 1 to 3 to be non-alcoholic and 4 to 5 being alcoholic.

6.1. Pre-process of empirical study

In this section, the pre process of empirical study has been illustrated. The processed dataset has primarily two decisions such as alcoholic i.e., $d = 1$ (having decision value > 3) and non-alcoholic i.e., $d = 0$ (having decision value ≤ 3). Rough set data analysis and rule generation algorithm is employed over training dataset of 372 students. A total of 43 rules were generated out of which 26 rules corresponded to the decision non-alcoholic and 17 rules corresponded to the decision alcoholic.

The rules generated for decision alcoholic is presented in the following Table 6. The rules generated with the help of training data are validated on testing data which comprises of 305 students. For each rule, the number of supporting objects and non-supporting objects are noted and then the accuracy of each rule is calculated by using equation (8). The validation process for the decision alcoholic is presented in Table 7.

Table: 6. Decision rules of the decision alcoholic.

Rule Number	Description	Rule Number	Description
1	$a_1 = 1, a_3 = 0, a_{12} = 1, a_{15} = 1, a_{18} = 1, a_{20} = 1, a_{22} = 4$ then $d = 1$	2	$a_{12} = 2, a_{22} = 4, a_{24} = 5, a_{25} = 5$ then $d = 1$
3	$a_1 = 1, a_3 = 1, a_7 = 1, a_{13} = 0, a_{21} = 1$ then $d = 1$	4	$a_3 = 1, a_6 = 4, a_7 = 4, a_9 = 2, a_{11} = 1, a_{15} = 1, a_{18} = 1$ then $d = 1$
5	$a_1 = 1, a_6 = 1, a_{10} = 0, a_{22} = 3$ then $d = 1$	6	$a_2 = 2, a_3 = 0, a_{15} = 0, a_{20} = 1, a_{24} = 3$ then $d = 1$
7	$a_8 = 2, a_{15} = 0, a_{24} = 4, a_{25} = 2$ then $d = 1$	8	$a_1 = 1, a_3 = 1, a_9 = 3, a_{18} = 0, a_{25} = 5$ then $d = 1$
9	$a_2 = 1, a_6 = 1, a_7 = 1, a_{12} = 1$ then $d = 1$	10	$a_1 = 1, a_5 = 0, a_{12} = 2, a_{26} = 0$ then $d = 1$
11	$a_4 = 1, a_{13} = 1, a_{20} = 0, a_{27} = 1$ then $d = 1$	12	$a_4 = 0, a_8 = 2, a_{12} = 1, a_{17} = 0, a_{23} = 5$ then $d = 1$
13	$a_1 = 1, a_{15} = 1, a_{17} = 1, a_{19} = 0, a_{21} = 1$ then $d = 1$	14	$a_{22} = 1, a_{24} = 5$ then $d = 1$
15	$a_9 = 3, a_{10} = 1, a_{13} = 0, a_{15} = 1, a_{23} = 1$ then $d = 1$	16	$a_8 = 0, a_{13} = 1, a_{14} = 0, a_{26} = 0$ then $d = 1$
17	$a_2 = 2, a_6 = 4, a_{22} = 5, a_{23} = 4$ then $d = 1$		

Table: 7. Validation of decision rules of the decision alcoholic.

Rule Number	Support	Non-support	Accuracy	Rule Number	Support	Non-support	Accuracy
1	3	1	75	2	2	0	100
3	2	2	50	4	0	0	0
5	1	0	100	6	0	0	0
7	2	0	100	8	0	1	0
9	1	0	100	10	1	0	100
11	0	1	0	12	1	0	100
13	2	0	100	14	1	1	50
15	1	1	50	16	2	2	50
17	2	2	50				

On considering the threshold of 90%, the rules 1, 3, 4, 6, 8, 11, 14, 15, 16, and 17 are discarded. Finally, 7 rules are selected out of 17 rules for the decision alcoholic and it is passed to post process for identifying the chief attributes. The reason of taking high threshold value because of getting stringent characteristics for a student to be alcoholic can be found out. However, the threshold value can be reduced to get less stringent attribute characteristics.

