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Mining Educational Data to Improve Student Performance

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Abstract
Educational data mining is a new and expanding field of study due to the increased interest in it. The field of scientific research known as educational data mining, or "EDM," is centered on developing methods for discovering information in learning environment data sets and applying those methods to gain insight into students and the learning environment. It is an extremely effective tool for uncovering hidden patterns and valuable information that would otherwise be challenging to identify and understand via the use of conventional statistical techniques. The benefits and drawbacks of educational data mining are discussed in this research. explains educational data mining methods by doing out sequential procedures also determined the possible domains where data mining methods may be applied.
It takes time and a high degree of precision to access a lot of data. The potential impact of data mining on student learning outcomes and procedures was recognized in higher education. Particularly in the realm of education, given that practically all public and private educational institutions have thousands of student records covering a wide range of programs and disciplines. Gaining an understanding of the advantages of data retrieval can help the educational process. A student-focused approach and the provision of appropriate tools for institutions to utilize for quality improvement are two benefits of using data mining in education. This chapter will examine the advantages of using data mining in the field of education.

Keywords: Educational Data, Educational data Mining, Prediction, Clustering, Association rule, Data Mining, Education, Data, Data Mining Process

Introduction

The EDM process turns unprocessed data from educational systems into information that may be used to inform research and study in the field of education. Data mining may be used to find predictive information that experts might overlook because of a variety of circumstances that go beyond their expectations. Particularly in higher education, data mining can forecast a student's likelihood of failing or graduating. Information from data mining itself may be used by a variety of institutions to concentrate on raising the performance of students who are most likely to fail. Nonetheless, data mining's use in education is still relatively new and requires further study.
The way educational systems function has drastically changed as a result of the growing usage of echnology in the classroom. The amount of data that is available and easier to obtain for decision-making has also expanded due to the growing usage of electronic-based learning systems. This abundance of data is also simpler to analyze because to advancements in data mining technologies. The topic of educational data mining has seen a surge in attention and study in recent years [1]. As the subject of educational data mining, which focuses on creating techniques that extract information from data coming from educational institutions, grows in popularity, so does research interest in the application of data mining in educational systems[2].
Data from various educational systems may be gathered and stored in respective databases. The information, which may include academic or personal records, may be used to better understand how students learn, help teachers improve their instruction, assess and enhance e-learning platforms, enhance curricula, and inform decisions in general.[2] [3].

Educational Data

Citation [4][5], Data from many sources, including distributed and diversified, organized and unstructured data, are used in education. As seen in fig. 1, they may come from online or offline sources. Traditional classroom activities, interactive teaching and learning environments, learner and educator data, student attendance, emotional data, course data, and data gathered by an institution's academic division are all sources of offline data. Web-based learning and the remote learning education system are the sources of the online data.system, geographically dispersed educational stakeholders, and computer-assisted collaborative learning utilized in online forums and social networking sites. For example: Web logs, emails, text messages, phone conversations that have been transcribed, medical records, spreadsheets, business contracts, publishing databases, Legal Details[4][5]

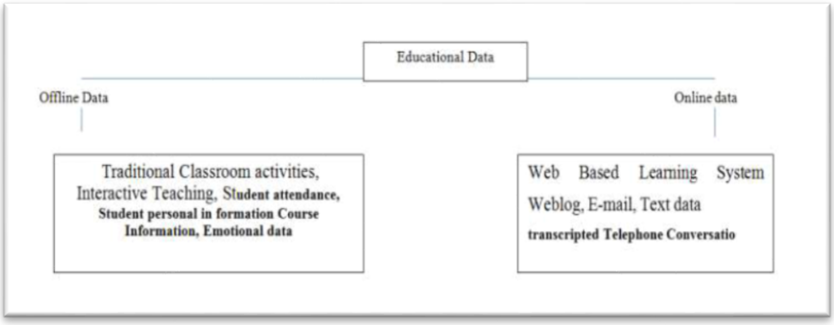

Figure1. Educational Data

In order to better understand students and the environments in which they learn, EDM is "an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings." "The field of scientific inquiry centered around the development of methods for making discoveries within the unique kinds of data that come from educational systems, and using those methods to better understand students and the system where they learn" is how Reference [7] defined educational data mining, or "EDM." In order to explicitly take use of the several levels of meaningful hierarchy present in educational data, educational data mining approaches frequently diverge from those used in the larger data mining literature. Machine learning techniques are frequently used with psychometrics techniques.

