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Rough Sets Theory Based Approach for Predicting Studentś Performance in e-Learning Systems

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Abstract: In the recent days, educational data mining Strategies have captured the notice of Scientists according to the rapid growth of educational data and the need for developing methods to discover the hidden knowledge to predict the success of students' learning. Many methods are used in the previous literature such as ANN, SVM, Naive Bayes classifiers and logistic regression. The original motivation of this work is to fill the gap between the very large dynamic data on educational institutions and the computational programming tools which is not sufficient to find solutions in some cases. The current work proposes a strategy based rough sets theory to generating a set of classification rules to predict student's performance in the e-Learning Systems. The data of 480 student records and 16 features are used to fetch all reducts and finally a set of classification rules are created to build a knowledge base with excellent accuracy to find the relationship between student's behaviors and their academic. The findings of this study are expected to give the educational institutions the chance for early interference to prevent the potential failure of students to achieve learning objectives by making changes to learning strategies. as well as predict students who have a high chance of achieving academically, solve student academic problems, optimize the educational environment, identify key factors that influence student academic success and explore the relationships between these key factors and enable data-driven decision making.

Keywords: Classification ; e-Learning Systems; Student's Performance ; Rules Extraction; Educational Data; Rough Sets Theory; Feature Selection.

1 Introduction

To effectively understand students, support them, and understand the framework which they study in, data were collected from the educational institutions (universities and schools) or from interactive learning environments, computer-supported collaborative learning. Then new methods are developed to analysis these data and extract the hidden knowledge from it, that which is called educational data mining [1]. Many studies had been done to represent these issues. Wang et.al. [2] Investigate how to use decision tree in analysis the performance of the students in online learning. Arizmendi et.al [3] of machine learning and investigate the analytical considerations such as sampling methods, feature extraction and evaluating the performance of the models. Parr [4] studied the Role of family background and their effect in determining student behaviors. Shaojie [5] propose a method to predict the student's achievement for MOOCs taking into considerations the temporal learning behaviors of students. Holzberger et. al [6] explain how to Predict teachers' instructional behaviors and submit an study on the common relation between self-efficacy and intrinsic needs. It is observed that using the Learning Management System (LMS) has increased more and more and became a customary tool in schools and universities, the record data collected through LMS is a big data and contain a huge information about frequency, time, activities that reflect learning processes [7] . Also, there is a great interest in the timely identification of students who are likely to perform poorly in for-credit Science, Technology, Engineering, and Math (STEM) classes. So In this paper, we introduce a methodology based on rough set theory to analysis educational data set which collected from e-learning system to predict and understand the nature of student's behavioral.

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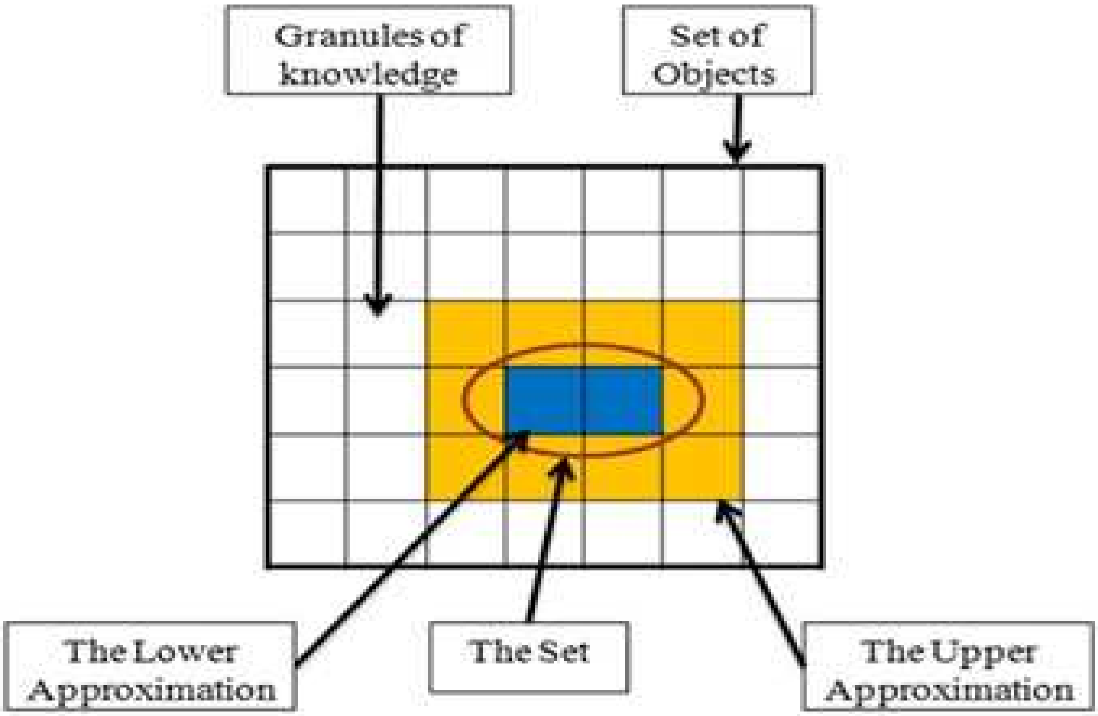

