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An Intelligent Educational Data Mining Classification Model for Teaching English for Slow Learner Students

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ABSTRACT

The educational data mining is an emerging interdisciplinary field. Therefore, it is deeply connected to a number of research areas containing adaptive hypermedia, intelligent and adaptive web-based educational systems, intelligent tutoring systems, and other online courses mining systems. In addition, its applications demand taking into consideration the academic aspects of the system and the learner background and classification. The slow learners' students suffer from low rate of understanding and they are considered a sub branch of disability students who need special models of teaching and hence special models of evaluation. This paper presents a study on building an intelligent educational data mining classification model that is designed for teaching English for slow learner's students in order to obtain the most effective learning pattern and achieve an improvement in their performance. The proposed system is achieved through implemented four main phases. These are Phase:1 (development of English E-course), Phase: 2 (database design & implementation), Phase: 3 (collecting data) and Phase:4 (Applying Mining technique). For teaching English e-course, the results showed that the student who followed the pattern (Reading- Writing – Speaking – Grammar) reached the highest academic achievement's rates, (79.5%.and above). Thus the proposed IEDM-SL system can be significance for helping the slow learners and also, save effort and time for the teachers of slow learners.

KEYWORDS – Data mining, E-learning, Classification, Slow learners, English curriculum

1. INTRODUCTION

The educational data mining is an emerging interdisciplinary field. Therefore, it is deeply connected to a number of research areas containing adaptive hypermedia, intelligent and adaptive web-based educational systems, intelligent tutoring systems, and other online courses mining systems. In addition, its applications demand taking into consideration the academic aspects of the system and the learner background and classification. E-learning is the use of digital technologies to support the processes of teaching and learning and instruction that is delivered on a digital device such as a computer or mobile device that is intended to support learning [1,2]. E-learning systems are categorized into two classes: intelligent and non-intelligent. In non-intelligent learning, the tutor develops course topics previously, and then the software engineer presents them in variant methods and the same style to learners. Therefore, non-intelligent e-learning systems are static, inflexible and don't consider variant learner background, awareness and mentality. On the other hand, intelligent e-learning systems realize the customized and adaptive course content, learner type and education method [3]. These systems can recognize the student type and chooses appropriate course content from knowledge base and present the contents in proper style to the learners. Several e-learning systems have boundaries for instance sensitive personalization problems and the lack of intelligent context and search in which they are considered the demanding tasks for the researchers. In these days, the environments of web-based learning are comprehensively utilized. This environment has the ability to produce and maintain huge amount of data. Hence, it leads to the usage of the techniques of data mining applications in order to improve the quality and usability of platform courses content of e-learning [4]. Additionally, the applications of the data mining in the recent days have been improved in order to classify and mine the characteristics and the records of the learners in the environment of E-learning for the reason of helping the learners and predicting their studying results [5]. Classificationis a process of grouping physical or abstract objects into classes of similar objects. It is a supervised model where it predicts class labels for unseen data. When using a classification for educational system, it allows characterizing the properties of a group of user profiles, similar pages or learning sessions [6-8]. Recently, the classification is one of the most useful tasks in e-learning since many objectives can be achieved in e-learning environments by utilizing the classification task such as; (a) classifying students into groups according to the similarity in their reactions and characteristics as an educational strategy, (b) identifying students whom need more motivation as a kind of minimizing the rates of students dropping out, and (c) predicting the levels of students' intelligence for giving them special courses, and many other objectives [9]. The slow learners' students suffer from low rate of understanding and they are considered a sub branch of disability students who need special models of teaching and hence special models of evaluation. This paper presents a study on building an intelligent educational data mining classification model that is designed for teaching English for slow learner's students in order to obtain the most effective learning pattern and achieve an improvement in their performance [10].The rest of the paper is organized as follow; section 2 presents some of recent related work on educational data mining. Section 3, explains who the slow learner students are and what kind of characteristics they hold differently than normal students. Details of the proposed classification model for teaching English for slow learners are in section 4. Section 5 shows the computational results and discussion. Section 6, concludes the paper.

