Rough Sets: An Approach to Predict the Key Symptoms of Addiction in Social Networking Sites by School-Age Children

Tapan Nayak [#1], Dr.Raju R Gondkar[*2]

[#]*Dept. of Computer Science, CMR University, Bangalore, Karnataka, India*

Abstract**—** *This paper focus on the prediction of addiction in social networking sites (ASNS) in school -age children using rough set theory on application of data mining techniques. Rough sets data analysis based on a data table called an information table, which contains data about objects of interest, characterized represented as attributes and represented by value of attributes of each case. These levels of attributes (symptoms) consist of the properties of addiction and its level as low, medium and high. By finding the closet associations between these attributes (symptoms), the redundant attributes can be eliminated and most relevant attributes determined the levels of addiction. The prediction of ASNS is accurately done by using Rosetta, the rough set tool kit for analysis of data in case basis for detecting ASNS. Also, rule mining for detection of ASNS is performed in rough sets using the algorithm LEM1. The output result obtained from this study is compared with the output of a similar study conducted by us using Support Vector Machine along with Advance Sequential Optimization algorithm proposed. It is found that, using the concepts of reduct and global covering, we can easily predict the ASNS.*

Keywords**— *Data Mining, Information Table, Indiscernibility Relation, ASNS, Reduct and Core***

I. INTRODUCTION

The affected children addicted in social networking sites' databases have increased rapidly in recent year. This has necessary requirements for parent and school in the development of tools capable in the automatic extraction of knowledge from data. According to this definition, data mining is the non-trivial extraction of implicit previously unknown and potentially useful information about data [7]. Knowledge Discovery in Databases (KDD) is the process of identifying useful information in data [8]. The term Data Mining or Knowledge Discovery in databases has been adopted for a field of research dealing with the automatic discovery of implicit information or knowledge within databases [19]. Conventionally, the information mined is denoted as a model of the semantic structure of the datasets. The model might be utilized for prediction and categorization of new data [4]. Rough set theory is a new intelligent mathematical tool introduced by Z. Pawlak in 1982[8, 12, 11]. A rough set is an approximation tool that works well when in environments heavy with inconsistency and ambiguity in data or involving missing data [8]. Rough set theory represents an objective approach to imperfections in data. As per this theory, there is no need for any additional information about data and hence no feedback from additional expert is necessary. All computations are performed directly on data sets. Along the years, rough set theory has earned a well-deserved reputation as a sound methodology for dealing with imperfect knowledge in a simple though mathematically sound way [2]. A majority of areas related to medical services such as prediction of effectiveness of surgical procedures, medical tests, medication and the discovery of relationship among clinical and diagnosis data also make use of data mining methodologies [3].

This paper presents the basic concept of rough set theory with relevant application and shows how these technique may be utilized for data mining in proposed case. The rough set approach seems to be of fundamental importance to artificial intelligence and especially in the case of machine learning, knowledge acquisition, and decision analysis, knowledge discovery from databases, expert systems, inductive reasoning and pattern recognition [1]. The rough set approach of data analysis has much important advantage. It provides efficient algorithms for finding hidden patterns in data from database and has the following advantages [10].

- Find information from set of data
- Find minimal set of data (data reduct).
- Evaluates significance of data.
- Generates set of decision rules from data.
- Suit for straightforward interpretation of obtained results.
- The rough set theory and algorithms are particularly suited for the parallel processing.
- It is easy to understand and knowledge extraction.

In this rough sets theory, the datasets are represented in two forms as information tables and decision tables. The information table contains attributes (symptoms) for assessment and objects as per the cases are presented in columns and rows respectively. The decision table present decision in terms of conditions that must be satisfied in order to carry out the decision specified in the decision table.

II. **ADDICTION IN SOCIAL NETWORKING SITES**

Social networking sites such as Facebook, MySpace, Twitter and dozens of others allow people to stay in touch like never before. However, some people spend so much time on these sites that it begins to interfere with their lives. Psychologists are referring to this as a social networking compulsion or addiction [9]. Although there is no official medical recognition on social media addiction as a disease, the negative habit of excessive use of social media has become a subject of much discussion and research [15]. Today's teenagers are the first generation to have lived their teenage years using digital devices and social platforms. The desire to share and socialize is natural; however, what is unnatural is constantly worrying about virtual friends or constantly checking what is going on in Twitter or Instagram [14]. The child may need to be evaluated to see if he or she has an addiction in social networking sites. Everybody should find out how much time they are spending on social media, once you look to see how much time you are using for social media, then you can see if you have an addiction or not [14]. Addictionsimply means a compulsive behavior that leads to negative effects. And in this case, social media addiction is referring to someone who has a compulsive use of social media. For example, people who constantly check updates on Facebook or "stalking" other people for hours [15]. The level of addiction vary from child to child. One child with ASNS may not have the same kind of problems or symptoms as another child with ASNS. There is no cure for ASNS. They are life-long. However, children with ASNS can be high achievers and can be taught ways to get around the ASNS. With the right help, children with ASNS can live successfully.