Fig. 1: representation of a set approximation of an arbitrarily set X in U

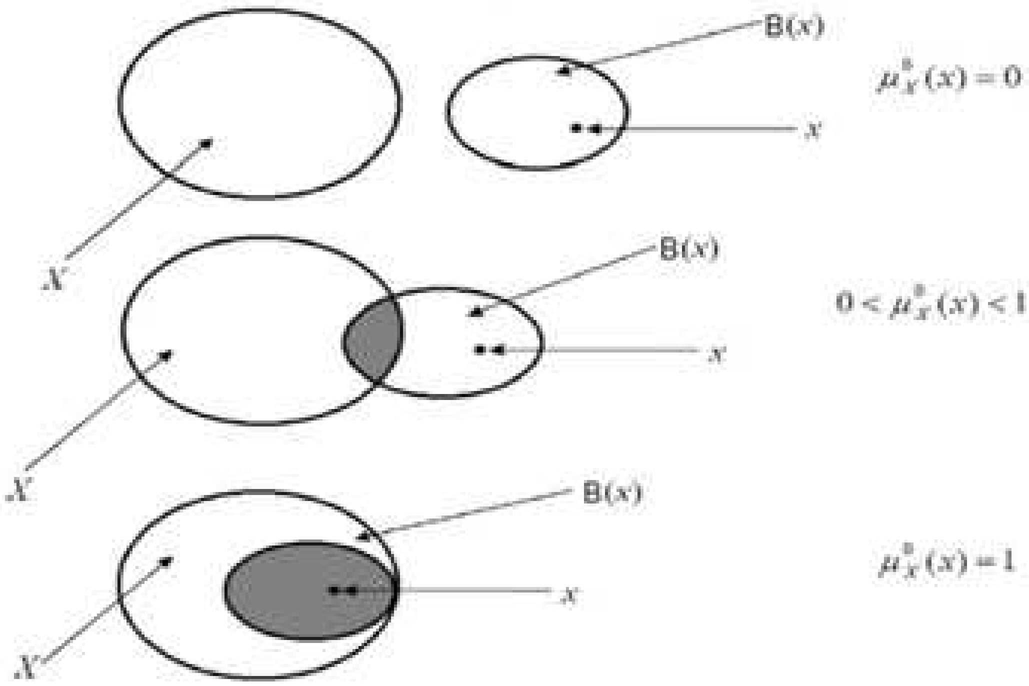

Fig. 2: The Meaning of rough membership function

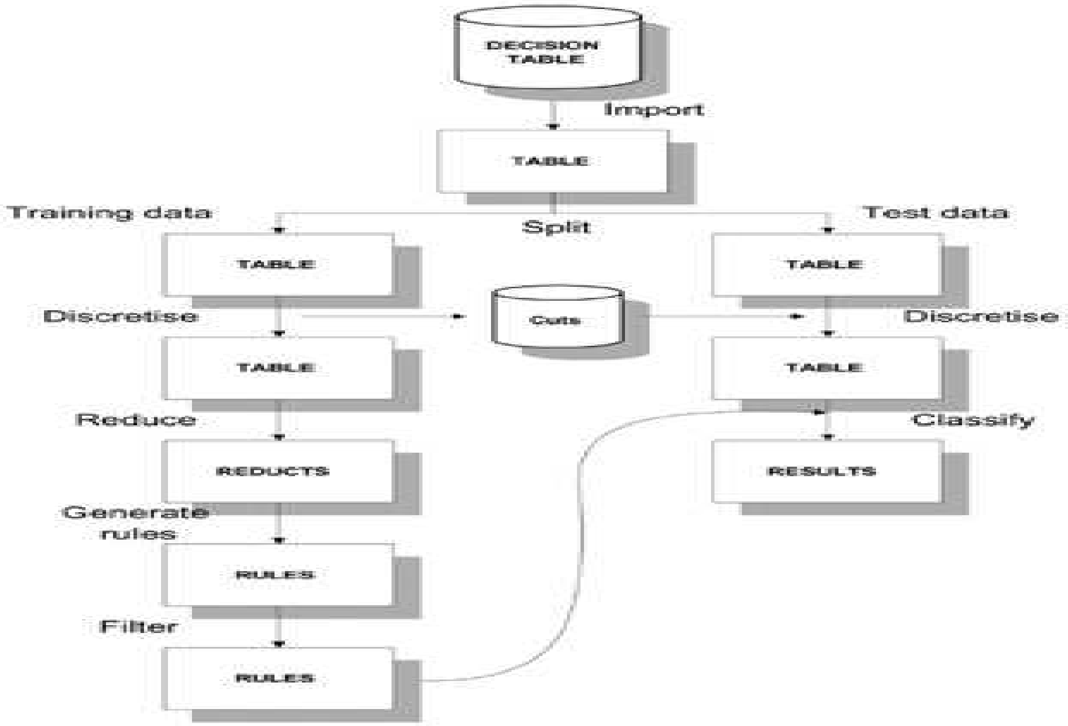

Fig. 3: Complete steps of the proposed methodology

2 Rough Sets Theory

One of the recent theories to investigate the structural relationships in big data within imprecise and uncertainty is the Rough Sets theory [8-12]. RST is used to acts as classification platform which has no restriction in the type of attributes, i.e. it can deal with continues and discrete attributes with the same accuracy but with some preprocess techniques such as discretization. rough set theory can be considered as a state of approximation, where it approximate the crisp set by two sets called, Upper approximation and Lower approximation [13] as shown in fig. 1. Where each rectangular portray an equivalence class. The lower approximation contain the entire region where every rectangular is within the same class without ambiguity. While the upper approximation is region which contains that class while also some compounds in other classes. The region in between the lower and upper approximation called the boundary region. Some of the most important definitions which represent the core of rough set theory can be summarized as follow:

$$IND(B) = \{(x,y) \in U : \text{for all } a \in B, a(x) = a(y)\} \quad (1)$$

$$\underline{B}(x) = \{x \in U : [x]_B \subseteq X\} \quad (2)$$

$$\overline{B}(x) = \{x \in U : [x]_B \bigcap X \neq \Phi\} \quad (3)$$

$$BND(X) = \overline{B}(x) - \underline{B}(x) \quad (4)$$

$$POS_B(X) = \overline{BX} \quad (5)$$

$$NEG_B(X) = U - \overline{BX} \quad (6)$$

$$\alpha_B(X) = \frac{|\underline{BX}|}{|\overline{BX}|} \quad (7)$$

Obviously $0 \leq \alpha_B(X) \leq 1$.

Where (U,A) is the decision system,
IND(B) is the indiscernible relation,
$\underline{B}(x)$ is the lower approximation,
$\overline{B}(x)$ is the upper approximation,
BND(X) is the boundary region,
$POS_B(X)$ is the B-positive region of X ,
$NEG_B(X)$ is the B-negative region of X ,
$|x|$ is the cardinality of X.