In order to comprehend how students react to the educational system and how their reactions affect their learning, education data mining, or EDM, applies data mining techniques related to learning analytics and quantitative observation methods. Its goal is to answer educational research problems by analyzing educational data. Due to the education sector's recent rapid expansion, which has resulted in an increase in education data, educational data mining has become crucial for comprehending student learning behavior during the learning process as well as their issues [8]. The educational system was improved by the educationists in order to guarantee student performance. as demonstrated that: The academician will create the educational system, construct it, and—above all—maintain such systems.

➢ Traditional classroom settings, e-learning platforms, intelligent and flexible web-based learning platforms, and more are all included in these educational systems.

• Since learners are closely related to the educational system, the data set may be gathered from them.

• These data are provided as input to data mining procedures, which use a variety of data mining techniques, including as clustering, classification, association rule, etc., to provide results that are recommended to learners and help instructors learn new things [8].

EDUCATIONAL DATA MINING GOALS

EDM's primary objective is to enhance the educational system as a whole. In order to assist in resolving their issues, all of these objectives rely on the perspectives of the end users, who include students, educators, administrators, and researchers [5].

1. The process of creating a student model involves incorporating specific information about the student's learning progress, motivation, satisfaction, knowledge, skills, metacognition, attitudes, experiences, and/or specific problems that have a negative impact on their learning outcomes. Here, the objective is to develop or enhance the student model.
2. Predicting future learning behavior: Using information from course activities, predictive models can forecast students' performance and learning outcomes.

Making Suggestions: The objective is to suggest to students the most pertinent assignments or

information at the moment.
3. Analyzing the outcomes of educational support and suggesting more initiatives This is something that learning systems can help with.
4. Enabling teachers to better understand the social, cognitive, and behavioral components of their students' learning processes and update their teaching strategies in order to enhance student performance
5. Developing computational models that integrate student models is one way to advance broad scientific understanding about learning and learners. EDM research also makes use of technology and software.
Finding or improving domain models: The goal is to determine ways to improve courses or materials, activities, connections, etc. using data (particularly) on student usage and learning. Students actively participate in educational materials to select the most effective teaching sequences to supplement their desired learning style.
For the general growth of the educational system, administrators should be aware of the most effective ways to expand the institutional resources, both material and human [4].

LIMITATION OF DATA MINING

- The trend in educational data mining research indicates that the majority of studies are only concerned with academic goals. [5] are the other problems.
  Incremental nature of educational data: Data warehouse management is extremely challenging due to the exponential growth of data. Determining the interest, objectives, and influence of students at a given school is the primary concern in the monitoring of operational data sources. The alignment and understanding of the incremental data are additional problems. Time, context, and sequencing should be its main concerns. The best use of human computing and resources is another problem with incremental [5].
  The occurrence of uncertainty: Due to the existence of uncertain mistakes, no model is able to forecast with 100% accuracy the outcomes of
- Overfitting existing data, missing and noisy data, and dealing with very big databases are all issues that need to be overcome when dealing with very high dimensionality. Moreover, high-performing algorithms like neural networks and evolutionary algorithms have to deal with lengthy computation times and interpretation challenges for large-scale, real-world applications [9].
- It is necessary to enhance methods related to probabilistic learning. The methods related to probabilistic learning must be improved in order for educational data mining and analytics in classrooms, schools, districts, and other institutions to be successful. This will allow students to ask important questions for teachers and other users, as well as to present findings in a way that is informative, thoughtful, and highlights and suggests specific actions. With the exception of visual data analytics, the importance of human judgment is occasionally overlooked in stories on the newest technologies for recommendation, personalization, and adaptability [9].
- The teacher-student relationship in research expertise. It is not feasible to assign all students and supervisors with similar areas of interest, which may result in project outcomes that are not applicable to real-world situations. In the majority of higher education institutions, supervisors are assigned based on availability and area of expertise in various departments. Finding the relationship between students' interests, areas of interest, the project's or research's applicability, and mining cross-interest is necessary. Optimizing this problem will benefit from the introduction of Association Mining [4].

