



## **REDUCING ATTRIBUTES OF FACEBOOK USERS USING ROUGH SET THEORY**

W. Abdallah

S. Sarhan

Samir Elmougy

Dept. of Computer Science, Faculty of Computers and Information, Mansoura University, Mansoura 35516, Egypt.  
Wass7375@gmail.com                      Shahenda\_sarhan@yahoo.com                      mougy@mans.edu.eg

**Abstract:** *Using social networks have become one of the daily activities that billions of peoples around the world do. So, great research efforts had been done to analyze and understand these virtual communities. Among other things, link prediction is a paramount task to analyze and understand these social networks. In this paper, we investigate link prediction problem using rough set theory to discard the irrelevant attributes that could be found in the profiles of Facebook users and the proposed work induces accuracy 97.79%.*

**Keywords:** *Link Prediction, Social Networks, Rough Set Theory, Facebook, Self-Organization Map.*

### **1. Introduction**

User profiles are very important component in social network sites. These profiles provide a great variety of user-provided data. However, studying and analyzing the effects of user profiles on their online connections still at the infancy stage and there is a big room for research to be done at this field. We believe that a lot of benefits can be gained from analyzing the user profiles and figuring out the relationship between the user profile and the interests of users. But, to do so we need to know what type of included information matters. That is what motivates our research to answer the question [4]: how do elements in a profile affecting the outcomes of using an online social network?

To test the role of online interactions of profile, we choose Facebook.com as the biggest online social network. Facebook allows a user to create full profiles to describe himself and then able to build obvious connections with others [1]. On the other hand, this largeness of data comes with its demerits and we need to focus only on the most effective attributes that have a relation with the users' behavior and filtering the irrelevant ones. For this purpose we have, used one of the most common theories namely Rough Set (RS).

Pawlack [2] had been proposed Rough Set Theory (RST) as an alternative data mining technique. It has the power to deal with inexactness, uncertainty, and vagueness that may appear in datasets. RST can be used for selecting the most influencing features. The whole possible feature subsets are used to select the most influencing features by minimal cardinality. These features can be reduced later keeping only the indiscernible ones by using a sort of discernibility function [2, 3]. RST can also be used for discovering the rules that can be used in the decision making process and identifying the patterns in the

data that would be hidden otherwise [4]. It is applied in important fields like knowledge discovery [5], machine learning [6], image analysis [7], data analysis [8], economics [9] and engineering. In this paper, RST is used to reduce the attributes of Facebook users using Rosetta toolkit. The dataset was collected from 680 users. This work is structured as follows. Section 2 explores the background and related work while Section 3 provides a brief explanation about RST concepts and the cross validation process. Then, the proposed model, results, and discussion are introduced next in Section 4 and the last section present our conclusions.

## 2. Related Work

RTS is a mathematical tool that can be used to deal with inexactness, uncertainty, and vagueness that may appear in datasets. It can be seen as improvement for the set theory for building intelligent system that based on incomplete data [10]. This section is dedicated to address some of previous work that based on RST.

In [11], RST was used to identify the most influencing features that identify the e-mail usage habits. Also RST was used to discover the decision rules from real dataset pertaining 266 academic staff. Each record contains 13 conditions and one decision features. The discovered rules were used later for classification taking into account that the dataset contains uncertain information with accuracy 96.3%.

In [12], a new hybrid technique is proposed to classify web object either to cash or not to increase the access speed in mobile environment. The proposed technique was based on Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO). Also, it generates rules from log data using RST. In [13], a computationally efficient method based on rough set was used for ranking the documents to be used in content based retrieval. In [14], the RS was used again to classify and cluster in social network. It provided a critique that covers the limitation of rough set and suggested that the use of Covering Based Rough Set would be a better alternative.