When an ASNS is suspected based on parent and/or teacher observations, a formal evaluation of the child is necessary. A parent can request this evaluation, or their school's Principal might advise it for surety. Consent from Parent is needed before a child being tested. Many types of assessment tests are available for detection of ASNS. The age of the child and depending on their problem's type determines the tests and that affected child needs to identify the problem. The professionals help can be taken in the testing process.

The main purpose of any evaluation for ASNS is to determine child's strengths and weaknesses and to understand how he or she can live normal life and to access their difficulty. However, many people do not want to do that because they are afraid to see to what extent they are addicted to social media. Having access to Facebook everywhere increases the dependency [14]. The information obtained from an evaluation for ASNS is important for finding out how the parents and the school authorities can provide the best possible atmosphere for child and come out from the addiction.

III. PROPOSED ROUGH SET APPROACH

This study of detection addiction is based on rough set approach. The rough set approach enables reduction of superfluous data in the information system and generation of classification rules showing relationships between the description of objects and their assignment to classes of a technical state. Rough set theory is useful for rule induction from incomplete data sets. Using this approach we can distinguish between three types of missing attribute values: lost values, attribute-concept values and do not care conditions [6]. Rough set can be defined as Let X C U be a target set that we wish to represent using attribute subset P; that is, we are told that an arbitrary set of objects X comprises a single class, and we wish to express this class, i.e., this subset, using the equivalence classes induced by attribute subset P. In general, X cannot be expressed exactly, because the set may include and exclude objects, which are indistinguishable on the basis of attributes P. The target set X can be approximated using only the information contained within P by constructing the P-lower and P-upper approximations of X [16]:

$$\underline{P}X = \{ x \mid [x]P \subseteq X \} \qquad (1)$$

$$\mathrm{P}X = \{x \mid [x]P \cap X \neq \emptyset \} \qquad (2)$$

The P -lower approximation, or positive region, is the union of all equivalence classes in [x]P which are the subsets and are contained by the target set. The P-upper approximation is the union of all equivalence classes in [x]P which have non-empty intersection with the target set. The lower approximation of a target set is a conservative approximation consisting of only those objects, which can positively be identified as members of the set. The upper approximation is a liberal approximation, which includes all objects that might be members of target set. The accuracy of the rough-set representation of the set X can be given by the following [6].

$$\alpha_P(X) = \frac{|\underline{P}X|}{|\overline{P}X|} \quad (3)$$

Rough set used to consider the features to predict the important signs and symptoms of addiction in social networking sites (ASNS) among school children, the concept of decision table, information table, global covering and data reduct are using for the purpose of detection ASNS. The variables are present in columns and cases in rows. A table contain information consists of different variables called attributes (symptoms) and cases called objects. The list of attributes contained in the information table are the signs and symptoms of addiction in social networking. In this paper, we are using a checklist containing the 18 most frequent signs & symptoms (attributes) generally used for the assessment of ASNS. This attribute list is shown at Table 1 below.

Sl. No	Attributes	Signs and Symptoms of ASNS
1.	AD	Anxiety and Depression
2.	BP	Blood Pressure
3.	DA	Difficulty with Attention
4.	DB	Difficulty with Behavior
5.	DF	Difficulty with Food
6.	DM	Difficulty with Memory
7.	DP	Difficulties with Parents
8.	DS	Difficulty with Studies
9.	DSS	Difficulty with Study Skills
10.	DT	Difficulty with Teachers
11.	DTM	Difficulty with Time Management
12.	DWF	Difficulty with Friends
13.	DWS	Difficulty with Society
14.	ED	Easily Distracted
15.	LD	Learning Difficulties
16.	NLS	Not Like School
17.	RG	Result Grade
18.	VI	Vision Issues

Table 1. List of Attributes for ASNS

In this paper, we are presenting only six attributes and five cases in the sample information table given at Table 2 below, for illustration. For this study, we have collected more than 550 datasets (cases) from the addiction in social networking OR ASNS clinics/ Secondary and higher secondary schools in and around Bangalore. By using the real time datasets for assessing the ASNS in children, we have identified the level of ASNS like Low, Medium or High belongs to each child. Since such identification of ASNS in each child using all the attributes is a very difficult task, we are using certain rules which enable us to identify different symptoms easily which are causing ASNS. The mined rules are used for finding the relationship between the symptoms of addiction in social networking.