PHASES IN EDUCATIONAL DATA MINING

Educational Data Mining Phases Finding new hidden knowledge through the translation of raw data gathered from educational systems is the focus of educational data mining. EDM typically consists of the following stages, as seen in fig. 2 below.

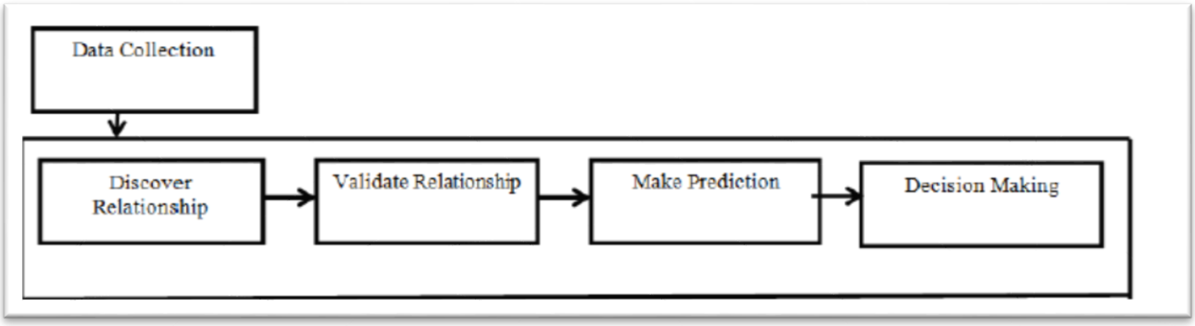

Figure 2 Educational Data Mining Phases

 The information to be mined is gathered from various educational system resources, such as course management, e-learning environments, and web-based data (like YouTube and Twitter) that is pertinent to students' learning activities, such as their grades and posts on social media platforms.

Data Mining Phase: The following process steps make up the data mining phase.

• Discover Relationship: Using data mining techniques such as classification, clustering, and regression, the initial step in educational data mining is to identify the linkages among the educational environment's data. with the intention of identifying reliable correlations between the variables in the data

• Checking Connections In the second stage of educational data mining, discovered connections between data are validated to avoid overfitting and uncertainty.

• Predicting the Future: The third stage involves forecasting the future based on relationships that have been verified in the learning environment. Valid relationships are utilized in order to forecast additional activities in the classroom

• Decision Making: Using forecasts to support the decision-making process is the fourth step. Decision-making procedures and policy decisions are supported by the predictions established in the preceding phase. In stages three and four, data is frequently displayed or otherwise used to condense human judgment. [8]

MATERIALS AND METHODS

A. **EDUCATIONAL DATA MINING TECHNIQUES**

1. In addition to using data mining techniques like classification, clustering, and association analysis, educational data mining also uses other approaches and techniques derived from various EDM-related fields (statistics, machine learning, text mining, web log analysis, etc.), according to [5]. Researchers in educational data mining employ these five types of technological methodologies to categorize the vast array of educational data mining techniques: [7]
   1. Prediction: with this method, a model is created to deduce one feature of the data (the predicted variable) from a set of other features (the predictor variables). In general, predictions may be divided into three categories:
2. 2. Regression, density estimation, and classification (IF-THEN rules, decision trees). A binary or categorical variable is the anticipated variable in classification. Support vector machines, logistic regression (for binary predictions), and decision trees are a few common categorization techniques. The predicted variable in regression is a continuous variable. Neural networks, support vector machine regression, and linear regression are a few of the widely used regression techniques in educational data mining. A probability density function is the anticipated variable in density estimation. A range of kernel functions, including Gaussian functions, can serve as the foundation for density estimators. The input variables

can be continuous or categorical for each form of prediction; the type of input variables utilized determines whether prediction techniques are more successful [7].