The rough membership function shown in fig.2 can be written as

$$\mu_X^B(x) = \frac{|X \bigcap [x_i]_{Ind(B)}|}{|[x_i]_{Ind(B)}|} \quad (8)$$

Obviously

$$\mu_X^B(x) \in [0,1] \quad (9)$$

Table 1: SAMPLE OF THE DECISION TABLE OF STUDENTS' PERFORMANCE

	Gender	Grade ID	Course Topic	Student's Contact Parent	Nu. of Raised Hand on Class	Visited Open Resources
x_1	Male	G-04	IT	Father	15	16
x_2	Male	G-04	IT	Father	20	20
x_3	Male	G-04	IT	Father	10	7
x_4	Male	G-04	IT	Father	30	25
x_5	Male	G-04	IT	Father	40	50
x_{12}	Male	G-07	Math	Father	19	6
x_{13}	Male	G-04	IT	Father	5	1
x_{14}	Male	G-08	Math	Father	20	14
x_{27}	Male	G-07	IT	Father	19	19
x_{28}	Male	G-08	Arabic	Father	25	15
x_{29}	Male	G-08	Science	Father	75	85
x_{30}	Female	G-08	Arabic	Father	30	90
x_{31}	Female	G-08	Arabic	Father	35	80
x_{32}	Male	G-07	IT	Father	4	5
x_{33}	Female	G-07	IT	Father	2	19
x_{34}	Male	G-05	English	Father	8	22
x_{35}	Male	G-07	Science	Father	12	11
x_{79}	Male	G-11	Quran	Father	13	3
x_{80}	Female	G-07	Math	Mother	80	90
x_{81}	Male	G-07	Math	Father	8	15
x_{154}	Male	G-11	Spanish	Father	10	51
x_{155}	Male	G-11	English	Father	70	50
x_{156}	Male	G-11	Math	Father	70	58
x_{157}	Female	G-11	French	Father	70	15
x_{170}	Male	G-02	French	Mother	30	12
x_{181}	Female	G-02	French	Father	60	70
x_{182}	Male	G-02	French	Father	50	62
x_{206}	Female	G-08	Arabic	Mother	72	51
x_{207}	Male	G-08	Arabic	Father	67	31
x_{208}	Male	G-08	Spanish	Father	17	21
x_{209}	Male	G-08	Spanish	Mother	27	41
x_{280}	Male	G-06	English	Mother	72	41
x_{281}	Male	G-06	English	Mother	74	71
x_{282}	Male	G-06	English	Mother	74	60
x_{283}	Female	G-06	English	Mother	95	94
x_{284}	Female	G-06	English	Mother	97	87
x_{313}	Female	G-04	Science	Mother	55	79
x_{314}	Female	G-04	Science	Mother	62	64
x_{315}	Female	G-04	Science	Mother	78	88
x_{316}	Female	G-04	Science	Mother	72	84
x_{409}	Male	G-07	Biology	Father	50	79
x_{421}	Female	G-08	Chemistry	Mother	82	89
x_{426}	Female	G-08	Geology	Mother	84	77
x_{442}	Male	G-08	Geology	Mother	90	86
x_{443}	Male	G-08	History	Mother	69	77
x_{444}	Male	G-08	History	Mother	70	76
x_{445}	Male	G-08	Chemistry	Mother	75	72
x_{477}	Female	G-08	Geology	Father	50	77
x_{478}	Female	G-08	Geology	Father	55	74
x_{479}	Female	G-08	History	Father	30	17
x_{480}	Female	G-08	History	Father	35	14