Similarly, the rules generated for decision non-alcoholic is presented in the following Table 8. The rules generated with the help of training data are validated on testing data which comprises of 305 students. For each rule, the number of supporting objects and non-supporting objects are noted and then the accuracy of each rule is calculated by using equation (8). The validation process for the decision non-alcoholic is presented in Table 9.

On considering the threshold of 90%, the rules 1, 3, 4, 7, 9, 10, 11, 12, 15, 16, 17, 18, 20, 21, 22, 24, and 26 are selected for the post process to be carried out. The rest of the rules are discarded. On lowering the threshold value, some more number of rules can be included. But, the reason of taking high threshold value because of getting stringent characteristics for a student not to be alcoholic can be found out. This will help us to find the alcoholic traits.

Table: 8. Decision rules of the decision non-alcoholic.

Rule Number	Description	Rule Number	Description
1	$a_1 = 0, a_5 = 1, a_{14} = 0, a_{15} = 1, a_{16} = 0$ then $d = 0$	2	$a_3 = 1, a_{13} = 0, a_{17} = 1, a_{18} = 1, a_{21} = 0, a_{27} = 1$ then $d = 0$
3	$a_1 = 1, a_4 = 0, a_{11} = 1, a_{17} = 0, a_{27} = 1$ then $d = 0$	4	$a_1 = 0, a_3 = 1, a_{13} = 0, a_{14} = 0, a_{19} = 1, a_{21} = 1$ then $d = 0$
5	$a_9 = 2, a_{13} = 0, a_{15} = 0, a_{21} = 0$ then $d = 0$	6	$a_{11} = 2, a_{13} = 0, a_{19} = 1, a_{22} = 5, a_{27} = 1$ then $d = 0$
7	$a_{11} = 2, a_{12} = 2, a_{22} = 4, a_{26} = 1$ then $d = 0$	8	$a_3 = 1, a_{13} = 0, a_{22} = 4, a_{24} = 3, a_{27} = 1$ then $d = 0$
9	$a_{10} = 1, a_{20} = 1, a_{21} = 1, a_{23} = 5, a_{27} = 1$ then $d = 0$	10	$a_{12} = 3, a_{27} = 1$ then $d = 0$
11	$a_{12} = 2, a_{16} = 0, a_{19} = 1, a_{27} = 1$ then $d = 0$	12	$a_{11} = 1, a_{13} = 1, a_{21} = 0, a_{27} = 1$ then $d = 0$
13	$a_1 = 0, a_{27} = 0$ then $d = 0$	14	$a_9 = 2, a_{26} = 1, a_{27} = 0$ then $d = 0$
15	$a_7 = 4, a_{27} = 1, a_{26} = 1$ then $d = 0$	16	$a_{18} = 0, a_{25} = 3$ then $d = 0$
17	$a_5 = 1, a_{10} = 2, a_{13} = 1, a_{26} = 0$ then $d = 0$	18	$a_5 = 0, a_9 = 2, a_{26} = 1$ then $d = 0$
19	$a_5 = 1, a_{10} = 1, a_{21} = 0, a_{23} = 2$ then $d = 0$	20	$a_5 = 0, a_{18} = 0, a_{25} = 2$ then $d = 0$
21	$a_2 = 2, a_6 = 3, a_6 = 2, a_{21} = 0$ then $d = 0$	22	$a_{10} = 1, a_{13} = 1, a_{16} = 0, a_{17} = 0, a_{22} = 4$ then $d = 0$
23	$a_4 = 0, a_6 = 1, a_{19} = 1, a_{20} = 0, a_{27} = 1$ then $d = 0$	24	$a_4 = 0, a_{12} = 2, a_{16} = 0, a_{25} = 5$ then $d = 0$
25	$a_8 = 0, a_{19} = 0, a_{26} = 1, a_{27} = 1$ then $d = 0$	26	$a_8 = 1, a_9 = 1$ then $d = 0$

Table: 9. Validation of decision rules of the decision non-alcoholic.