In [15], an effective method was proposed to enrich tweets representation based web search engine and RST by adding synonyms for the original terms. It integrated and tested Arabic tweets categorization based on Naïve Bayesian (NB) and Support Vector Machine (SVM). Its results concluded that the categorization system is greatly enhanced. In [16], an enhanced algorithm was proposed based on RS and K-means clustering to find overlapping communities in social networks. RST was used to handle the several disadvantages that belong to the K-means clustering method such as determining the value of K and the relations between the community vertex and the community. In [17], RST is used to predict connections over Facebook based on hemophilic attribute.

## 3. Preliminaries

### 3.1 Self-Organization Map (SOM)

SOM algorithm is well-known clustering algorithm in which Teuvo Kohonen presented in 1981. SOM had been used in fields especially in clustering and visualization analysis of exploratory data. It has the ability to reduce the dimensionality of data while preserving its original structure.

SOM network is comprised by an input vertices set  $V = \{v_1, v_2, \dots, v_N\}$ , an output vertices set  $C = \{c_1, c_2, \dots, c_M\}$ , a weight parameters set  $W = \{w_{11}, w_{12}, \dots, w_{ij}, \dots, w_{NM}\}$  ( $1 \leq i \leq N, 1 \leq j \leq M, 0 \leq w_{ij} \leq 1$ ), and a transfer topology which allocates the distances between any specified two output vertices.

In SOM, the output vertices are often arranged in a 2-D array forming a "Topological Map". Every vertex is entirely linked to each output vertex through different weighted connections. These weights iteratively change throughout the training process till the criteria of termination are met. For every input vector  $v$ , there would be a winner vertex that is linked on the output map. A winner vertex is vertex of output which has the least distance to input vector [18].

### 3.2. Rough Set Theory (RST) and Attributes Reduction

RST is a new intelligent mathematical tool presented by Z. Pawlak in 1982. RS introduces an approach with main objective to handle the shortages in data such as missing, noisy, uncertain, ambiguous, and inconsistent data. RS is an approximation tool that works well when in environments heavy with inconsistency and ambiguity in data or involving missing data [15]. RST has earned a well-deserved reputation as a sound methodology for handling imperfect knowledge effectively and efficiently in a simple mathematically sound way [19].

RS approach gained paramount importance to artificial intelligence especially machine learning, knowledge acquisition, knowledge discovery from databases, inductive reasoning, and pattern recognition [20]. Also, RST has been successfully adopted in many real life problems in medicine, pharmacology, engineering, banking, environment management and others [21]. It comprises suitable algorithms for the discovery of hidden data patterns from dataset. Figure (1) illustrates attribute reduction framework. RS has the following advantages [22].

- Finding the least dataset (data reduct).
- Makes an evaluation of the data importance.
- Produces decision rules set from data.
- Proposes direct clarification of attained results.
- Most algorithms which use RST were suitable with the equivalent processing.
- RST methods are comprehensible.

In RST, the datasets are signified in two forms: information and decision tables. The information table covers qualities and objects. The decision table offers a description of decision concerning conditions which ought to be satisfied so that it would be capable of carrying out the indicated decision in the decision table.

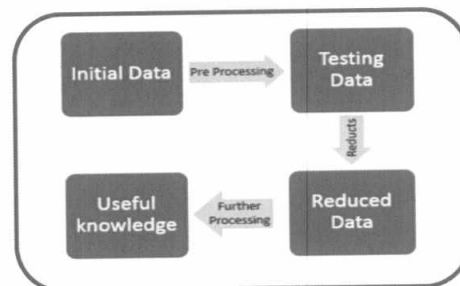


Figure (1): Attribute reduction framework [23]