2. LITERATURE RELATED WORK

Many studies have been held in order to improve the implementation of data mining means and algorithms through e-learning systems [1-9]. But there is a clear need for the learning environment's design in order to utilize the chance provided by the internet where certainly, the online learning environment is not just the changing of print-based material to online delivery. In the following some of recent research papers ordered descending based on year of publications. These papers focuses on educational data mining model with different target mining techniques but certainly, they helped us reaching the results of this paper. (2013), A.Kangaiammal et.al [11], focused on assessment through multiple choice questions at the beginning and at the end of learning course. Also, the learning activities of the learner are tracked during the learning phase through a continuous assessment test to realize the understanding level of the learner. Actually, the scores recorded in the database is analyzed using rough set approach based decision system. The tool developed assists the teacher to be aware of the learning ability of the learner before preparing the content and the presentation structure towards complete learning. In other words the developed tool helps the learner to self-assess the learning ability and thereby identify and focus to gain the lacking skills. Also, Prema and Prakasam [12], proposed a model for increasing the quality of the learning materials and enhancing the concepts of self –learning, and enhance the student examination performance. The paper focused on visualization mining task using the DMBELS tool. They indicated a positive results for the usage of data mining based e-learning system on the quality of learning and teaching. (2012), AlAjmi et al. [13] held a study about "Using Instructive Data Mining Methods to Revise the Impact of Virtual Classroom in E-Learning". In their study, they have focused on the use of educational and instructive data mining approaches in finding out the impact of virtual classroom in e-learning which is considered as a kind of virtual learning environment. They followed using a data mining techniques to observe the records of students' behaviors in the virtual classrooms environment. They have classified the performance indicators of students as variables of the data mining algorithm. After that, they calculate the weights of those variables (for each student) based on exams scores and then, classify the students to conclude their study. Hung & Saba [14], developed a generic model for Educational Data Ming (EDM) examined by the existed model of the data mining and EDM literature. The target was visualization of the collected educational knowledge, where the case study displayed the relationships and the patterns that were exposed from the model of EDM. They reported that their model of education help in improving pedagogical decision making. (2011), Chellatamilan and Suresh [15] utilized the data mining tools in recording and classifying the behaviors of e-learning students in order to find the impacts of the e-learning systems on the students. Mamcenckoet. al., [16], developed an educational data mining model to analyze the data of the electronic examination. They used association rules (AR) mining technique to achieve clustering task of their data. Their model aid in defining the relationship and patterns in the data of electronic exams and enhanced the system of E-examination. Anitha& Krishnan [17], build a model to link the E-learners at their early stages of learning by presenting navigation recommendation. They combined the clustering task with (AR) technique to achieve their goals. Their results showed that the usage of the patterns of clustered access decreased the size of data set and enhanced the accuracy of recommendation.(2010), Carmona et al.[18], developed an EDM model to reach the subgroup discovery techniques' to the E- learning data from the Learning Management System (LMS) of the universities of Andalusia. They used optimization-evolutionary algorithms. Their results reached a reduced group of comprehensible rules are obtained that make them more explanatory for the instructor and get same quality measures. Dominguez, et al [19], presented a method where the current and past data of students is utilized live to produce hints for students that are ending the exercises of programming during the online competition. The paper used (AR) targeting clustering and numerical analysis. They found that the users who are presented with hints accomplished higher marks than other who were not provided with system hints. (2009), Kazanidiset. al. [20], suggested a platform that depends on the framework for recording, analyzing and processing data from Learning Management Systems (LMS) with main target of full visualization. The benefits of the usage of the frame work are utilizing the tools of data mining for the evaluation of the users and the content, suggesting new metrics and indexes to be utilized with the algorithms of the data mining, and its ability to be simply adapted to any LMS. Marijanaet. al,[21], created an adaptive courses for e-learning depend on the style of learning utilizing the intelligence tools and with main objective of building a classification model. Their system's demonstrated that students accomplished good results with high satisfaction's level while attended the adapted courses upon the styles of learning. From the previously abstracted literature related work, the idea of our study appears to cover the effects of e-learning systems on the slow learners by using classification techniques of data mining. This approach is considered a result of the founded gaps through the previous literatures.