Table 2. Sample Information Table

Cases	Attributes					
	AD	DS	DB	DWS	DTM	DA
1.	Y	Y	N	Y	N	Y
2.	Y	N	N	N	Y	N
3.	Y	Y	N	N	N	N
4.	Y	Y	Y	Y	Y	N
5.	Y	Y	Y	Y	Y	N

Let U denotes the set of all cases. A be the set of all attributes and V be the set of all attribute values. The information table defines an information function ρ: U×A→V. For example, ρ (1, AD) =Y. Let x Є U and B≤A. An elementary set of B containing x is denoted by [x]B. Elementary sets are subsets of U consisting all cases from U. Elementary set may be defined in another way, through the notion of an indiscernibility relation [18]. The indiscernibility relation IND (B) is a binary relation on U defined for x, y Є U as follows.

(x,y)Є IND (B) if and only if ρ(x, a)=ρ(y, a) for all aЄB

Obviously, IND (B) is an equivalence relation. Equivalence relation is present through partitions [17]. In mutually disjoint nonempty sets of U where partition relation is a family member, called blocks. The union of all blocks is U. B* is the partition induced by IND (B). The elementary set of B is a part of blocks of B*.

IV. REDUCT AND CORE

The set of attributes which is common to all reducts is called the core: the core is the set of attributes which is possessed by every legitimate reduct, and therefore consists of attributes which cannot be removed from the information system without causing collapse of the equivalence-class structure [19]. If core to be empty, which means without indispensable attribute. There is subsets of attributes, which can, by itself, fully characterize the knowledge in the database; such an attribute set is called a reduct [19]. In an information system reduct is not unique: there may be many subsets of attributes, which may preserve the equivalence-class structure in the information system. In this paper, it is important to determine the core attributes of ASNS and we can create different attribute reducts. From the sample information table, the minimum number of reducts has to be determined, first we compare a single attribute with the set of all attributes, viz. A*= {1},{2},{3},{4,5}. Subsequently, we take two attributes, three attributes and then four attributes for similar comparison, as shown below.

(i) {AD}*={1,2,3,4,5}; comparing with A* {AD}*≠A*,

therefore {AD} is not a reduct.

(ii) {AD, DS}*={1,3,4,5},{2}; comparing with A*, {AD, DS}*≠A*, therefore {AD, DS} is not a reduct.

(iii) {AD, DS, DB}*={1,3},{2},{4,5};comparing with A*, {AD,DS,DB}*≠A*, therefore {AD, DS, DB} is not a reduct.

(iv) {AD, DS, DB, DWS}*={1},{2},{3}, {4,5}; But here, {AD,DS,DB,DWS}*=A*, therefore {AD, DS,DB,DWS} is a reduct.

Reducts are important subsets of attributes. A subset B of the set A is called a reduct, if and only if (i) B* = A* and (ii) B is minimal with the property (B-{a})* ≠ A* for all a Є B [17]. Based on these properties, only {AD, DS, DB, DWS} is reduct. Similarly, for another set of attributes, we are also getting {DH, DWS, DTM, DA} as reduct. In this method the number of attributes considered to compute all reducts is time consuming and it is a complex tusk. So, we restrict to compute a single reduct using a heuristic algorithm LEM1 [20]. In this algorithm the first step is to elimination of the leftmost attribute from the set and check whether the remaining set is reduct or not. Put the attribute back into that set if the set is not reduct, and for similar checking eliminate the next attribute. Similarly, we are eliminating until the last attribute for reduct checking. As we have already two properties, {DA, DS, DB, DWS} and {DB, DWS, DTM, DA}, as reducts from our sample information table. Now, the left most attribute, DA is eliminated from the reducts and check whether the remaining combined set is reduct or not. Then we are getting {DS, DB, DWS, DTM, DA}* = A*; therefore {DS, DB, DWS, DTM, DAA} is a reduct. Next we are eliminating the left most attribute, DS and check whether the remaining set is reduct or not. Now we are getting