#### 3.2.1. Johnson's Reduction Algorithm

This algorithm considers more heuristic and it has special kind of techniques. The main objective of this algorithm is choosing the attribute that occurs in clause. It is important to remember that the Johnson's algorithm starts with setting  $S$ , which is candidate for the current reduction for the empty set. The next

step for implementing this algorithm is counting the appearance for each one of attributes into clause. The highest count of the attribute has added into S, and the whole clauses within f have removed from discernibility function. Then, the algorithm return S as a reduction [4]. For example, the step by step procedures for obtaining the reduction of  $k = (f1 \vee f3) \wedge (f2 \vee f5 \vee f4) \wedge (f3 \vee f5) \wedge (f1) \wedge (f2 \vee f5 \vee f4)$  are:

1. Count the appearance of the attributes,  $f1 = 2, f2 = 2, f3 = 2, f4 = 2, f5 = 3$ .
2.  $f5$  represents occurring attributes therefore, it will be added into S. All clauses that contained  $f5$  from k will be removed by the classifier. So,  $k = (f1 \vee f3) \wedge (f1)$  and  $S = \{f5\}$ .
3. Counting the appearance for each attribute in k. It finds that  $f1$  is usually represents occurring attribute. Then, the whole clauses of  $f1$  are removed. thus, k becomes  $\emptyset$  and  $S = \{f5, f1\}$ .
4. End the algorithm as a result of  $k = \emptyset$ , and we obtain reduction  $f5 \wedge f1$

In concerning of this algorithm, the appearance attribute is greatly significant and that is not true all the times. However, this algorithm can find a solution close to the optimal [24].

### 3.2.2. Genetic Reduction (GA) Algorithm

GA is a developing method of computing global search which stimulates the biological evolution. It is capable of solving the complicated problems of optimization, nonlinear and even involving space. GA has the following characteristics:

- (1) It is an intelligent type of algorithm which has the capability to self-learning, self-organization and adaptation.
- (2) It has the capability for a direct contact with the code set parameters, instead of the parameters of the problem itself.
- (3) It utilizes fitness function for the evaluation of the intermediate persons and the guidance of the search direction through the search process.
- (4) It is a type of parallel algorithm. It is founded on the population instead of an individual for the completion of the search process in the solution space for every iteration.
- (5) It is easy to recognize its expression, it has a main idea that is simple, and an operation mode and implementation steps that are standard [25]. Therefore, using both of GA and RS T is proper for performing the reduction of attributes. Such hybrid model is capable of leading to the optimal or semi-optimal attribute reduction result [25].

### 3.3. Naïve Bayesian (NB) Classification

Consider training instances set with class labels and a test case,  $E$ , given as  $n$  attribute values  $(a1, a2, \dots, an)$ , NB classifier uses the following Equation (1) to classify  $E$ :

$$CNB(E) = \arg_{c \in C} \max P(c) \prod_{i=1}^n p(ai \setminus c) \quad (1)$$

where,  $C_{NB}(E)$  represents the classification specified by NB on  $E$ . Based on this equation, every probability can be determined directly from the training data.

Compared to other classifiers, NB has many advantages such as being simple, computationally efficient, needs not too much data for training, do not have lot of parameters, and can deal with incomplete and noisy data. All these advantages made an attractive classifier in many research areas. But, as we say nothing is perfect, NB may suffer from difficulties when applied to real life domains violating its main assumptions [26].

### 3.4. Cross-Validation

Cross-Validation (CV) denotes an untried testing process that is broadly utilized. The CV procedure is a method to get estimates that are more reliable and more mileage by way of probable uncommon data. In the method of k-fold CV the is a random division of database into k disjoint blocks of 3 objects, regularly have the same size. Then there is a training for the algorithm of data mining using k-1 blocks. The block which remains is utilized for testing the algorithm performance. There is a repetition for this process for each of the k blocks where there is a record of a measure for all iterations [24].

The measure relies on the utilized task of data mining. For task of classification, there is a common use of the measure of classification. By the completion, the measures that have been recorded are averaged. Through this procedure, there is a guarantee for every object to be once in the test set and k-1 times in the size of training. Choosing k=6 or any other size is common relying on the original dataset size.