3. THE SLOW LEARNER STUDENTS

Most disabilities with a clear medical basis are recognized by the child's physician or parents soon after birth or during the preschool years. In contrast, the majority of students with disabilities are initially referred for evaluation by their classroom teacher (or parents) because of severe and chronic achievement or behavioral problems. There is evidence that the prevalence of some disabilities varies by age, where the high-incidence disabilities such as learning disabilities and speech-language disabilities occur primarily at the mild level, the mild disabilities exist on broad continua in which there are no clear demarcations between those who have and those who do not have the disability, and even "mild" disabilities may constitute formidable barriers to academic progress and significantly limit career opportunities [10,22].

Understanding the needs and interests of the children is a key area that the teacher should focus on. The difficulties in learning students with disabilities appear as very big problems that face teachers in schools. Many suggested strategies have appeared to aid teachers in dealing with those students. One of the most well-known categories of special needs' students is the "slow learners". The slow learners suffer from low rate of understanding for the materials; therefore, they need special education methods and strategies to educate them. One of the suggested strategies is the technological learning such e-learning systems.

3.1 Diagnostic Category & Eligibility for Special Education

It is important to understand that slow learning is not a learning disability that can be classified as a diagnostic category. It is simply a term used to describe a student with the ability to acquire all necessary academic skills, but at a rate and depth below that of the average student. In order to grasp new concepts, a slow learner needs more time, more repetition, and often, more resources from teachers to be successful. Reasoning skills are typically delayed, which makes new concepts difficult to grasp [10, 22]. Additionally, special education services are provided for students who have a disability but, slow learners typically do not have a disability, even though they need extra support. Their cognitive abilities are too high for them to be considered for an Intellectual Disability (Mental Retardation). However, their abilities are usually too low to be considered for a Learning Disability (difficulty with learning in a typical manner). Slow learners tend to perform at their ability level, which is below average. Many parents opt to make their child repeat a few grades so that he is given more time to grasp the same concepts rather than being introduced to a cluster of new ones every year. Another option is to enrol the child in the least demanding syllabus available and supplement classroom learning with one-on-one teaching by special educators and occupational therapists [10, 22]..

3.2 Identification of Slow Learner Characteristics

Inclusion of students with slow learner into regular classes is generally an effective strategy and is also beneficial for the whole class. But slow learner should receive special help to outside the classroom. Teacher should spent great deal of time with slow learner. Since slow learners cannot be a grouped as a separate diagnostic category they are often overlooked and not considered as individuals who need intervention. Here are a few distinguishable traits of a slow learner [10,22]. :

1. Scores consistently low on achievement tests
2. A below average ability to comprehend academic concepts
3. Functioning ability is significantly below that of grade level
4. Prone to immature interpersonal relationships and prefers playing with younger children
5. Tends to be ignored by peers and may not have common peer interests
6. Faces difficulty in following multi-step directions
7. Frequently has impaired fine motor coordination such as delayed ability to tie shoe laces
8. Has few internal strategies (i.e. organisational skills, transferring/generalising information)
9. Works well with "hands-on" material (i.e. labs, picturised texts, manipulative, activities)
10. May have poor self-image and lacks self-confidence
11. Works on all tasks slowly and mostly tries the same
12. strategies; relies on trial and error learning and less on insightful learning
13. Masters skills slowly and does not master some at all

4. THE PROPOSED IEDM-SL APPROACH

The technological developments in educational fields lead to develop the e-learning systems until its databases seem to be huge. Classifying those databases and finding out suitable methods to retrieve information from them have led to develop data mining methods to utilize within e-learning systems. Our objective was building an intelligent educational

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data mining classification model that is designed for teaching English for slow learner's students in order to obtain the most effective learning pattern and achieve an improvement in their performance. Actually, to achieve the aim of this paper four main phases are accomplished. These are building *Phase:1* (development of English E-course), *Phase: 2* (database design & implementation), *Phase: 3* (collecting data) and *Phase:4* (Applying Mining technique).

Phase 1: Development of English E-Course

1. All lessons were developed by our effort where they contain image, sound and emotions that together form an attractive lesson environment and also consider the simulation of the slow learner student's way of thinking and connectivity between various contents and without forcing a specific order to be followed by the slow learner's students. Ex: some students start with reading section while others start with listening section and so on. (Microsoft power point slides plus "iSpring" are used by this stage).

