E-learning and COVID-19: Predicting Student Academic Performance Using Data Mining Algorithms

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Abstract

The satisfaction of E-learners has the main effect on the success of the E-learning process and leads to improvements in the E-learning system's quality and several factors affect this satisfaction. Based on the dimensions of e-learning, the main objective of this study was to evaluate the factors that contributed to students' satisfaction with e-learning during pandemic the Covid-19 and to give a thorough understanding and knowledge of different data mining techniques that have been used to predict student performance and development, as well as how these techniques help in the identification of the most relevant student attribute for prediction. Currently, to search for information in large databases, data mining techniques have become very popular and proven itis effective. Because of the performance and effectiveness of data mining techniques, it has been adopted by many areas such as telecommunication, education, sales management, banking, etc. In this paper, data mining algorithms were relied on to build e-learning classification models for a "student performance" data set, the proposed model includes 1000 instances with 35 attributes. Data mining algorithms have been implemented on the student performance data set in E-learning. Among these algorithms are the Decision Tree algorithm, Random Tree algorithm, Naive Bayes algorithm, Random Forest algorithm, REP Tree algorithm, Bagging algorithm and KNN algorithm. After comparing the results and conducting the assessment, the impact of the proposed features in e-learning on the student's performance was clarified. The final result of this study is important for providing greater insight into evaluating student performance in the COVID-19 pandemic and underscores the importance of data mining in education.

Keywords

E-learning, COVID-19, Data Mining, Attribute, Classification.

Introduction

The propagation of the Covid-19 virus has caused great stress among the worldwide population, in addition to disrupting education around the world. Here was the need to make fundamental changes in education for all students to get the best level of education, and one of the most important of these procedures is to give classes online (E-learning). Today under the current circumstances E-learning provides rich educational resources not only in order to complete educational requirements but to maintain communication between educational staff and students.Coinciding with the development of information technology, which had a rapid leap in the past decade with the instability of health conditions and new changes in line with the huge changes in the world, most universities have turned towards e-learning institutions at the global level tended to design and launch E-learning courses (Babolan, Kia, & Derakhshanffard, 2016; Esmaeeli, Rahmani, Kazemi, & Ali Ahmadi, 2016). For the development of any country, the educational system must be taken seriously. Each country has its educational system and evaluation criteria after the multiplicity of education sources to include (smart education system, project-based learning, online education, MOOC course, seminars, web-based education, etc.). However, if not accurately evaluated, not all of these systems will succeed. As a result, a well-defined assessment system is maintained to ensure the success of any educational institution. Each educational institution creates a large amount of data on each student while registering, and if that data is not correctly analyzed, all resources will be wasted, and no future use of data will occur (Salal, Abdullaev, & Kumar, 2019).

Currently, the scope of data mining has covered many areas. All organizations benefit from using data mining to increase their revenue and growth. Here, this technique analyzes the old data of any organization using some algorithm and then finds the hidden information inside the big databases especially from those that are not usually identified. Due to a large amount of student data, predicting a student's academic success is one of the most difficult challenges in the education sector (Kumar, Singh, & Handa, 2017).

Now we need a framework that allows for analysis and monitoring of a student's performance, particularly in the educational system. For evaluating student success, each institution has its own set of criteria. A comprehensive strategy to forecasting student performance using data mining techniques is suggested to better understand the situation. The main objective of this paper is to build e-learning classification models for a "student performance" data set depending on data mining approaches that have been used to forecast student development and performance, as well as how these techniques to aid in the identification of the most relevant student qualities for prediction. This work is to offer a thorough examination of a student performance dataset through the development of a classification model. WEKA data mining tools are being used for this research. It includes a diverse set of data mining techniques for categorizing and evaluating data. All creation and testing of classifying models will follow the data mining method to achieve the highest level of prediction accuracy.

Literature Review

During the Covid-19 pandemic and with the development of the Internet and the World Wide Web, the possibility for students all over the world to get access to information has exploded. The goal of these online classes is to educate students on a variety of topics (E-learning), also, universities embraced digital media to make student instruction simpler all over the world (Kaur, Dwivedi, Arora, & Gandhi, 2020; Prober & Heath, 2012). Despite the great scope of E-learning, students may choose to drop out of school or be irresolute to continue; consequently, it is important to identify factors in order to accept it and urge the students to continue their education. Among the factors, satisfaction is a critical component and a significant indication of educational quality (Poortavakoli, Alinejad, & Daneshmand, 2020). The satisfaction with e-learning is affected by a number of factors in (Paechter, Maier, & Macher, 2010) the authors refer to flexibility, structure, instructor experiences and support, motivation, and communication are some of the elements that contribute to E-learning significant.