A great variant of selecting k is choosing  $k = |U|$ , i.e., letting every test set consist of one example. This is known as leave-one-out CV, and, even though possibly enormously computer intensive can be instinctively fair as it best mimics the actual training set size. The procedure of doing Data Mining for the dataset by means of the 6-fold cross validation method is illustrated in Fig (2). The chosen objects for training are not required to be head-to-head [24].

## 4. The Proposed System

Users in Facebook can enhance their social network profile by adding information such as interests, activities, language, favorite movies, etc. Additionally, users may join common-interest groups, organized by workplaces, schools or colleges, or other organizations. Also users like other pages on the network [18]. The goal of this research is to get the lowest number of user attributes which are more effective and can give a clear idea of the interest and recommendations of the social network users.

The main framework of the proposed modeling system is shown in Figure (3). It is composed of six stages (data collection, data preprocessing, clustering using SOM, reduction, classification, cross-validation).

### 4.1. Data Collection

The dataset was collected from 680 Facebook users. We had collected the data through making a survey from (Family, friends circle, college students from the third and fourth years at the Faculty of Computers and Information, Mansoura University, Egypt).

### 4.2. Data Preprocessing

To explore the behavior of database, we had selected (16) attributes (age, gender, education, post average, average Facebook time, average internet, time, friends number, friend like sharing, find new friends, interest play game in Facebook, proposal page, interaction, research, like, interest, post). Table (1) presents description statistic values of each attribute used in this work.

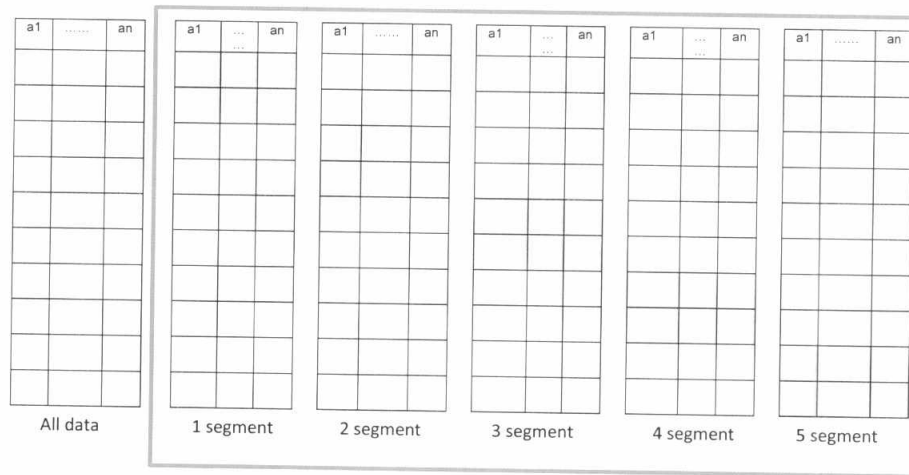


Figure (2): Classifier Evaluation using 6-Fold Cross-Validation

### 4.3. Clustering

The following stage is to use SOM to cluster the selected attributes. It uses the 16 attributes as one input vector for each user and the maps input matrix of all input vectors to two dimension to cluster them. The first dimension is the input vector itself and the other is the cluster type.

The cluster type is number from 1 to 6 that represent the classified (scientific, policy, religion, sporty, general culture, education). That represent a new attribute for each user based on this new matrix, rough set algorithms is applied. Here, we apply Johnson and genetic algorithm.

### 4.4. Reduction

In this stage, attributes in clustering data is reduced through applying two different rough sets (Genetic reduction and Johnson reduction) algorithms, to select the best reduction based on reduction, rule, cardinality numbers, and support.

### 4.5. Classification

In this stage, we apply NB classifier on the reduced, previous step, the result of classifier is confusion matrix had shown in Table (2) (predict, actual, and accuracy) where TP denotes True Positive, FP is False Positive, TN is True Negative, and FN is False Negative.