2. For every lesson, we developed a quiz for reporting the understanding degree of each student. Additionally, a final exam is also maintained to report the best access pattern of teaching (ASP.net plus C# are used to accomplish this stage).

3. For concluding the steps (1) and (2), the final quizzes and exams marks of each student are stored in our system database for further analysis on teaching patterns and arrangement of quizzes and hence a better future recommendation for both teachers and students.

Phase 2: Database Design & Implementation

In this phase, we designed and implemented the system database which consists of four main datasets. These are the English course dataset, the student navigation behaviors dataset, the student academic level dataset and the linked form dataset. The SQL server 2008 was used to implement the database ADO.net and is also used to link ASP.net with the database

English e-Course Dataset

The English course dataset contains five different units. Each unit has four parts; (1) Listen and Chant, (2) Listen and Read, (3) Listen and Match, and (4) Read and choose. Each part contains two levels; material level that explains the idea of the part, and the quiz level that assesses the understanding level of the student for the required skills. A total score is calculated for each unit in the material, and also a total score is calculated for the total student achievement as it appears in Fig. 1

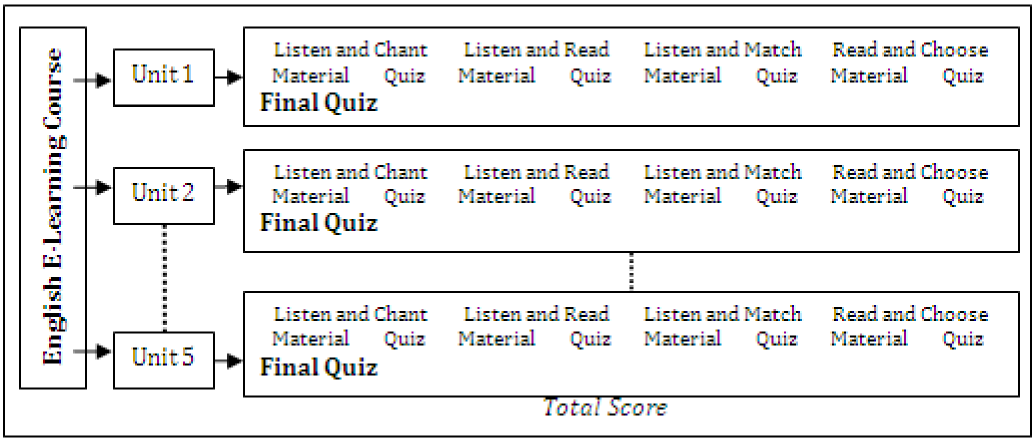

Figure 1 the English e-Course Database fields

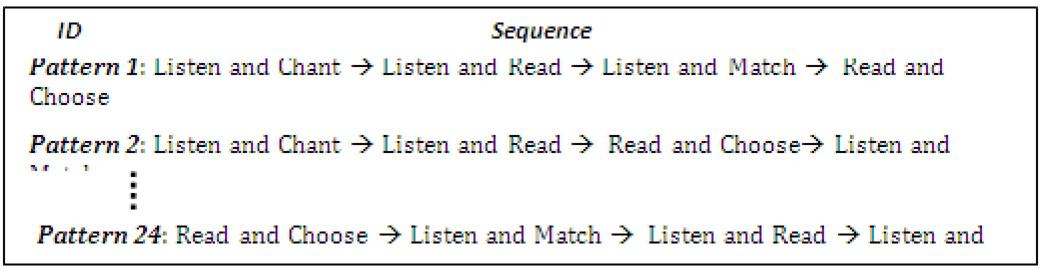

Figure 2: Patterns of student's behaviors in the e-learning environment

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Student Navigation Behaviors Dataset

The student navigation behaviors dataset consists of 24 patterns in the e-learning environment. These patterns resulted from the 4 parts of each five units of the English e-course that we developed and previously explained. Based on the probability and permutation rules, then the number of these patterns are equals (4*3*2*1=4!). Fig. 2 and Fig.3, details some of these patterns with pattern ID and its corresponding followed sequence.