Table 2: SAMPLE OF THE DECISION TABLE OF STUDENTS' PERFORMANCE

	Student Absence Days	**Viewing Announ-cements**	**Discussion**	**Parent Answering Survey**	**Parent School Satisfaction**	**Student Classif-ication**
x_1	Under-7	2	20	Yes	Good	Middle-Level
x_2	Under-7	3	25	Yes	Good	Middle-Level
x_3	Above-7	0	30	No	Bad	Low-Level
x_4	Above-7	5	35	No	Bad	Low-Level
x_5	Above-7	12	50	No	Bad	Middle-Level
x_{12}	Under-7	19	12	Yes	Good	Middle-Level
x_{13}	Above-7	0	11	No	Bad	Low-Level
x_{14}	Above-7	12	19	No	Bad	Low-Level
x_{27}	Under-7	25	40	Yes	Bad	Middle-Level
x_{28}	Above-7	12	33	No	Bad	Low-Level
x_{29}	Under-7	52	43	Yes	Good	Middle-Level
x_{30}	Under-7	33	35	No	Bad	Middle-Level
x_{31}	Under-7	50	70	Yes	Good	High-Level
x_{32}	Above-7	40	16	Yes	Good	Low-Level
x_{33}	Above-7	10	50	Yes	Good	Low-Level
x_{34}	Above-7	9	40	No	Bad	Low-Level
x_{35}	Above-7	8	40	No	Bad	Low-Level
x_{79}	Above-7	11	9	No	Bad	Low-Level
x_{80}	Under-7	49	55	Yes	Bad	High-Level
x_{81}	Under-7	10	40	Yes	Bad	Low-Level
x_{154}	Above-7	40	40	No	Bad	Low-Level
x_{155}	Above-7	33	41	No	Bad	Middle-Level
x_{156}	Under-7	73	91	Yes	Bad	High-Level
x_{157}	Under-7	30	49	Yes	Good	Middle-Level
x_{170}	Under-7	29	23	No	Bad	Middle-Level
x_{181}	Under-7	63	93	Yes	Bad	High-Level
x_{182}	Above-7	13	33	Yes	Bad	Low-Level
x_{206}	Above-7	42	24	Yes	Bad	High-Level
x_{207}	Under-7	42	14	Yes	Good	Middle-Level
x_{208}	Under-7	42	14	No	Good	Middle-Level
x_{209}	Under-7	49	14	No	Bad	Middle-Level
x_{280}	Under-7	46	27	No	Good	Middle-Level
x_{281}	Under-7	56	37	No	Good	High-Level
x_{282}	Under-7	56	37	No	Good	High-Level
x_{283}	Under-7	72	80	No	Good	High-Level
x_{284}	Under-7	82	86	No	Good	High-Level
x_{313}	Under-7	44	43	Yes	Good	High-Level
x_{314}	Under-7	69	49	Yes	Good	High-Level
x_{315}	Under-7	74	83	Yes	Good	High-Level
x_{316}	Under-7	89	89	Yes	Good	High-Level
x_{409}	Under-7	10	31	No	Bad	Middle-Level
x_{421}	Under-7	22	31	Yes	Good	High-Level
x_{426}	Under-7	79	68	Yes	Good	High-Level
x_{442}	Under-7	85	10	Yes	Good	Middle-Level
x_{443}	Above-7	76	75	Yes	Good	Middle-Level
x_{444}	Above-7	65	70	Yes	Good	Middle-Level
x_{445}	Above-7	64	39	Yes	Good	Low-Level
x_{477}	Under-7	14	28	No	Bad	Middle-Level
x_{478}	Under-7	25	29	No	Bad	Middle-Level
x_{479}	Above-7	14	57	No	Bad	Low-Level
x_{480}	Above-7	23	62	No	Bad	Low-Level