{DB, DWS, DTM, DA}* = A*, therefore {DB, DWS, DTM, DA} is a reduct. Similarly, after eliminating DB we are getting {DWS, DTM, DAA}* = A*, therefore {DWS, DTM, DA} is also a reduct. And after eliminating DWS, the remaining set {DTM, DA}* ≠ A*, therefore, the set {DTM, DA} is not a reduct. Similarly putting the attribute DWs into this set and eliminate next attribute DTM, getting the set {DWS, DA} for confirming reduct. Now, {DWS, DA} ≠ A*, hence {DWS, DA} is also not a reduct. Finally, after eliminating all other attributes other than the last one, we are getting {DHA}* ≠ A* resulting {DHA} is also not a reduct. From these checks, our conclusion is that, the LEM1 algorithm forms the set of attributes {DWS, DTM, DA} as the core reducts. The determination of reducts using LEM1 algorithm from the real world data set, as explained above, is time consuming, tedious, and complex in nature.

V. IMPORTANCE OF DECISION TABLE

Decision table is important for identification of the most important attribute from the data set. Another important aspects in the analysis of decision tables for the extraction and elimination of redundant attributes. Redundant attributes are attributes that could be eliminated without affecting the degree of dependency between the remaining attributes and decision [12].

Cases	Attributes						Decision (ASNS)
	AD	DS	DB	DWS	DTM	DA	
1.	Y	Y	N	Y	N	Y	M
2.	Y	N	N	N	Y	N	L
3.	Y	Y	N	N	N	N	L
4.	Y	Y	Y	Y	Y	N	H
5.	Y	Y	Y	Y	Y	N	H

Table 3. Sample Decision Table

In a decision table, variables are presented in columns and each column represents one condition or one action. Like information tables the rows of decision table are labeled by case names. A general checklist, containing signs & symptoms of ASNS, i.e. attributes, is used for evaluating ASNS. Decision table has only one decision L, M or H, i.e. ASNS Low, Medium or High. The ability to discern objects from each other, the degree of dependency used to measure. But it contains two categories- attributes and decisions. In the Sample Decision Table given at Table 3 above, there are three elementary sets-{ASNS}:{1,2,3,4,5} for ASNS has value Low (L) and {ASNS}:{2,3} for ASNS has value Medium (M) and {ASNS}:{1} and for ASNS has value High (H) and {ASNS}:{4,5}. Decision table contains the cases diagnosed by experts. The elementary sets of decisions are called concepts and also decision tables are crucial to data mining. Based on RST, there are two approaches of data mining from complete data sets. They are Global Covering and Local Covering [2]. In this paper, we are considering only global covering the entire attributes and consistent data are used for analysis.

In this study, it is important to define the number of reducts from decision table and selecting the best reduct, from a decision table, is important in this study. Any of the reducts can be used to replace the original table if a decision table contain more than one reduct. In this paper, for the prediction of addiction in social networking sites, we adopted a criteria for getting best types of reduct with minimum number of attributes. We are evolving to a solution that, a single attribute is enough for the prediction of ASNS based on the sample decision table.

VI. GLOBAL COVERING APPROACH

In global covering, a minimal subset of the set of all attribute, such that the substitution partition depends on it,. In this approach, each concept is represented by the substitution partition. It may be selected on the basis of lower boundaries. In the case of inconsistent data the system computes lower and upper approximations of each concept [1]. Relative reducts or rule sets may be induced using Global Coverings. We start from the definition of a partition being finer than another partition. Let α and β be the partitions of U. α is finer than β , denoted α ≤ β , if and only if, for each block X of α, there exists a block Y of β such that X ≤ Y. Let d be a decision. Then, a subset B of the attribute set A is a global covering if and only if (i) B* ≤ {d}* and (ii) B is minimal with the property (B-{a})* ≤ {d}* is false for any a B [17]. Based on these properties, we are checking all subsets of A in the sample decision table, with {ASNS}* = {1,4,5},{2,3}, with cardinality equal to one.

(i){AD}* = {1,2,3,4,5}; THEN {AD}*≤ {ASNS}* IS FALSE.

(ii){DS}*={1,3,4,5},{2}; THEN {DS}*≤ {ASNS}* IS FALSE.

(ii) {DB}*={1,2,3,},{4,5}; THEN{DB}*≤{ASNS}*ISFALSE.