In the literature, there are several definitions of student academic performance prediction and for assessing student performance, several authors use different attributes and factors. As prediction criteria, most of the authors depend on CGPA, extracurricular activities, internal evaluation and examination final score. Internal assessment, laboratory file work, external assessment, viva-voce, and sessional test are all factors that influence a student's final mark. According to (Bin Mat, Buniyamin, Arsad, & Kassim, 2013) the authors suggest the number of grades a student receives on the final examination determines his or her performance, and they explained: "what are the implications of academic analytics for an educational institution". In (Sarker, Tiropanis, & Davis, 2013) the author showed that using both institutional external data sources (EDS) and internal data sources (IDS) generate better results than using just institutional internal student’s databases.

According to (Abu Tair & El-Halees, 2012; Ahmad, Ismail, & Aziz, 2015; Al-Barrak & Al-Razgan, 2015; Azwa & Fadhilah, 2014; Goga, Kuyoro, & Goga, 2015; Kolo & Adepoju, 2015; Koutina & Kermanidis, 2011; Osmanbegovic & Suljic, 2012; Pandey & Taruna, 2016) the significant personal attributes of the student are taken into consideration, such as age, gender, admission type, interest in the study and study behaviour. In (Abu Tair & El-Halees, 2012) Family attributes such as employment, parent's education, family status, family income and family support for study are also taken into consideration. Whereas in (Angeline, 2013; Asif, Merceron, & Pathan, 2014; Sumitha, Vinothkumar, & Scholar, 2016) academic attributes of the student are taken into consideration such as previous semester marks, high school grade, seminar performance, attendance in class, lab work, class test grade and assignment performance. In (Sarker et al., 2013) institutional attributes of the student are taken into consideration such as accommodation type, teaching methodology, medium of teaching and transportation facilities. After reviewing many of study papers, we found that in the majority of situations, student variables that influence student academic performance prediction are: high school grade, gender, student's parental education, living location, financial background, medium of teaching, students' previous semester marks, student's family status, class test grade, assignment performance, attendance in class and lab work, Study behaviour, parent's occupation and et al. All of these attributes are divided into several categories, including familial, personal, academic, social and institutional. Based on the dimensions of e-learning, research was undertaken to evaluate the elements linked to students' contentment with e-learning during the Covid-19. There was a strong link between satisfaction with e-learning and gender and history of taking online classes before the coronavirus, according to the findings. Female students and students who had previously taken online classes before Covid-19 had greater levels of satisfaction with e-learning. However, other studies such as (Kaur et al., 2020) found that just the age element influenced satisfaction with holding e-learning. The use of Data Mining methods in educational field research has exploded. The goal of educational data mining is to uncover hidden patterns and information regarding student performance. The prediction for a student's academic performance is common in the field of educational data mining. To construct a predictive model, we must take several data mining approaches such as clustering, classification, regression analysis and association rule mining. For predicting student academic performance in almost each research paper only a classification algorithm is taken into consideration. There are several classifications approaches for prediction accessible such as (Decision Tree algorithm, Random Tree algorithm, Naive Bayes algorithm, Random Forest algorithm, REP Tree algorithm, Bagging, KNN algorithm) (Kumar et al., 2017).

Data Exploration for Dataset of Students Performance in E-Learning

The performance dataset particular students were collected from three secondary schools of Iraq. The dataset includes attributes suggested about the students, such as their age, gender, academic grades and et al, our data set includes 1120 instances, a number of questionnaires were excluded because they didn't meet the conditions, so it became the final number1000 instances with 35 attributes. Table 1 shows the details for this Dataset.