Table 3: SAMPLE OF THE DISCRETIZED DECISION TABLE OF STUDENTS' PERFORMANCE

	Gender	Grade ID	Course Topic	Student's Contact Parent	Number of Raised Hand on Class	Visited Open Resources
x_1	Male	G-04	IT	Father	[11, 18)	[12, 20)
x_2	Male	G-04	IT	Father	[18, 24)	[20, 35)
x_7	Male	G-07	Math	Father	[24, 52)	[12, 20)
x_8	Male	G-07	Math	Father	[24, 52)	[4, 12)
x_{27}	Male	G-07	IT	Father	[18, 24)	[12, 20)
x_{28}	Male	G-08	Arabic	Father	[24, 52)	[12, 20)
x_{29}	Male	G-08	Science	Father	[74, 82)	[83, 87)
x_{36}	Male	G-07	English	Father	[10, 11)	[12, 20)
x_{37}	Male	G-07	Science	Mother	[*, 10)	[4, 12)
x_{48}	Female	G-12	English	Mother	[52, 73)	[4, 12)
x_{230}	Male	G-08	Spanish	Father	[*, 10)	[12, 20)
x_{233}	Male	G-07	Quran	Father	[18, 24)	[62, 75)
x_{234}	Female	G-07	Science	Mother	[24, 52)	[80, 83)
x_{320}	Female	G-02	French	Mother	[24, 52)	[92, *)
x_{321}	Female	G-02	French	Mother	[52, 73)	[87, 92)
x_{322}	Female	G-02	French	Mother	[24, 52)	[80, 83)
x_{377}	Male	G-02	Arabic	Mother	[18, 24)	[87, 92)
x_{378}	Male	G-02	Arabic	Mother	[24, 52)	[80, 83)
x_{379}	Male	G-02	Arabic	Father	[10, 11)	[20, 35)
x_{419}	Male	G-07	Biology	Father	[86, *)	[87, 92)
x_{420}	Male	G-07	Biology	Father	[86, *)	[92, *)
x_{421}	Female	G-08	Chemistry	Mother	[82, 86)	[87, 92)
x_{422}	Female	G-08	Chemistry	Mother	[82, 86)	[92, *)
x_{423}	Female	G-08	Geology	Mother	[52, 73)	[62, 75)
x_{477}	Female	G-08	Geology	Father	[24, 52)	[75, 80)

The rough membership function allow us to know how strongly an element x belongs to the rough set X in view of information about the element expressed by the set of attributes B. in other words it allow us to measure the degree with which any object with given attribute values belongs to a given set X.

2.1 RESEARCH PROBLEM

Due to the great development in the field of the internet and the accompanying development of computer labs in schools and universities, in addition to the increase in students' ownership of computers and mobile devices and their ability to learn through these devices. A digital environment appeared so-called learning management system (LMS) and its use increased rapidly in Education [14]. Teachers use this platform to communicate with the students, manages learning resources such as registration, classroom and the online learning delivery, as well as conducting exams. The log files of this platform containing the traced data which is captured by the system. These data can be used by the decision makers in the educational schools and universities to update their plans to improve the educational process and to decrease attrition rates in specific fields. So as shown in fig 3 this work proposes an intelligent technique depend on the basic principles of rough sets theory to obtain a set of decision (classification) rules which can act as a predicting schem for student's performance in the e-Learning Systems for the data which captured by researchers in the literature [15-17] for 480 student records and 11 conditional attributes and one decision attribute. a learner activity tracker tool was used to collect the data and it is called experience API (xAPI) [18]. The condition attributes are gender, grade student belongs, course topic, Student's contact parent, the number of days which the student was absence, Number of times that the student raises his/her hand on classroom, visits a course resources, checks the new announcements, participate on discussion groups, parent answered the surveys which are provided from school or not, the Degree of Parent satisfaction from school. The decision attribute is the classification of students according to the total mark as follows: Low-Level: Marks from 0 to 69, Middle-Level: Marks from 70 to 89, High-Level: Marks from 90-100 as shown in the Decision Table I and Table II. In this stage we used a software toolkit named ROSETTA which depend on the RST principles, the data of Table I and Table II was discrtesized (i.e. transfer the numerical values into nominal) with the aid of BROrthogonalScaler (Boolean reasoning algorithm) as shown in Table III and