(iv){DTM}*= {1, 3}, {2, 4, 5}; THEN {DTM}*≤ {ASNS}* IS

FALSE.

(v){DA}*= {1}, {2, 3, 4, 5}; THEN {DA}*≤ {ASNS}* IS

FALSE.

(vi){DWS}*={1,4,5}{2,3};THEN{DWS}*={ASNS}*ISTRUE.

Since in the cases (i) to (v) above are not in global covering as the attribute sets {A}* is not finer than {ASNS}*. The similar algorithm used for computing all reduct as algorithm used for the global covering and local covering. In this approach, first we have to check whether {A}* ≤ {d}*, where d is the decision. But, for the last case (vi) above, A* is finer than {ASNS}*. Therefore, there is only one global covering of size one, i.e. {DWS}. Then we are checking all subsets of A with the cardinality equal to two.

(i) {AD, DS} = {1,3,4,5},{2}; then {AD, DS}*≤{ASNS}* is false

(ii) {DS, DB} ={1,3},{2,4,5}; then {DS, DB}*≤ {ASNS}* is false

(iii) {DB, DWS} = {1},{2},{3},{4,5}; then {DB, DWS}*≤ {ASNS}* is false

(iv) {DTM,DA}={1},{2,4,5},{3};then{DTM,DA}*≤{ASNS}* is false

Therefore, there is no global covering of size two since in all the above cases A* is not finer than {ASNS}*. Then we are checking all subsets of A with the cardinality equal to three.

(i) {AD, DS, DB}*={1,3}{2}{4,5}; THEN {AD, DS, DB}* ≤ {ASNS}* IS FALSE.

(ii) {DWS, DTM, DA}* = {1}{2}{3}{4,5}; THEN {DWS, DTM, DA}*≤{ASNS}* IS TRUE.

Hence, there is only one global covering of size three, ie. {DWS, DA, DTM}. Then we are checking all subsets of A with the cardinality equal to four.

(i) {AD, DS, DB, DWS}*= {1}{2}{3 }{4,5}, THEN {AD, DS, DB, DWS}*≤{ISNS}* IS TRUE.

Hence, there is only one global covering of the size four, ie. {AD, DS, DB, DWS}.

From the above, we are getting 3 sets of attributes, viz. {DWS}, {DWS, DTM, DA} and {AD, DS, DB, DWS} as global covering, considering our sample decision table. We restrict our check the cases in the decision table in attributes from the global covering. For computing a single global covering we are using the same procedure of elimination of left most attribute, one by one, and checking the condition $\{A\}^* \leq \{d\}^*$, until the last element is eliminated. A single global covering is used for rule induction [17]. If such a rule condition is found in the decision table, it is not consistent and this rule condition can be dropped. From this concept, we can induce certain rules. As derived from the global covering, the mined rule (AD, Y) (DS, Y) (DB, N) (DWS, Y) = (ASNS, M) is consistent and which is existing as first case in the decision table. So we simplify by removing the left most attribute from the mined rule. Then, we get {DS, DB, DWS} as not consistent. By applying the process of elimination, we are getting {DB, DWS} and {DWS} as consistent. From the above, the following rules can be mined.

(AD,Y) (DS,Y) (DB,N) (DWE,Y) = (ASNS,M) (R1)

(DB,N) (DWS,N) = (ASNS, L) (R2)

(DB, Y) (DWS, Y) = (ASNS, H) (R3)

(DB, N) (DWS, Y) = (ASNS, M) (R4)

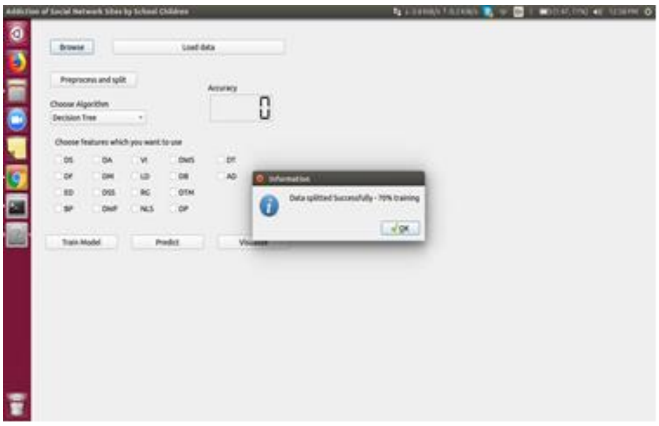
(DWS, Y) = (ASNS, H) (R5)