3. Clustering: The data set is separated into different groups, or clusters, using the clustering approach. Data points in one cluster should be more similar to those in the same cluster and more different to those in another cluster, according to the clustering phenomenon. The clustering method can be started in one of two ways: The first step is to begin the clustering algorithm without any preconceived notions, and the second is to begin the clustering algorithm with a preconceived notion [8][10].
4. 4. Finding correlations between variables in a dataset and encoding them as rules for subsequent usage is known as relationship mining. Numerous connection types may be found in mining techniques, including correlation mining, sequential pattern mining, and association rule mining, which look for any links between variables across time.
5. 5. Relationship mining is used in EDM to model learners' problem-solving activity sequences and to find correlations between students' online activities and their final grades [8][10].

   6. Discovery with Models: the purpose of discovery with models is to employ a validated model of a phenomena (using prediction, clustering, or knowledge engineering) as a component in additional research such as prediction or relationship mining. For instance, it is employed to determine the connections between the traits and conduct of the learner. [8] [10].

   6. Distillation of Data for Human Judgment: In this situation, when data is presented properly, humans are able to draw conclusions about it that are outside the direct purview of fully automated data mining techniques. Information visualization techniques are employed in this field of educational data mining. Identification and categorization are the two reasons why data is distilled for human judgment. Data that has been distilled for identification is presented in ways that make it simple for people to recognize patterns that are not too hard to articulate formally. The learning curve is an illustration of educational data mining visualization. In order to facilitate the subsequent creation of a prediction model, data may also be extracted for human labeling. Subdivisions of a data collection are shown here in visual

APPLICATION AREAS

The potential area of Educational data mining application
includes:

1 PREDICTION OF STUDENTS ENROLMENT INTO PROGRAMS

Educational data mining can be applied to find an accurate estimate of how many male or female will enrol in a particular program by using the Prediction techniques this will
in-turn lead to efficiency in allocation of resources.

2.PREDICTING STUDENT PERFORMANCE

To forecast student performance, several studies employed various data mining approaches. Learning has been increasingly crucial to the advancement of our society in recent years. Learning is both a communal process and an individual behavior. A result evaluation system that helps instructors and students understand the shortcomings of the conventional classroom teaching model may be created with the use of data mining tools. Additionally, it will assist them in adapting to the present teaching realities and navigating the quickly changing real-life environment [11]. Investigating and effectively proposing models for assessing learning attempts that combine theory and practice is too time-consuming. The university's objectives are primarily to advance education by efficient instruction, research, anddispositions. Collections of randomly selected student work are examined and assessed by small groups of faculty teaching courses within some general education categories [12].

3. ORGANIZATION OF SYLLABUS

Maintaining a high-quality curriculum is crucial for educational institutions since it enhances the learning process overall and aids in resource optimization. A normal university student must finish a number of courses before graduating, and investigating subjects and their connections can directly help with better syllabi and offer insights into current educational program curricula in order to maximize students' learning capacity. Finding similar topics in the curricula of educational programs across a vast educational system is one use for data mining [13].

4. ERRONEOUS/ABNORMAL/VALUES IDENTIFICATION

A database's data may contain outliers, noise, or incomplete data objects, or unusual cases, which might complicate the entire analysis process and cause the data to be overfitted to the model's expertise. Consequently, the identified pattern might not be precise [14]. Identifying anomalous results in a student's result sheet is one use case for outlier analysis.

OUTCOMES AND CONVERSATION

Using prediction techniques, we can forecast the future enrollment of students at the University of Abuja, where they are enrolled in a program as seen in Figure 4.

Year Number of male Number of Female

2015	60	35
2016	50	30
2017	65	45
2018	55	30
2019	70	50
2020	80	?

In college of parli, student participation data in activities are used in assessing performance and the quality of
Student All the predictor and response variables which were derived from the database are given in the table 1.