Table 1 Description of the student's attributes that were used to create the dataset

NO	ATTRIBUTE	CHARACTERIZE	FACTORS	PROBABLE VALUE
1	age	Age of the student	numeric	age
2	F.size	Family size of the student	numeric	3,4,5,6,7,8
3	Gender	Sex of the student	binary	M, F
4	M.edu	Mother Qualification	numeric	0, 1, 2, 3, 4
5	F.edu	Father Qualification	numeric	0, 1, 2, 3, 4
6	F.job	Job type of the Father	nominal	Employee, free business, home, other
7	M.job	Job type of the Mother	nominal	Employee, free business, home, other
8	P.status	parent's cohabit	binary	A, T
9	Reason	Reason to desire this school	nominal	Reputation,Home, course, other
10	F.sup	family study support	binary	No, Yes
11	Guardian	Guardian of the student	nominal	Father,Mother, other
12	School sup	Extra study support	binary	Yes, no
13	Failures	No's of past class failures	numeric	n When (1<=n<3); else (4)
14	Study time	Weekly study time	numeric	1, 2, 3, 4
15	Travel time	Home to school travel time	numeric	1, 2, 3, 4
16	Paid	Extra paid classes	binary	No, Yes
17	Nursery	Attended nursery school	binary	No, Yes
18	Activities	Extra-curricular activities	binary	No, Yes
19	Internet	Internet at home	binary	No, Yes
20	F.rel	Family relation	numeric	1, 2, 3, 4, 5
21	S.level	Satisfaction level of education	numeric	0 to 10
22	Free time	Free time after school	numeric	1, 2, 3, 4, 5
23	Health	Current health status	numeric	1, 2, 3, 4, 5
24	Absences	School absenteeism	numeric	0 to 100
25	Go out	Going out with friends	numeric	1, 2, 3, 4, 5
26	Higher	Wants higher study	binary	No, Yes
27	Probability	Probability of graduated on time	numeric	0,25,50,75,100
28	AAT	Academic Aptitude Test score	numeric	0,25,50,75,100
29	EEs	Entrance Examination score	numeric	0,25,50,75,100
30	AE	Annual Evaluation	numeric	0,25,50,75,100
31	School	School of student	binary	middle, secondary
32	G1	First term grade	numeric	0 to 10
33	G2	Second term grade	numeric	0 to 10
34	G3	Third term grade	numeric	0 to 10
35	G4	Final grade	numeric	0 to 10

A three-part questionnaire was used to collect data:

A) **Demographic Information:** including Age of the student, Family size of the student, gender of the student, Mother Qualification, Father Qualification, Father Job, Mother Job, parents cohabit, Reason to desire this school, family study support, Guardian of the student.

B) **To measure the Feasibility and Effectiveness of E-learning:** the data of databases were searched, examined and mention the basic elements of E-learning: Extra-curricular activities, Internet at home, Family relation, Satisfaction level of education, Free time after school, Current health status, School absenteeism, Weekly study time, Annual Evaluation, Teaching-learning activities and Evaluation methods.

C) **Measuring student satisfaction with conducting E-learning:** According to studies conducted in (Kaur et al., 2020) the researchers was used, including only 7 questions and this tool's rating scale was a 5-point Likert scale, so that the score 5 was assigned to the much-satisfied option and in this study, the dependability was validated by assigning a score of 1 to those who are dissatisfied. In our study, we relied on the evaluation scores of Extra study support, No's of past class failures, Satisfaction level of education, wants higher study, Probability of graduating on time, Academic Aptitude Test score, Entrance Examination score and Final grade.

We used the WEKA toolset for the analysis, which is free to use and comes with a number of supporting algorithms for clustering, classification, and association rule mining. After that, we use the pre-process function to import our dataset. The process of a data mining model for classification is depicted in Figure 1 the data mining model is depicted as a flowchart. The educational data is initially subjected to feature choices algorithms. The next step is to apply classification algorithms to create a good model that can accurately translate inputs to desired outputs. The model assessment phase feeds back to the attributes selection and learning stages, allowing them to make changes to enhance classification performance. After a model is created, it is utilized to predict the label of new student data in the second phase.