(DWS, N) = (ASNS, L) (R6)

VII. RESULT ANALYSIS AND FINDINGS

This study consists of two parts, first part explains the features of rough set using LEM1 algorithm and second part addiction in social networking sites in children is predicted using the Rosetta tool is well explained. The major findings from this study are the determination of core attributes of ASNS, the accuracy of rough set classification and the importance of rule mining for ASNS prediction in children. The classification results and core attributes (reduct) on the 550 real data sets with 18 attributes are obtained from the rough set tool kit Rosetta for analysis of data. For obtaining the reduct results Rosetta tool, Johnson's reduction algorithm is used and Naive Bayes Batch classifier is used for obtaining the classification results.

It is important for data mining to pre-process the data to subset of original data and represent the whole data set in the information system. The subset of whole data contains only minimum number of independent attributes for prediction of ASNS. The selected attribute is used to study about the original large data set. The database can be dived into two parts for creating training set and test set as shown below.



Whereas 10% of the data, is used as training set and other part for testing purpose by the data mining system for checking whether the knowledge acquired from the training set is general or not. The validation process with 550 data sets, to obtain knowledge in datasets, the system create general rules and descriptions of the patterns and relations which is valid not only in the specific database considered but also for other similar data. The knowledge gained from the training set is the general knowledge, it is correct for most parts of the test set as well. For making decision from the rules generated from original data set give a strong platform for this process to detect ASNS. The rules are playing important roles for making decisions.

VIII. COMPARISON OF RESULT

In this study, LEM1 algorithm are used for forming rough set knowledge for prediction of addiction in social networking sites in children. The rough set tool Rosetta used for obtaining the reduct and classification results from the datasets. The result found from this study is compared with the result of a similar study conducted by us using Support Vector Machine (SVM) with Sequential Minimal Optimisation (SMO) algorithm. The accuracy results is shown in Table 6 below.

Table 6. Accuracy of SVM

TP Rate	FP Rate	Pre-cision	Recall	F Mea-sure	ROC Area	Class
0.989	*0.031*	*0.980*	*0.991*	*0.985*	*0.981*	*T*
0.978	*0.017*	*0.973*	*0.980*	*0.976*	*0.979*	*F*
Correctly Classified Instances					*533 Nos.*	*97.05%*
Incorrectly Classified Instances					*17 Nos.*	*2.95%*
Time taken to build a model						*2.96 Sec*

In supervised learning algorithms as SVMs belong to the class of which the learning machine is given a set of examples with the associated labels. On comparison, it is found that, SMO is relatively simple, faster and easy to implement.

In this study, for prediction of ASNS in children we compared the results obtained from the study with SMO algorithm in SVM along with the results Naive Bayes Batch classifier for rough set classification. In data mining concept, it is difficult to mine rules from incomplete data sets. The result obtained in SVM method is more accurate than the rough set method in accuracy of rule mining. It is found that ASNS can accurately be predicted by using both the methods. The data or the output in SVM is very complex while rough set method is much easier. This study reveals that, out of the 550 real data sets, the SVM correctly classifies 533 instances in 2.96 seconds whereas Naive Bayes Batch classifier in rough sets correctly classifies 289 true-true instances. The ROC curve determined the accuracy of the classifiers. The area under ROC curve in both cases is nearer to 1, means the accuracy of both classifiers is found good. The significant advantages of rough set concept is that it leads to many areas including machine learning, expert system and knowledge discovery tool in uncovering rules for the diagnosis of ASNS affected children.

IX. CONCLUSION AND FUTURE WORK

This paper use of Rosetta tool in rough set data analysis in particular emphasis to classification methods, and highlights the application of rough set theory in LERS data mining system in prediction of addiction in social networking sites in school age children. The prediction of addiction extracted rules are very effective. But using the extracted rules, we can easily predict the addiction level of any child. Rough set method capability in discovering knowledge behind the ASNS identification procedure. Obliviously, as the school class strength is 50 or so, the manpower and time needed for the assessment of ASNS in children is very high. The main contribution of this study is the selection of the core attributes of ASNS, which has the capability in prediction of addiction levels. The knowledge discovered rules also prove its potential in correct identification of children with addiction in social networking sites. In this paper, we are considering an approach to handle database and predicting the ASNS in school age children. Our future research work focuses on, new fuzzy sets, to predict the percentage of addiction in social networking sites, in each child.