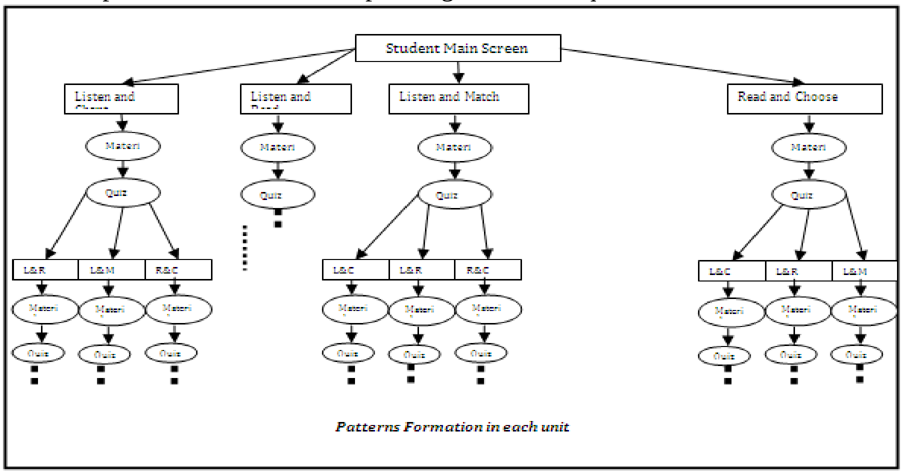

Figure 3: Patterns Formation in Each Unit

Academic Levels Dataset

The student academic level dataset contains the student academic scores in each unit and each part of every unit in addition to access and exist time and date. The main target of this datasets is to let teachers keep track of their students' achievement. Fig.4 shows sample of this dataset.

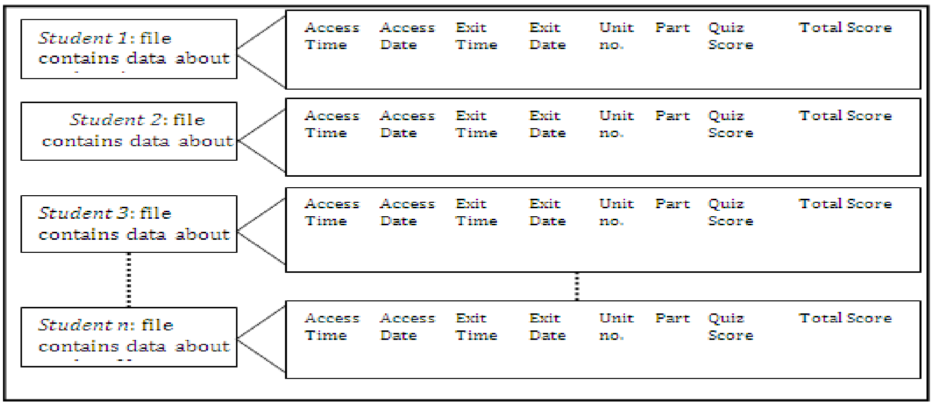

Figure 4: Students' Records Database

Linked form Dataset

The linked form dataset contains the relation between all the previously discussed datasets. Its main target is to connect between student academic achievements and pattern or behavior where each pattern is linked with the total achievement of the students that follows this pattern. Fig. 5 and Fig.6, show sample of these design skeletons and the linked data in group of statements, respectively.

Pattern No.	Average Students Score in Unit 1 / No. of Students	Average Students Score in Unit 2 / No. of Students	...	Average Students Score in Unit 5 / No. of Students	Average Students Score in English Course
1					
2					
...					
24					

Figure 5: the form of linking collected data

Obtaining Relations:

Pattern x→ the Highest Academic Achievement of Students
Pattern y→ the Lowest Academic Achievement of Students
Pattern z→ Average Score between *m* and *n*
...

Figure 6: Final forms of obtained relations

Phase 3: Collecting Data

The data used in this paper was collected, designed and organized by our effort based on real slow learner students' information in the fourth grad at Kuwait. Actually, also, the programmed material is selected from their curriculums. The sampled population was selected randomly and it was aimed to reach (500) participants who used the e-learning software but only (456) students could completed the course successfully. The sign in for each student is achieved using internet and via their emails the students marks and patterns plus their personal information are grouped as a student record and saved in our corresponding database tables. We also maintained the procedure of automatic link between marks and patterns for much easier mining effort in next phases.