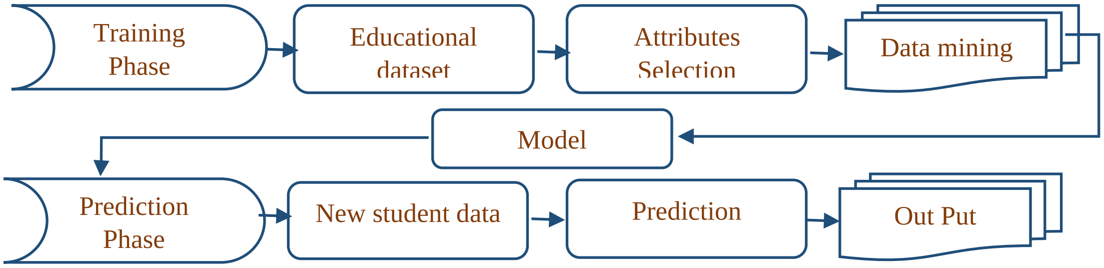

Figure 1 Data mining model

Student Performance Dataset Classification Models

We applied several classification algorithms on student performance datasets by choosing various parameters of the algorithms that most efficiently analyze the dataset and enhance their generalized reliability to discover optimal classifiers that generalize the data with higher accuracy. Here, to calculate algorithms accuracy, that the accuracy of all implemented classification methods is tested and calculated by using 15-fold cross-validation. The student's performance dataset was used to test a variety of classification methods. The many classification algorithms that are in use are (Decision Tree algorithm, Random Tree algorithm, Naive Bayes algorithm, Random Forest algorithm, REP Tree algorithm, Bagging algorithm and KNN algorithm). The maximum and minimum accuracy for predicting student's performance in algorithms are between 96.8 % and 58.0%. Table 2 explained student academic performance prediction in E-learning during the Covid-19 for different classification algorithms with their accuracy. Also, there is a framework for student academic performance prediction in E-learning during Covid-19 as shown in Figure 2.

Table 2 Student academic performance prediction in E-learning during Covid-19

Data Mining Techniques have been taken for implementation	Decision Tree	Random Tree	Naive Bayes	Random Forest	REP Tree	Bagging	KNN
Highest Accuracy with all attributes	87.8%	84.2%	89.9%	77.9%	76.7 %	89.5%	96.8%
Lowest Accuracy with all attributes	67.9%	58.6%	65.5%	65.7%	58%	59.9%	77%