The classification accuracy measure used in this experiment is computed using the confusion matrix. In which it contains information about real and predicted classifications using a classification algorithm. The accuracy is the proportion of the total number of predictions that were correct.

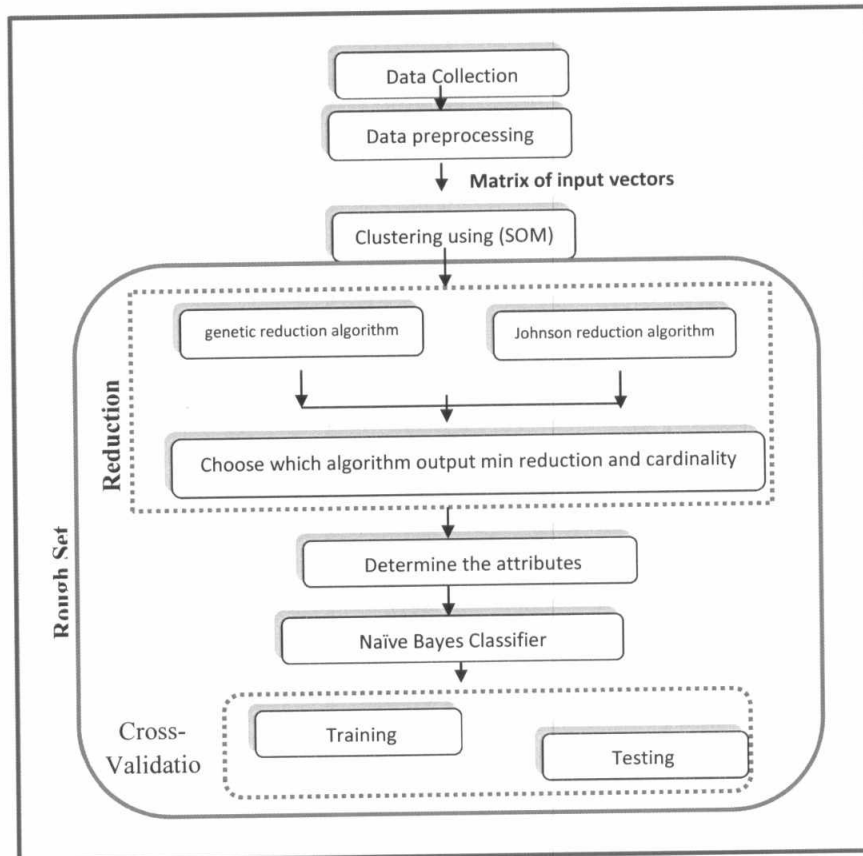


Figure (3): Basic structure of the framework

#### 4.6. Cross- Validation

In this stage, we apply cross-validation to reduction attributes matrix (all objects, reduction attribute) by using reduction algorithm and classifier reduction annotation. The mechanism of cross-validation is used for obtaining utilize observations. Figure 2 represents a graphical unit of five-fold cross validation. Every column indicates to single iteration of classification and training.

In concerning five-fold method, dataset is randomly classified into five subsets. In the first iteration, the examination set is used with the subset, and the remaining four are used to derive the rules. In the second iteration, subset number 2 is used as the examination set and so on. This process is iterates for five times. The result of this stage is computing sensitive, specificity and accuracy using Equation (2), Equation (3) and Equation (4) respectively. Sensitivity is the percentage of predicting the number of correctly classified as true positive while specificity is the percentage of predicting the number of true negatives by the classifier.

Table (1): Set of attributes in the used data set.