Variables	Description	Values
Midterm	Midterm test	Excellent>=80
		Very Good >=65
		&< 80
		Good >=50 & < 65
		Acceptable >= 45 &
		< 50
		Fail < 45
LAB	LAB TEST	poor,average,good
ASS	Attempt Assignment	(Yes,No)
CP	Class Participation	(Yes,No)
SEM	Seminar performance	(Yes,No)
ATT	Student Attendance	(Poor, Average, Good)
FGS	Final Grade Scored	Excellent>=80 Very Good >=65 &< 80 Good >=50 & < 65 Acceptable >= 45 & < 50 Fail < 45
CD	Class of Degree	(Good, Acceptable)

Table 1 student variable Table

Student Id.	Midterm	LAB	ASS	CP	SEM	ATT	FGS	CD
001	Excellent	Good	Yes	Yes	Good	Good	Excelle nt	Good
002	Excellent	Good	Yes	No	Average	Good	Excelle nt	Accep table
003	Good	Good	No	Yes	Average	Avera ge	Very Good	Accep table
004	Excellent	Good	No	Yes	Good	Good	Excelle nt	Good
005	Excellent	Average	Yes	Yes	Good	Good	Excelle nt	Good
006	Very Good	Average	No	No	Good	Avera ge	Good	Accep table

Table 2: Student Participation Table

Set of Decision Rule Generated from table
IF Midterm="Excellent" AND LAB= „Good" AND CP="Yes"
AND SEM="Good" AND ATT= „Good" AND ASS="Yes" AND FGS="Excellent" THEN CD="Good"
IF Midterm="Excellent" AND LAB= „Good" AND CP= „NO" AND SEM="Average" AND ATT= „Good" AND ASS="Yes" AND FG ="Excellent" THEN CD="Acceptable" IF Midterm="Very Good" AND LAB= „Average" AND CP= „NO" AND SEM="Good" AND ATT= „Average" AND ASS="NO" AND FG ="Good" THEN CD="Acceptable"
A study was conducted to find the strongly related subjects in a course offered by the student of the college, to find this: association rule mining was used to identify possible related two subject combinations in the syllabi which also reduce the search space, then Pearson Correlation Coefficient was applied to determine the strength of the relationships of the identified subject combination.

Student Identity	**Course I**	**Course II**	**Course III**
001	Database design and management	programming I	programming II
002	Database design and management	programming I	programming II
003	Database design and management	programming I	programming II
004	Database design and management	programming I	Microprocessor
005	Database design and	programming I	Computer Networks

Table3 course table

optimize the syllabi of an educational programme The Outlier Analysis is used to detect an abnormal values

in the student‟s result sheet which may be due factors such human error, software malfunction, or xtraordinary
performance from the student in that course as shown in Table

Student id	Score1	Score2	Score3	Score4	Score5
1	35	40	35	45	30
2	65	64	60	71	75
3	90	85	79	80	75
4	50	48	55	50	57
5	35	30	45	40	98

Table 4: Student Scores

In the table shown above the result of the student in Score5 with student Id. 5 will be identified as an exceptional case and can be further analyzed for the cause.

Conclusion

There are many benefits to using data mining techniques in higher education institutions when it comes to decision-making. In this paper, we discussed the different data mining techniques that can support the educational system and demonstrated how they can be used to predict student performance and enrollment in programs, maintain academic program retention over time, and organize the institution's syllabus for the best use of available resources.

It may be claimed that the use of data mining in the education sector, particularly at institutions like universities, is highly beneficial, particularly when it comes to forecasting, categorizing, and developing plans for raising student achievement. In a similar vein, data mining may be used by colleges to forecast student enrollment in different courses. Based on the traits gathered, we may forecast students' course outcomes using approaches like the Decision Tree.

To forecast students' performance in class, decision tree classifiers are applied to student data. These methods will assist in determining which pupils are performing poorly and who are not attending class. This technology's primary discovery is the information gathered from pupils' academic achievement.

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