Rule Number	Support	Non-support	Accuracy	Rule Number	Support	Non-support	Accuracy
1	59	2	97	2	25	3	89
3	19	0	100	4	25	2	93
5	25	3	89	6	25	3	89
7	12	1	92	8	25	3	89
9	32	1	96	10	18	0	100
11	34	1	97	12	7	0	100
13	5	1	83	14	25	3	89
15	26	1	96	16	29	1	97

17	3	0	100	18	17	0	100
19	10	2	83	20	32	1	97
21	12	1	92	22	8	0	100
23	6	1	85	24	18	1	95
25	2	1	66	26	2	0	100

6.2. Post-process of empirical study

The rules selected in the pre process are the input to the post process. In the post process we use formal concept analysis to obtain the major factors that help in deciding the alcoholic traits in teenagers. The 7 rules selected from Table 7 is the input to the cross table. The cross table or context table for the decision class alcoholic is presented in Table 10. In the cross table, we have omitted the attributes that has no relevance in the decision rules and for the purpose of ease presentation. The corresponding lattice diagram is depicted in Figure 4. Further we compute the implication set table and implication relation table for the decision class alcoholic. The implication relation table shows the relation between the sub-concept and super-concept. Table 11 and Table 12 represent the implication set and implication relation table respectively for the decision class alcoholic. Likewise, 17 rules are selected from Table 9 for the decision class non-alcoholic is passed into the formal concept analysis. The cross or context table for the decision class non-alcoholic is presented in Table 13. The corresponding lattice diagram is depicted in Figure 5. Further we compute the implication set table and implication relation table for the decision class non-alcoholic. Table 14 and Table 15 represent the implication set and implication relation table respectively for the decision class non-alcoholic.

Table: 10. Context table for the decision class alcoholic.

Rule	a_{1-2}	a_{2-2}	a_{3-1}	a_{4-1}	a_{5-2}	a_{9-3}	a_{13-1}	a_{15-1}	a_{21-1}	a_{22-1}
[2]	×	--	×	--	--	--	×	--	×	--
[5]	--	×	--	--	--	--	--	--	--	--
[7]	×	--	×	--	--	×	--	--	--	--
[9]	×	--	--	--	×	--	--	--	--	--
[10]	--	--	--	×	--	--	×	--	--	--
[12]	×	--	--	--	--	--	--	×	×	--
[13]	--	--	--	--	--	--	--	--	--	×

Fig: 4. Lattice diagram for the decision class alcoholic.

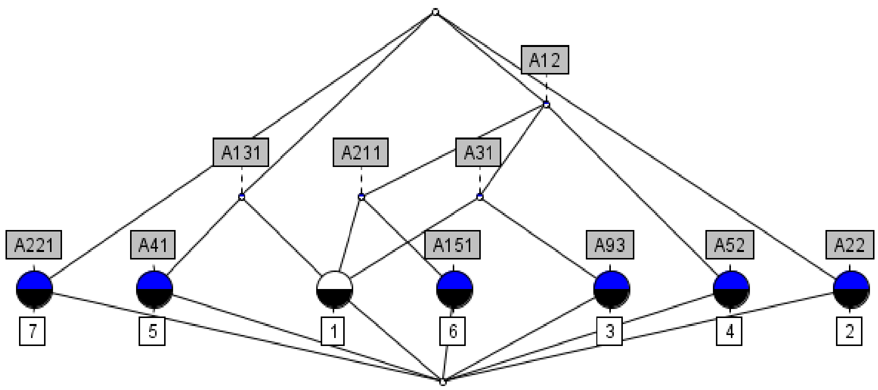

Table: 11. Implication set table for the decision class alcoholic.

Implication Sets		
1 < 2 > A31 ==> A12;	4 < 1 > A93 ==> A12 A31;	7 < 2 > A211 ==> A12;
2 < 1 > A41 ==> A131;	5 < 1 > A12 A131 ==> A31 A211;	8 < 1 > A12 A31 A211 ==> A131;
3 < 1 > A52 ==> A12;	6 < 1 > A151 ==> A12 A211;	

Table: 12. Implication relation table for the decision class alcoholic.

Superconcept	A12	A22	A31	A41	A52
Subconcept	A31,A211,A131	-	A12*2,A131	A131	A12
Frequency	3	0	3	1	1
Superconcept	A93	A131	A151	A211	A221
Subconcept	A12,A31	A31,A211	A12,A211	A12*2	-
Frequency	2	2`	2	2	0

Table: 13. Context table for the decision class non-alcoholic.