Features	Min	Max	Mean	Std. Dev.	Median
Age	13	52	33.9	10.903	35
Gender	0	1	0.377	0.485	0
Education	1	5	3.092	0.760	3
Post average	1	5	1.020	0.209	1
Average Facebook time	1	5	1.092	0.408	1
Average internet time	1	5	1.1926	0.472	1
Friends number	1	5	2.282	1.706	2
Friend like sharing	0	5	3.129	1.128	3
Find new friend	0	5	3.132	1.304	3
Interest play game in Facebook	0	5	3.952	1.038	4
Proposal page	0	5	3.230	1.203	3
Interaction	0	1	0.217	0.334	0
Search	1	33	62.208	72.685	20
Like	1	33	74.901	74.147	41
Interest	1	33	62.525	70.971	18
Post	1	33	18.636	34.231	1

Table (2): General Confusion Matrix [27]

		Predicted class	
		Positive	Negative
Actual class	Positive	TP	FN
	Negative	FP	TN

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100\% \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} * 100\% \quad (3)$$

$$\text{Specificity} = \frac{TN}{TN+FP} * 100\% \quad (4)$$

True Positive Rate (TPR) and False Positive Rate (FPR) are as well the additional metrics of performance. TPR and sensitivity are the same; FPR follows the above mentioned metrics of performance, a tool for measuring graphics, Receiving Operating Characteristics (ROC), is utilized as well. ROC curve demonstrates the cut-off between TPR and FPR that are computed as in Equation (5) and Equation (6) respectively.

$$\text{TPR} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{FPR} = \frac{FP}{FP+TN} \quad (6)$$



### 5. Experimental Results and Discussion

An adaptive system capability for the creation of environments is mainly determined by the sum and correctness of the stored data in every user model. Among the problems that face user modeling is the sum of available data for the creation of user models, the data capability, the noise inside that data, and the inevitability to capture the vague human conduct nature. The methods of data removal and machine learning are capable of handling great sums of data and for processing uncertainty. Such features enable these methods to be fit for user models' automatic generation which mimic the decision making of human. The data collected, it enables us to study the attribute users (favorites, profile and daily activities) in Facebook sit, for getting the lowest number of user attributes which are more effective and can give us a clear idea of the interest and recommendations of the social network users. The benefits of using machine learning and neural network applications that have been applied SOM algorithm for data, which adds a new feature to this data property clustering. Also, it combines similar properties within a single type.

The second stage is to apply RS with Johnson reduction in the first experimentation then apply RS with genetic in the second experimentation. Table (3) presents results of the implementation of GA and Johnson algorithm to get attribute data reduce. From this table, Johnson gives better result in which it gives less number of reducts, less number of rules and less number of cardinality. Johnson algorithm reduces the cardinality number to 4 attributes that represent {age, like, share-like, search new friend}. In Second stage, we apply NB on the reduced attributed and the output confusion matrix is shown in Table (4) the result of NB is confusion matrix.

Table (3): Results of the reduction algorithms.

Algorithms	# Reducts	# Rules	# Cardinality
Genetic.reduce	114	76634	7,8,9,10,11
Johnson.reduce	1	487	4

Figure (4) shows the percentage of reduction resulting from the implementation of Johnson Algorithm on the dataset features in which it that gives one reduct with four attributes. This means that the percentage of reduction is 80%.

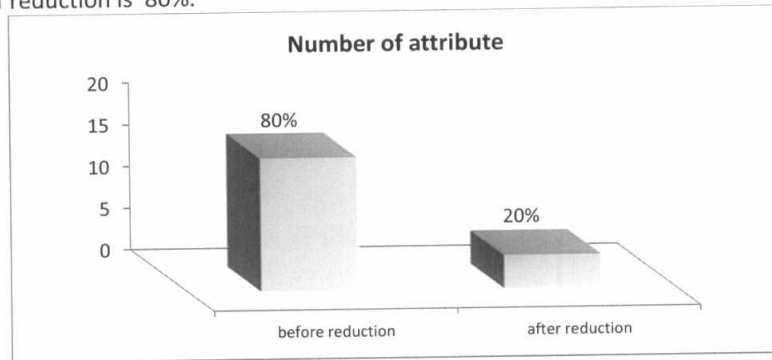


Figure (4) The percentage of the attributes before and after

Table (4): Result execute classifier algorithm.