Table 4: SAMPLE OF THE DISCRETIZED DECISION TABLE OF STUDENTS' PERFORMANCE

	Student Absence Days	Viewing Announ-cements	Discussion	Parent Answering Survey	Parent School Satisfaction	Student Classif-ication
x_1	Under-7	[*, 6)	[18, 26)	Yes	Good	Middle-Level
x_2	Under-7	[*, 6)	[18, 26)	Yes	Good	Middle-Level
x_7	Above-7	[*, 6)	[*, 18)	No	Bad	Low-Level
x_8	Under-7	[13, 23)	[18, 26)	Yes	Good	Middle-Level
x_{27}	Under-7	[23, 27)	[34, 41)	Yes	Bad	Middle-Level
x_{28}	Above-7	[10, 13)	[26, 34)	No	Bad	Low-Level
x_{29}	Under-7	[47, 64)	[41, 52)	Yes	Good	Middle-Level
x_{36}	Above-7	[13, 23)	[26, 34)	No	Bad	Low-Level
x_{37}	Above-7	[*, 6)	[18, 26)	Yes	Good	Low-Level
x_{48}	Under-7	[39, 47)	[85, *)	Yes	Good	High-Level
x_{230}	Above-7	[13, 23)	[*, 18)	No	Bad	Low-Level
x_{233}	Above-7	[13, 23)	[41, 52)	Yes	Good	Middle-Level
x_{234}	Above-7	[47, 64)	[41, 52)	Yes	Good	Middle-Level
x_{320}	Under-7	[23, 27)	[*, 18)	Yes	Good	High-Level
x_{321}	Above-7	[23, 27)	[*, 18)	Yes	Good	Middle-Level
x_{322}	Above-7	[13, 23)	[*, 18)	Yes	Good	Middle-Level
x_{377}	Above-7	[47, 64)	[52, 70)	Yes	Bad	Middle-Level
x_{378}	Above-7	[47, 64)	[52, 70)	Yes	Bad	Middle-Level
x_{379}	Above-7	[47, 64)	[85, *)	Yes	Bad	Low-Level
x_{419}	Under-7	[73, *)	[72, 85)	Yes	Good	High-Level
x_{420}	Under-7	[73, *)	[72, 85)	Yes	Good	High-Level
x_{421}	Under-7	[13, 23)	[26, 34)	Yes	Good	High-Level
x_{422}	Under-7	[27, 39)	[41, 52)	Yes	Good	High-Level
x_{423}	Above-7	[39, 47)	[41, 52)	Yes	Good	Middle-Level
x_{477}	Under-7	[13, 23)	[26, 34)	No	Bad	Middle-Level

Table 5: REDUCTS OF DISCRETIZED DECISION TABLE.

	Reduct	Support	Length
1	numer of Raised hand on class, Visied Open Resources, Student Absence Days, Viewing Announcements, Discussion, Parent Answering Survey}	100	6
2	{Gender, Course Topic, Student's contact parent, numer of Raised hand on class, Visied Open Resources, Student Absence Days, Viewing Announcements, Parent Answering Survey}	100	8
3	{Gender, Course Topic, Student's contact parent, numer of Raised hand on class, Visied Open Resources, Student Absence Days, Discussion, Parent Answering Survey, Parent school Satisfaction}	100	9

Table IV where "* means do not care condition". Hence, the minimal Reducts of Table III and Table are located by using the reduction techniques to define the minimal factors (attributes) that can characterize all the knowledge in the decision table as presented in Table V. Finally, a set of extracted rules can be outlined as shown in Table VI (see, Appendix A).