Rule	a_{1-1}	a_{4-1}	a_{5-1}	a_{6-3}	a_{6-4}	a_{7-1}	a_{8-1}	a_{10-1}	a_{13-1}	a_{17-1}	a_{18-2}	a_{19-1}	a_{20-1}	a_{23-3}	a_{25-3}	a_{26-1}	a_{26-2}	a_{27-1}
[1]	×	--	--	--	--	--	--	--	--	--	--	--	--	×	--	×	--	--
[3]	--	--	--	--	--	--	×	×	--	--	--	--	×	--	--	--	--	--
[4]	--	×	--	--	--	--	--	--	×	×	--	--	--	--	--	×	--	--
[7]	--	×	--	--	--	--	--	×	--	×	--	--	--	--	--	×	--	--
[9]	--	×	--	--	--	--	--	--	--	--	--	×	--	--	--	×	--	--
[10]	--	--	×	--	×	--	--	--	--	--	--	--	--	--	--	--	--	--
[11]	×	--	--	--	--	--	--	--	--	--	--	--	×	--	--	×	--	--
[12]	×	--	--	--	--	--	--	--	--	--	--	×	--	--	--	--	×	--

[15]	--	×	--	--	--	--	--	--	--	--	--	--	×	--	--	--	--	×
[16]	×	×	×	--	--	--	--	×	--	--	--	--	--	--	--	×	--	--
[17]	--	--	--	--	--	×	--	--	--	--	--	--	--	--	--	--	--	--
[18]	--	--	--	--	--	--	--	--	--	×	--	×	--	--	--	--	--	--
[20]	×	--	--	--	--	--	--	--	--	--	--	--	--	--	×	--	--	--
[21]	--	×	--	×	--	--	--	--	--	--	--	--	--	--	--	--	--	--
[22]	--	--	--	--	--	--	×	--	--	--	--	--	--	--	--	×	--	×
[24]	--	--	--	--	--	--	--	--	--	--	--	×	×	--	--	--	--	--
[26]	--	--	--	--	--	--	--	--	×	--	×	--	--	--	--	--	×	--

Fig: 5. Lattice diagram for the decision class non-alcoholic.

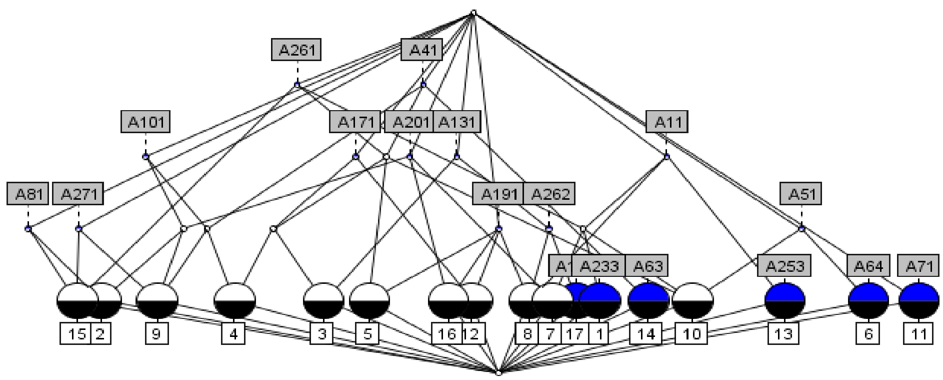

Table: 14. Implication set table for the decision class non-alcoholic.