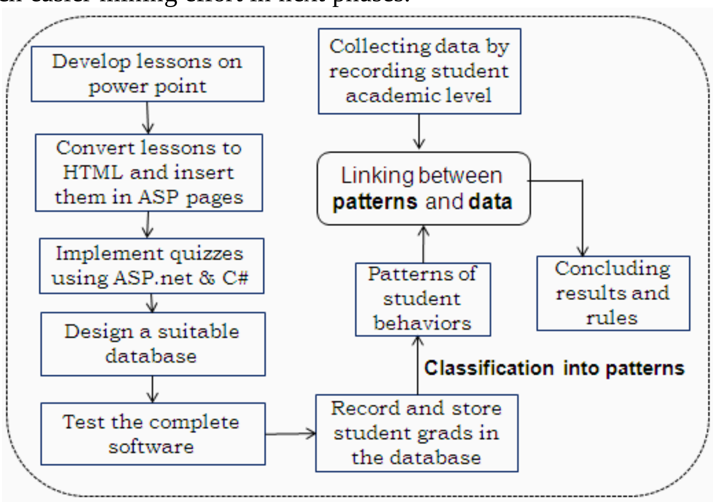

Figure 7: System model

Phase 4: Applying Mining Workflow

Fig. 7, shows the mining workflow of the IEDM-SL system. Phase 1, 2 and phase 3 are achieved. Then preparation and preprocessing of system data are achieved. Finally, whole consistency and integrity of system components are also achieved. A "WEKA" mining tool is used with target of classification task. The "WEKA" data analysis tool is a group of machine learning algorithms to solve problems used in real world. Java is the used programming language in "WEKA". It is freely available software. It is portable & platform independent because it is fully implemented in Java programming language and thus runs on almost any modern computing platform [23].

5. RESULTS & DISCUSSION

Our system is implemented using ASP.NET and C# with SQL database language. The results of this paper are based on random sample of data of the slow English learners in Kuwait. Each participant accessed the designed course will participate as a total of five times instead of one time, since the course consist of five units and each unit has a different material. Thus the reliability of the results will be higher. . Also, the system allows repeating the material to the slow learners in order to enhance their academic achievement based on scientific recommendation for teaching slow learners. Actually, the total number of participants was 300 students; thus, the total number of experiments was 1500 tries. In each experiment, we selected 500 tries randomly. These are inserted into "WEKA" for the following experimental results.

Experiment 1:

Analysis of Slow learner Behaviors Patterns

Fig. 8, shows the WEKA results for the analysis of slow learner behavioral pattern. The table in the middle of the right side shows the patterns in the column (Label) and the frequencies out of 500 in the column (Count). The flow chart in the lower right side of the figure shows the frequencies distribution graphically.

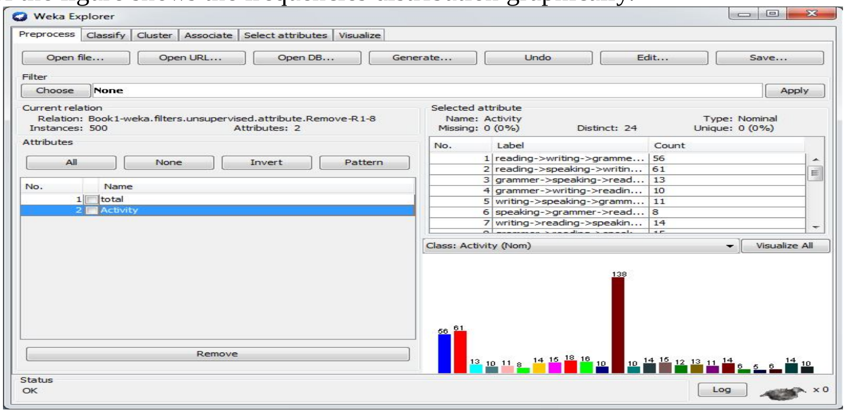

Figure 8: WEKA results of analyzing slow learner Behaviors pattern

Experiment 2:

Academic Achievement of the Participants

Each try of a participant, regardless of the followed pattern, ends with a total mark that indicates the academic achievement of this experiment. This mark represents the total grades in each activity of the unit in addition to the mark of the final quiz. Fig. 9 shows the distribution of these marks for a number of 500 instances that are distributed between the minimum value of 36 and the maximum value of 91. The mean of all the grades of academic achievement appears to be equal to 74.46 with a standard deviation of 8.403. The flowchart on the lower right corner of the next figure illustrates this distribution graphically

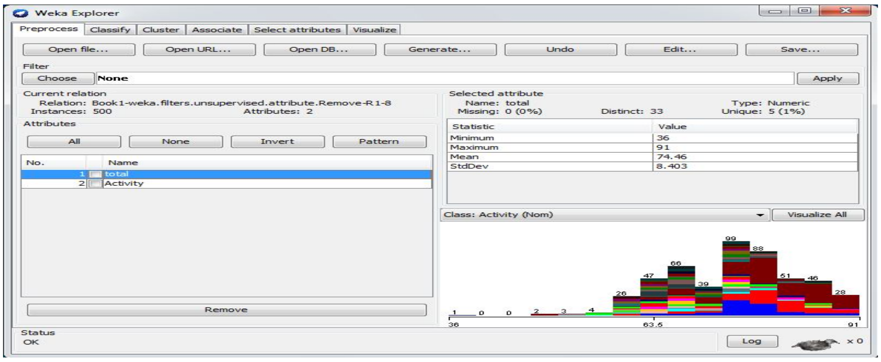

Figure 9: WEKA results of analyzing slow learner academic achievements

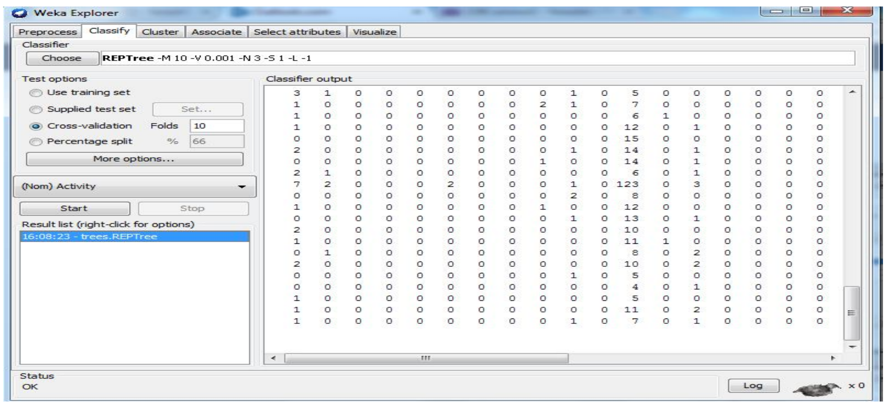

Figure 10: WEKA results of pattern classification

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=== Classifier model (full training set) ===
REPTree➔
total< 75.5
| total< 72 : reading->writing->speaking->grammer (127/114) [61/49]
| total>= 72
| | total< 73.5 : reading->writing->grammer->speaking (15/11) [7/6]
| | total>= 73.5 : reading->writing->speaking->grammer (28/23) [15/11]
total>= 75.5
| total< 79.5
| | total< 77 : reading->writing->grammer->speaking (21/14) [13/9]
| | total>= 77 : reading->writing->speaking->grammer (38/25) [21/15]
| total>= 79.5 : reading->writing->speaking->grammer (104/50) [50/27]
Size of the tree: 11
Time taken to build model: 0 seconds

Figure 11: WEKA REP results of pattern classification

=== Stratified cross-validation ===== Summary ===

Correctly Classified Instances	131	26.2 %
Incorrectly Classified Instances	369	73.8 %
Kappa statistic	0.0248	
Mean absolute error	0.0717	
Root mean squared error	0.1909	
Relative absolute error	96.8982 %	
Root relative squared error	99.4538 %	
Total Number of Instances	500	

Figure 12: WEKA summary results of pattern classification

Tabel 1: Related patterns as REP tree ordered

Grade	Pattern
Grade>=79.5	Reading- Writing – Speaking – Grammar
79.5> Grade >= 77	Reading- Writing – Speaking – Grammar
77> Grade >= 75.5	Reading- Writing – Grammar – Speaking
75.5> Grade >= 73.5	Reading- Writing – Speaking – Grammar
73.5> Grade >= 72	Reading- Writing – Grammar – Speaking
Grade < 72	Reading- Writing – Speaking – Grammar