3 Conclusion

This article introduced an intelligent approach based on Rough set theory to predict student's behavior with the aid of the data generated by learning management system LMS. The Resultant set of classification rules can be considered as a knowledge base for evaluating and enhancement of the academic achievement of the students. It is valuable in helping the decision maker to determine the weak points in the educational process and improve the learning system outcomes to trimming down academic failure rates. The main findings of this work are:

Table 6: THE SET OF GENERATED RULES

Rule	LHS Support	RHS Support	RHS Accuracy	LHS Coverage	RHS Coverage	LHS length
R_1	1	1	0.002083	0.004739	1	6
R_2	1	1	0.002083	0.004739	1	6
R_3	1	1	0.002083	0.007874	1	6
R_4	1	1	0.002083	0.007874	1	6
R_5	1	1	0.002083	0.007874	1	6
R_6	1	1	0.002083	0.007042	1	6
R_7	1	1	0.002083	0.004739	1	6
R_8	1	1	0.002083	0.007042	1	6
R_9	1	1	0.002083	0.007042	1	6
R_{10}	1	1	0.002083	0.004739	1	6
R_{11}	1	1	0.002083	0.004739	1	6
R_{12}	1	1	0.002083	0.004739	1	6
R_{13}	1	1	0.002083	0.004739	1	6
R_{14}	1	1	0.002083	0.004739	1	8
R_{15}	2	1	0.004167	0.014085	1	8
R_{16}	1	1	0.002083	0.004739	1	8
R_{17}	1	1	0.002083	0.007042	1	9
R_{18}	1	1	0.002083	0.007042	1	9
R_{19}	1	1	0.002083	0.007042	1	9
R_{20}	2	1	0.004167	0.015748	1	9
R_{21}	1	1	0.002083	0.015748	1	9
R_{22}	1	1	0.002083	0.015748	1	9
R_{23}	1	1	0.002083	0.004739	1	9
R_{24}	2	1	0.004167	0.015748	1	9

– Give the educational institutions the chance for early interference to prevent the potential failure of students to achieve learning objectives by making changes to learning strategies.
– predict students who have a high chance of achieving academically.
– solve student academic problems.
– optimize the educational environment.
– Identify key factors that influence student academic success.
– Enable data-driven decision making.

The accuracy of the proposed methodology is higher than the traditional methods and more realistic by comparing to the results in previous works. The challenges and limitations to this work are:

– The difference in indicators for assessing student's performance in each class, subject and educational institution.
– the richness of various datasets that are processed in various types

These challenges give us the chance to develope the proposed method in the future and try to built the system based on the neural networks, Fuzzy systems and genetic algorithms.

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Appendix A

In TABLE VI, the abbreviations are defined as:

R_1: Numer of Raised hand on class([11, 18)) AND Visied Open Resources([12, 20)) AND Student Absence Days(Under-7) AND Viewing Announcements([*, 6)) AND Discussion([18, 26)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_2:Numer of Raised hand on class([18, 24)) AND Visied Open Resources([20, 35)) AND Student Absence Days(Under-7) AND Viewing Announcements([*, 6)) AND Discussion([18, 26)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_3: Numer of Raised hand on class([*, 10)) AND Visied Open Resources([*, 4)) AND Student Absence Days(Above-7) AND Viewing Announcements([*, 6)) AND Discussion([41, 52)) AND Parent Answering Survey(No) => student classification(Low-Level).

R_4:Numer of Raised hand on class([*, 10)) AND Visied Open Resources([*, 4)) AND Student Absence Days(Above-7) AND Viewing Announcements([*, 6)) AND Discussion([70, 72)) AND Parent Answering Survey(Yes) => student classification(Low-Level).

R_5: Numer of Raised hand on class([*, 10)) AND Visied Open Resources([4, 12)) AND Student Absence Days(Above-7) AND Viewing Announcements([27, 39)) AND Discussion([34, 41)) AND Parent Answering Survey(Yes) => student classification(Low-Level).

R_6:Numer of Raised hand on class([24, 52)) AND Visied Open Resources([80, 83)) AND Student Absence Days(Under-7) AND Viewing Announcements([47, 64)) AND Discussion([70, 72)) AND Parent Answering Survey(Yes) => student classification(High-Level).

R_7: Numer of Raised hand on class([18, 24)) AND Visied Open Resources([80, 83)) AND Student Absence Days(Above-7) AND Viewing Announcements([10, 13)) AND Discussion([*, 18)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_8: Numer of Raised hand on class([11, 18)) AND Visied Open Resources([92, *)) AND Student Absence Days(Under-7) AND Viewing Announcements([13, 23)) AND Discussion([*, 18)) AND Parent Answering Survey(No) => student classification(High-Level).

R_9: Numer of Raised hand on class([52, 73)) AND Visied Open Resources([92, *)) AND Student Absence Days(Under-7) AND Viewing Announcements([47, 64)) AND Discussion([72, 85)) AND Parent Answering Survey(Yes) => student classification(High-Level).