Implication Sets		
1 < 1 > A11 A41 ==> A51 A261;	11 < 1 > A131 A171 ==> A41 A261;	21 < 1 > A101 A261 ==> A41 A171;
2 < 1 > A11 A51 ==> A41 A261;	12 < 1 > A182 ==> A131 A262;	22 < 1 > A131 A261 ==> A41 A171;
3 < 1 > A41 A51 ==> A11 A261;	13 < 1 > A11 A191 ==> A131 A262;	23 < 2 > A171 A261 ==> A41;
4 < 1 > A63 ==> A41;	14 < 1 > A41 A191 ==> A261;	24 < 1 > A191 A261 ==> A41;
5 < 1 > A64 ==> A51;	15 < 1 > A131 A191 ==> A11 A262;	25 < 1 > A201 A261 ==> A11;
6 < 1 > A81 A101 ==> A201;	16 < 1 > A11 A201 ==> A261;	26 < 2 > A262 ==> A131;
7 < 1 > A11 A131 ==> A191 A262;	17 < 1 > A81 A201 ==> A101;	28 < 1 > A41 A271 ==> A101 A201;
8 < 1 > A41 A131 ==> A171 A261;	18 < 1 > A233 ==> A11 A261;	31 < 1 > A81 A271 ==> A261;
9 < 2 > A41 A171 ==> A261;	19 < 1 > A253 ==> A11;	32 < 1 > A101 A271 ==> A41 A201;
10 < 1 > A101 A171 ==> A41 A261;	20 < 1 > A51 A261 ==> A11 A41;	33 < 1 > A201 A271 ==> A41 A101;
34< 1 > A261 A271 ==> A81;	35 < 1 > A41 A201 ==> A101 A271;	36 < 1 > A81 A261 ==> A271;

Table: 15. Implication relation table for the decision class non-alcoholic.

Super concept	A11	A41	A51	A63	A64	A71	A81	A101	A131
Sub concept	A51, A261, A261,A261 A41, A191, A262, A262, A131	A51, A261*2, A261, A261, A261 A261, A11, A171, A101, A101 A271, A201	A41, A41, A261, A261, A11, A11	A41	A51	-	A201, A101, A261, A271	A201, A201, A41, A41, A41 A261, A171	A191, A262, A262, A171, A261, A261 A41, A41 A11, A171
Frequency	9	13	6	1	1	0	4	8	9
Super concept	A171	A182	A191	A201	A233	A253	A261	A262	A271
Sub concept	A41,A41 A41*2, A261,A261, A261*2	A131, A262	A131, A262, A262 A261, A11, A41	A261, A101, A101, A101 A271, A11, A41	A11, A261	A11	A81, A11, A41*2, A41, A41, A41, A41, A171, A171, A11, A271	A131*2	A81, A101, A101, A201, A201 A261, A41, A41
Frequency	8	2`	6	7	2	1	11	2	8

Conclusion

In this case study with the help of rough set data analysis we came up with 43 rules. These rules were later reduced to 24 using threshold and domain knowledge. Further using formal concept analysis, implication sets and implication relation tables we could identify the chief factors that help determine the whether a high school teenager is alcoholic or non-alcoholic. According to our results it helps if a teen belongs to a family size greater than 3 to stay non alcoholic (A41) , also if the absences are high doesn't really mean a student is alcoholic as bunking classes is not something can be carried out by students without parents consent hence if a student is missing school he is highly likely to stay at home with parents keeping a check on the student (A261) and lastly if a person has less failures at school (A131) he is likely to be a non alcoholic. For alcoholic traits we conclude that males have a higher chance of being alcoholic then females hence Sex is a major determining factor (A12) and also if the person stays in rural areas he is more prone to alcoholism then urban – Address (A31). As the results are in tandem with psychological understanding we believe our results are quite credible and hence formal concept analysis and Rough Set can work as a major tool in such situations.