		Predicted			
		0	1		
Actual	0	115	3		0.974576
	1	1	17		0.944444
		0.991379	0.85		0.970588

From table (4), the accuracy is (97.05%), the sensitivity is (98.41) and the specificity is (87.17%) of the computed RS on basis of the confusion matrix.

Next cross-validation is applied through dividing the data in to tow sets, one for training (20%) and other for testing (80%).

The highest accuracy classification is 97.79% was obtained from the 60%-40% training-test partitions. An accuracy classification of 96.32% was obtained from the 50%-50% training-test partition, 97.79% from the 60%-40% training-test partition, 94.85% from the 70%-30% training-test partition, 96.85% classification accuracy was obtained from the 20%-80% training-test partition, and 97.05% classification accuracy was obtained from the 10%-90% training-test partition. Table (5) shows the values of classification accuracies, sensitivity, and specificity values of the test data.

Result Cross validation execute The values of Accuracy.Mean, Accuracy.Median, Accuracy.Std Dev, Accuracy.Minimum, Accuracy.Maximum, are presented in Table (6).

Table (5): Sensitivity, Specificity, and Accuracies (%) for 5 Different Participations.

Training	Accuracy	Specificity	Sensitivity
50-50%	96.29	0.96	0.04
60-40%	96.4	0.96	0.04
70-30%	98.41	0.98	0.02
80-20%	1	0.01	0.99
90-10%	1	0.01	0.99

Table (6): Cross Validation Result for all Partition.

Accuracy.Mean	0.966176
Accuracy.Median	0.970588
Accuracy.StdDev	0.011151
Accuracy.Minimum	0.948529
Accuracy.Maximum	0.977941

## 6. Conclusion

Prediction is a good method to understand and analyze the social networks based on statistics methods. In this work, we had used rough set theory to reduce the number of user attributes. Also, we have used an unsupervised learning method based on rough set theory to get good results pertaining speed, accuracy, and storage. The proposed model for Facebook users depends on the activity in social networking sites in addition to the daily activity at the same sites the accuracy were (97.79%). In future work, we plan to evaluate our work within the framework of the proposed model applied on Ready dataset.

## References

1. C. Lampe, N. Ellison and C. Stein field, "A familiar face (book): profile elements as signals in an online social network", In Proceedings of the SIGCHI conference on Human factors in computing systems. ACM, PP. 435-444, 2007.
2. Z. Pawlak, "Rough sets", International Journal of Computer and Information Sciences, 11(5), PP.341-356, 1982.
3. J.G. Bazan, J.F. Peters, A. Skowron and N.H. Son, "Rough set approach to pattern extraction from classifiers", Electronic Notes in Theoretical Computer Science, 82(4), PP.1-10, 2003.
4. X. Wang, J. Yang, R. Jensen, X. Liu, "Rough set feature selection and rule induction for prediction of malignancy degree in brain glioma", Computer Methods and Programs in Biomedicine, 83, PP.147-156, 2006.
5. P. Bartomiej, and S. Wilk, "Rough set based data exploration using ROSE system", Foundations of Intelligent Systems, Springer Berlin Heidelberg, PP.172-180, 1999.
6. S. Tsumoto, "Mining diagnostic rules from clinical databases using rough sets and medical diagnostic model", Information Sciences, 162(2), PP. 65-80, 2004.
7. C.C. Huang and T.L. Tseng, "Rough set approach to case-based reasoning application", Expert Systems with Applications, 26(3), PP. 369-385, 2004.
8. D. Sinha and P. Laplante, "A rough set based approach to handling spatial uncertainty in binary images", Engineering Applications of Artificial Intelligence, 17(1), PP. 97-110, 2004.
9. Z. Pawlak, "Rough sets and intelligent data analysis", Information Sciences, 147(1-4), PP.1-12, 2002.
10. M. N. Rahman, M. L. Yuzarimi, and F. Mohamed, " Applying Rough Set Theory in Multimedia Data Classification", International Journal on New Computer Architectures and Their Applications (IJNCAA), 1(3), PP.683-693. 2011.