R_{10}:Numer of Raised hand on class([74, 82)) AND Visied Open Resources([80, 83)) AND Student Absence Days(Under-7) AND Viewing Announcements([39, 47)) AND Discussion([52, 70)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_{11}: Numer of Raised hand on class([82, 86)) AND Visied Open Resources([80, 83)) AND Student Absence Days(Under-7) AND Viewing Announcements([47, 64)) AND Discussion([52, 70)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_{12}:Numer of Raised hand on class([24, 52)) AND Visied Open Resources([62, 75)) AND Student Absence Days(Above-7) AND Viewing Announcements([39, 47)) AND Discussion([26, 34)) AND Parent Answering Survey(No) => student classification(Middle-Level).

R_{13}: Numer of Raised hand on class([24, 52)) AND Visied Open Resources([80, 83)) AND Student Absence Days(Above-7) AND Viewing Announcements([27, 39)) AND Discussion([18, 26)) AND Parent Answering Survey(No) => student classification(Middle-Level).

R_{14}:Gender(Female) AND Course Topic(French) AND Student's contact parent(Mother) AND numer of Raised hand on class([24, 52)) AND Visied Open Resources([87, 92)) AND Student Absence Days(Under-7) AND Viewing Announcements([13, 23)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_{15}: Gender(Male) AND Course Topic(French) AND Student's contact parent(Mother) AND numer of Raised hand on class([24, 52)) AND Visied Open Resources([92, *)) AND Student Absence Days(Under-7) AND Viewing Announcements([39, 47)) AND Parent Answering Survey(Yes) => student classification(High-Level).

R_{16}:Gender(Male) AND Course Topic(French) AND Student's contact parent(Father) AND numer of Raised hand on class([24, 52)) AND Visied Open Resources([87, 92)) AND Student Absence Days(Under-7) AND Viewing Announcements([27, 39)) AND Parent Answering Survey(Yes) => student classification(Middle-Level).

R_{17}: Gender(Male) AND Course Topic(Biology) AND Student's contact parent(Father) AND numer of Raised hand on class([52, 73)) AND Visied Open Resources([87, 92)) AND Student Absence Days(Under-7) AND Discussion([72, 85)) AND Parent Answering Survey(No) AND Parent school Satisfaction(Good) => student classification(High-Level).

R_{18}:Gender(Female) AND Course Topic(Biology) AND Student's contact parent(Mother) AND numer of Raised hand on class([86, *)) AND Visied Open Resources([92, *)) AND Student Absence Days(Under-7) AND Discussion([70, 72)) AND Parent Answering Survey(Yes) AND Parent school Satisfaction(Good) => student classification(High-Level).

R_{19}: Gender(Female) AND Course Topic(Biology) AND Student's contact parent(Mother) AND numer of Raised hand on class([74, 82)) AND Visied Open Resources([87, 92)) AND Student Absence Days(Under-7) AND Discussion([72, 85)) AND Parent Answering Survey(Yes) AND Parent school Satisfaction(Good) => student classification(High-Level).

R_{20}:Gender(Male) AND Course Topic(Biology) AND Student's contact parent(Mother) AND numer of Raised hand on class([*, 10)) AND Visied Open Resources([4, 12)) AND Student Absence Days(Above-7) AND Discussion([*, 18)) AND Parent Answering Survey(No) AND Parent school Satisfaction(Bad) => student classification(Low-Level).

R_{11}: Gender(Male) AND Course Topic(Biology) AND Student's contact parent(Father) AND numer of Raised hand on class([24, 52)) AND Visied Open Resources([75, 80)) AND Student Absence Days(Under-7) AND Discussion([26, 34)) AND Parent Answering Survey(No) AND Parent school Satisfaction(Bad) => student classification(Middle-Level).

R_{22}:Gender(Female) AND Course Topic(Chemistry) AND Student's contact parent(Mother) AND numer of Raised hand on class([82, 86)) AND Visied Open Resources([87, 92)) AND Student Absence Days(Under-7) AND Discussion([26, 34)) AND Parent Answering Survey(Yes) AND Parent school Satisfaction(Good) => student classification(High-Level).

R_{23}: Gender(Male) AND Course Topic(Geology) AND Student's contact parent(Mother) AND numer of Raised hand on class([74, 82)) AND Visied Open Resources([80, 83)) AND Student Absence Days(Under-7) AND Discussion([72, 85)) AND Parent Answering Survey(Yes) AND Parent school Satisfaction(Good) => student classification(Middle-Level).

R_{24}:Gender(Female) AND Course Topic(History) AND Student's contact parent(Father) AND numer of Raised hand on class([24, 52)) AND Visied Open Resources([12, 20)) AND Student Absence Days(Above-7) AND Discussion([52, 70)) AND Parent Answering Survey(No) AND Parent school Satisfaction(Bad) => student classification(Low-Level).