Table 2: The accuracy distribution based on the class pattern

TP Rate	FP-Rate	Precision	Recall	F-Measure	ROC Area	Class
0.107	0.07	0.162	0.107	0.129	0.584	reading->writing->grammar->speaking
0.033	0.016	0.222	0.033	0.057	0.659	reading->speaking->writing->grammar
0	0	0	0	0	0.467	grammar->speaking->reading->writing
0	0	0	0	0	0.564	grammar->writing->reading->speaking
0	0	0	0	0	0.503	writing->speaking->grammar->reading
0	0.008	0	0	0	0.713	speaking->grammar->reading->writing
0	0	0	0	0	0.585	writing->reading->speaking->grammar
0	0	0	0	0	0.501	grammar->reading->speaking->writing
0	0.008	0	0	0	0.49	writing->reading->grammar->speaking
0	0.019	0	0	0	0.539	writing->grammar->reading->speaking
0	0	0	0	0	0.288	reading->speaking->grammar->writing
0.891	**0.815**	**0.294**	**0.891**	**0.442**	**0.654**	**reading->writing->speaking->grammar**
0	0.004	0	0	0	0.664	speaking->writing->reading->grammar
0	0.035	0	0	0	0.656	writing->speaking->reading->grammar
0	0	0	0	0	0.461	grammar->writing->speaking->reading
0	0	0	0	0	0.656	speaking->reading->grammar->writing
0	0	0	0	0	0.56	speaking->grammar->writing->reading
0	0	0	0	0	0.487	reading->grammar->writing->speaking
0	0	0	0	0	0.535	grammar->reading->writing->speaking
0	0	0	0	0	0.321	writing->grammar->speaking->reading
0	0	0	0	0	0.569	speaking->reading->writing->grammar
0	0	0	0	0	0.324	speaking->writing->grammar->reading
0	0	0	0	0	0.524	grammar->speaking->writing->reading
0	0	0	0	0	0.531	reading->grammar->speaking->writing

Experiment 3:

Patterns classification

In this experiment, an illustration of the relations between patterns and academic achievement is analyzed and classified. REP tree from "WEKA" software with the '10-fold cross-validation' for test model is used. Fig. 11 shows the REP tree of this experiment. Fig. 12 shows summary of results of this experiment. From the figure, it is clear that the correctly classified instances of the total instances were only 131 out of 500 instances with a percentage of 26.2%. Also Kappa statistic=0.0248 and the mean absolute error =0.0717. The root mean squared error=0.0717. The percentage of relative absolute error was 96.9% and the percentage of root relative squared error was 99.45%. The best results in students' academic achievement were related to the pattern:

Reading- Writing – Speaking – Grammar

Where, the students who followed this pattern achieved the highest academic achievement's rates, which are higher than 79.5%. The following table shows the related patterns as REP tree classified ordered in regards to the achieved academic achievements. Table 2 shows the detailed accuracy distribution based on the class, where the values of TP rate, FP rate, Recall, Precision, F-measure, ROC area, and class are shown in these results.

6. CONCLUSION

The paper proposed an intelligent educational data mining system called IEDM-SL for teaching English language for the slow Learner students. The proposed system is achieved through implemented four main phases. These phases were Phase:1 (development of English E-course), Phase: 2 (database design & implementation), Phase: 3 (collecting data) and Phase:4 (Applying Mining technique). Each phase was presented in detailed inside the paper. ASP.NET and C# with SQL database language plus the "WEKA" data mining tool were used for the implementation of these four phases. The results showed that the proposed system is a very helpful in defining the patterns of better achievement in order to help the slow learners in enhancing their academic achievements. For teaching English e-course in specific, the results showed that the student who followed the pattern (Reading- Writing – Speaking – Grammar) reached the highest academic achievement's rates, (79.5%.and above). Thus the proposed IEDM-SL system can be significance for helping the schools of slow learners: where they can guide slow learners to achieve higher educational and academic achievements and also, save effort and time for the teachers of slow learners themselves.

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