References

1. Zeigler, D. W., Wang, C. C., Yoast, R. A., Dickinson, B. D., McCaffree, M. A., Robinowitz, C. B., & Sterling, M. L. [2005]. The neurocognitive effects of alcohol on adolescents and college students. Preventive medicine, 40(1), 23-32.
2. Clark, D. B., Lynch, K. G., Donovan, J. E., & Block, G. D. [2001]. Health problems in adolescents with alcohol use disorders: Self-report, liver injury, and physical examination findings and correlates. Alcoholism: Clinical and Experimental Research, 25(9), 1350-1359.
3. Mauras, N., Rogol, A. D., Haymond, M. W., & Veldhuis, J. D. [1996]. Sex steroids, growth hormone, insulin-like growth factor-1: neuroendocrine and metabolic regulation in puberty. Hormone Research in Paediatrics, 45(1-2), 74-80.
4. Dunn, M. E., & Goldman, M. S. [1996]. Empirical modeling of an alcohol expectancy memory network in elementary school children as a function of grade. Experimental and Clinical Psychopharmacology, 4(2), 209.
5. Percy, A., Wilson, J., McCartan, C., & McCrystal, P. [2011]. Teenage drinking cultures. Joseph Rowntree Foundation.
6. Atkinson, A., Elliot, G., Ellis, M., & Sumnall, H. [2011]. Young people, alcohol and the media.
7. Manning, V., Best, D. W., Faulkner, N., & Titherington, E. [2009]. New estimates of the number of children living with substance misusing parents: results from UK national household surveys. BMC Public Health, 9(1), 1.
8. Kim, K., Ryu, E., Chon, M. Y., Yeun, E. J., Choi, S. Y., Seo, J. S., & Nam, B. W. [2006]. Internet addiction in Korean adolescents and its relation to depression and suicidal ideation: a questionnaire survey. International journal of nursing studies, 43(2), 185-192.
9. Caudwell, K. M., & Hagger, M. S. [2014]. Pre-drinking and alcohol-related harm in undergraduates: the influence of explicit motives and implicit alcohol identity. Journal of behavioral medicine, 37(6), 1252-1262.

10. Reda, A. A., Moges, A., Wondmagegn, B. Y., & Biadgilign, S. [2012]. Alcohol drinking patterns among high school students in Ethiopia: a cross-sectional study. BMC public health, 12(1), 1.

11. Cortez, P., & Silva, A. M. G. [2008] Using data mining to predict secondary school student performance.

12. Fabio Pagnotta, Mohammad Amran Hossain. “Using data mining to predict secondary school student alcohol consumption”

13. Jolliffe, I. T. [1986]. Principal Component Analysis. Springer-Verlag

14. Random Forests

15. Fodor,I. [2002] "A survey of dimension reduction techniques". Center for Applied Scientific Computing, Lawrence Livermore National, Technical Report UCRL-ID-148494

16. Pawlak, Z. [1982] ‘Rough Sets’, International Journal of Computer and Information Sciences, Vol. 11, No. 5, pp.341–356.

17. Saleem Durai, M. A., Acharjya, D. P., Kannan, A., & Sriman Narayana Iyengar, N. C. [2012]. An intelligent knowledge mining model for kidney cancer using rough set theory. International journal of bioinformatics research and applications, 8(5-6), 417-435.

18. Wille, R. [2005]. Formal concept analysis as mathematical theory of concepts and concept hierarchies. In Formal concept analysis (pp. 1-33). Springer Berlin Heidelberg.

19. Tripathy, B. K., Acharjya, D. P., & Cynthya, V. [2013]. A framework for intelligent medical diagnosis using rough set with formal concept analysis.arXiv preprint arXiv:1301.6011.

20. D. P. Acharjya and Geetha Mary A: Privacy Preservation in Information System (Chapter 3); In: Advances in Secure Computing, Internet Services, and Applications; B. K.Tripathy and D. P. Acharjya (Eds.); IGI Global Publishers, USA, pp. 49 – 72. ISBN 10: 1466649402 (2014)

21. M. A. Saleem Durai, D. P. Acharjya, A. Kannan and N. Ch. Sriman Narayana Iyengar: An Intelligent Knowledge Mining Model for Kidney Cancer using Rough Set Theory; International Journal of Bioinformatics Research and Applications, Vol. 8 (5/6), pp. 417-435, (2012)

22. D. P. Acharjya, Debasrita Roy and Md. A. Rahaman: Prediction of Missing Associations using Rough Computing and Bayesian Classification, International Journal of Intelligent Systems and Applications, Vol. 4 (11), pp. 1-13, (2012)

23. Reference Weley Formal concept analysis (Get the Reference)

24. Development of lattice theory by Garrett Birkhoff (Give Reference)

25. B. K. Tripathy, D. P. Acharjya and V. Cynthya: A Framework for Intelligent Medical Diagnosis using Rough Set with Formal Concept Analysis; International Journal of Artificial Intelligence & Applications; Vol. 2 (2), pp. 45 – 66, (2011).

Corresponding Author:
Saurabh Thakur*,
Email: *saurabh.chandrakantthakur2013@vit.ac.in*