11. Y.Kay, O.F.Erturul and R.Tekin, "A Rough Set Approach for Modeling E-mail Usage Habits", *Computer Science*, 1(4), PP.259-264, 2014.
12. S. Sulaiman , S.M. Shamsuddin and Ajith Abraham, "Rough neuro-PSO web caching and XML prefetching for accessing Facebook from mobile environment", *Nature & Biologically Inspired Computing*, 2009 (NaBIC 2009), World Congress on. IEEE, 2009.
13. S. K. Ray and S.Singh, "Rough set based social networking framework to retrieve user-centric information". In *Rough Sets, Fuzzy Sets, Data Mining and Granular Computing*. Springer Berlin Heidelberg, PP.184-191, 2009.
14. A.Mitra, S. Rani and S. S. Paul, "Clustering Analysis in Social Network using Covering Based Rough Set", *IEEE 3rd International Advance Computing Conference (IACC)*, 2013, PP.476-481, 2013.
15. M. Bekkali, I. Sahnoudi and A. Lachkar, " Enriching Arabic Tweets Representation based on Web Search Engine and the Rough Set Theory", In: *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, PP. 1573-1574, 2015.
16. W. Zuo and W. Zhe, "Research in Social Network Based on Rough Set Clustering Algorithm", *International Journal of Advancements in Computing Technology*, 4(15), 2012.
17. R. A. Abookhachfeh and I. Elkabani, "Using rough sets in homophily based link prediction in online social networks", In *Computer Applications and Information Systems (WCCAIS)*, World Congress on, PP.1-6, January 2014.
18. E. F. Martinez, S. Y. Chen, and X. Liu, "Survey of Data Mining Approaches to user modeling for adaptive hypermedia", *IEEE transactions on systems, man, and cybernetics part c: applications and reviews*, 36(6), PP.737-749, November 2006.
19. M. Magnani, "Technical report on Rough Set Theory for Knowledge Discovery in Data Bases", 2003.
20. A.Ajith, F. Rafael, B., Rafael, "Rough Set Theory: A True Landmark in Data Analysis", *Series: Studies in Computational Intelligence*, 174, ISBN: 978-3-540-89920-4, 2009
21. J.W. Grzymala-Busse, "Knowledge Acquisition under Uncertainty-A Rough Set Approach", *Journal of Intelligent & Robotic Systems*, 1, PP.3-16, 1988.
22. H. Chen, S.S. Fuller, C. Friedman, W. Hersh, "Knowledge Discovery in Data Mining and Text Mining in Medical Informatics", PP. 3.34, 2005.
23. B. Aqil, and Z. Abbas. "Applications of Rough Sets in Health Sciences and Disease Diagnosis", *Recent Researches in Applied Computer Science*, PP.153-161, 2013.
24. L. Xiaohan, "Attribute Selection Methods in Rough Set Theory", PhD Thesis, San Jose State University, 2014.
25. C. Lian, H. Liu, and Z. Wan, "An attribute reduction algorithm based on rough set theory and an improved genetic algorithm", *Journal of Software*, 9(9), PP. 2276-2282, 2014.
26. K. Al-Aidarous, A. Abu Bakar, and Z. Othman, "Improving Naive Bayes Classification with Rough Set Analysis." *International Journal of Advancements in Computing Technology*, 5(13), P.49, 2013.
27. H. K. Mahdi, H. K. Mohamed and S. S. Attia, "Data Mining for Decision Making in Multi-Agent Systems", *Multi-Agent Systems - Modeling, Interactions, Simulations and Case Studies*, Dr. Faisal Alkhateeb (Ed.), InTech, 2011.