REFERENCES

[1] J.W. Grzymala-Busse, Knowledge Acquisition under Uncertainty-A Rough Set Approach. Journal of Intelligent & Robotic Systems, 1988, 1: 3-16

[2] Abraham, Ajith; Falcón, Rafael; Bello, Rafael (Eds.). "Rough Set Theory: A True Landmark in Data Analysis",Series: Studies in Computational Intelligence, Vol. 174, ISBN: 978-3-540-89920-4, 2009

[3] Blackwell Synergy: Learning Disabilities Research Practices, vol. 22, 2006

[4] U.M. Fayyad, "From Data Mining to Knowledge Discovery: An Overview- Advances in Knowledge Discovery and Data Mining", 34, AAAI Press/MIT Press, ISBN 0-262-56097-6, 1996

[5] C. Carol, K. Doreen.: Children and Young People with Specific Learning Disabilities : Guides for Special Education, Vol. 9 UNESCO, 1993

[6] Z. Pawlak Rough Sets: "Theoretical Aspects of Reasoning About Data". Dordrecht: Kluwer Academic Publishing. ISBN 0-7923-1472-7, 1991

[7] Frawley, Piaatetsky: Shaping Knowledge Discovery in Database; an Overview. The AAAI/MIT press, Menlo Park, 1996

[8] Matteo Magnani. Technical report on Rough Set Theory for Knowledge Discovery in Data Bases, 2003

[9] Dr. Lawrence Wilson, SOCIAL MEDIA ADDICTION,© March 2015, L.D. WilsonConsultants, Inc. Web.Address: http://drlwilson.com/ARTICLES/ADDICTION,%20SOCIAL%20M.htm

[10] A. Kothari, A. Keskar : "Paper on Rough Set Approach for Overall Performance Improvement of an Unsupervised ANN - Based Pattern Classifier", Journal on Advanced Computational Intelligence and Intelligent Information, Vol. 13, No.4, 2009, pp 434-440

[11] S. Greco, B. Matarazzo, R. Slowinski, "Dealing with missing data in rough set analysis of multi-attribute and multi-criteria decision problem", Kluwer Academic Publishers, Boston Dordrecht, London, 2000

[12] Hameed Al-Qaheri, Aboul Ella Hassanien and Ajith Abraham. "Discovering Stock Price Prediction Rules using Rough Sets", 2008

[13]H. Chen, S.S. Fuller, C. Friedman, W. Hersh, Knowledge Discovery in Data Mining and Text Mining in Medical Informatics, 2005, pp. 3– 34

[14] Brenda Reyn, "How are students addicted to social media?", April 20,2015,WebAddress:https://www.statesmanshs.org/1112/features/how-are-students-addicted-to-social-media/

[15]Team The WisdomPost & Sophia, "Social Media Addiction: Meaning, Symptoms, Causes, Effects, and Treatment | Essay", Web Address:http://www.thewisdompost.com/essay/addiction/social-media-

addiction/social-media-addiction-meaning-symptoms-causes-effects-treatment/1293
[16]Julie M. David, Kannan Balakrishnan, Prediction of Key Symptoms of Learning Disabilities in School-Age Children Using Rough Sets, International Journal of Computer and Electrical Engineering, Vol.3, No.1, February, 2011, 1793-8163 [accessed on 12/10/2018]
[17] J.W. Grzymala-Busse, Rough Set Theory with Applications toData Mining, 2005
[18] Julie M. David, Kannan Balakrishnan. "Paper on Prediction of Learning Disabilities in School Age Children using Decision Tree". In: Proceedings of the International Conference on Recent Trends in Network Communications-Communication in Computer and Information Science, Vol 90, Part - 3 N. Meghanathan, Selma Boumerdassi, Nabendu Chaki, Dhinaharan Nagamalai (eds), Springer- Verlag Berlin Heidelberg, ISSN:1865-0929(print), 1865-0937(online),ISBN 978-3-642-14492-9(print) 978- 3-642-14493-6(online), DOI : 10.1007/978-3-642-14493-6_55, 2010, pp 533-542
[19] Z. Pawlak, Rough Sets. Int. J. Computers and Information Sci., Vol 11, 1982, pp 341-356
[20] J. W. Grzymala-Busse, A New Version of the Rule Induction System LERS, Fundamenta Informaticae, 1997, 31: 27-39