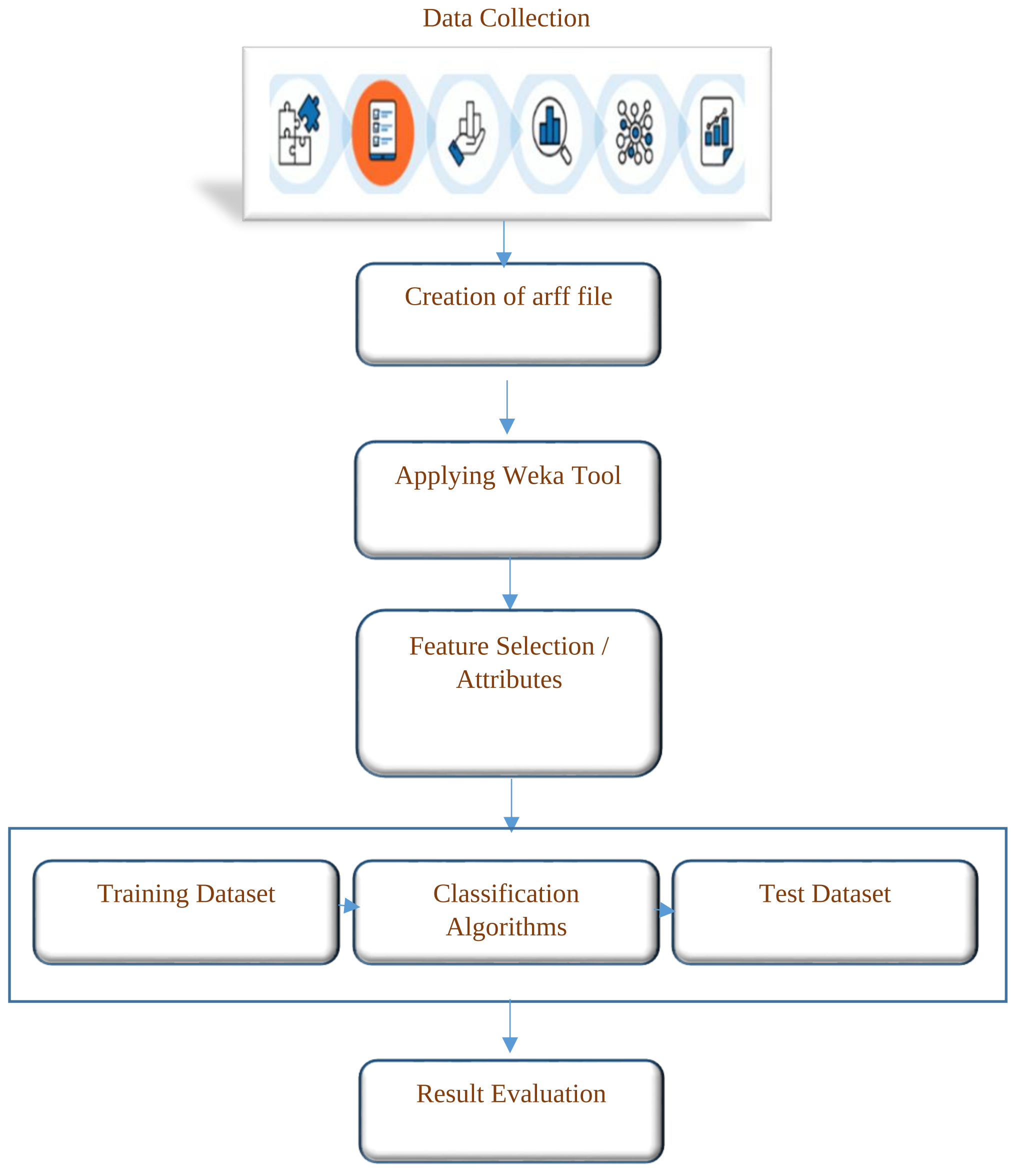

Figure 2 Framework for Student Academic Performance Prediction in E-learning

As mentioned previously, relied upon the WEKA tool for standard classifier's model building, also we use the "Ranker Search Method" to find the best attribute from the student's performance dataset. We are testing three various attribute evaluator using Ranker Search Method: Info Gain Attribute Eval, Gain Ratio Attribute Eval and Correlation Attribute Eval. In Table 3, the result of the whole procedure that was applied to the student dataset, after determining the result of the attribute evaluator algorithm implementation.

Table 3 Attribute Selection from the dataset of Students Performance with the help of Ranker Search Method

Attribute Evaluator		Attribute order of Ranker
1	Gain Attribute Eval	35,34,31,1,5,2,3,4,33, 32,23, 24,19,13, 16,6,7,8,9, 30,10,11,12,25,17,14, 18,15,20,21,22,26,27,28,29
2	Gain Ratio Attribute Eval	32,35,34,33,27,13,4, 21,7,19,12,11,31,23,1,30,8, 29,28,6,22,2,25,9,16,18,26,20,24,10,5,15,3,17,14
3	Correlation Attribute Eval	35,34,32,33,31,30,26, 19,27,13,5,1,21,20,2,23,4, 17, 18,16,28,15,14,11,29,12,10,9,7,24,25,8,6,3,22

Model Selection for Dataset of Students Performance in E-Learning and Discuss the Predicting Student's

The accuracy of classification algorithms with parameter change is changed as shown in table 4. In the implementation **Decision Tree Classification Algorithm,** when we experimented with whole 35 attributes, this algorithm showed 87.8% as the highest accuracy and 67.9% as the lowest accuracy as shown in Table 2. When we put Kernel Estimator parameter as false and Upervised Discretization parameter as true and we choose only ten most significant attributes, also to improve the prediction accuracy minNumObj is put as 5 and binary Splits as true the accuracy in this algorithm increased to 90.8% that means the accuracy increased up to 3%. In implementation **Random Tree Classification Algorithm**, when we experimented with whole 35 attributes, this algorithm showed 84.2% as the highest accuracy and 58.6% as the lowest accuracy as shown in Table 2. When we put Kbatch Size is set to 230 and we choose only the ten most significant attributes the accuracy in this algorithm increased to 88.9% that meaning the accuracy increased up to 4.7%. In implementation **Naive Bayes Classification Algorithm**, when we experimented with the whole 35 attributes, this algorithm showed 89.9% as the highest accuracy and 65.5% as the lowest accuracy as shown in Table 2. When we put the Kernel Estimator parameter as false and the Supervised Discretization parameter as true and we choice only the ten most significant attributes the accuracy in this algorithm increased to 92.8% that meaning the accuracy increased up to 2.9%. In implementation **Random Forest Classification Algorithm,** when we experimented with whole 35 attributes, this algorithm showed 77.9% as the highest Accuracy and 65.7% as the lowest accuracy as shown in Table 2. When we choose only the ten most significant attributes the accuracy in this algorithm increased to 80.8% that means the accuracy increased up to 2.9%. In implementation **REP Tree Classification Algorithm**, when we experimented with the whole 35 attributes, this algorithm showed 76.7% as the highest accuracy and 58% as the lowest accuracy as shown in Table 2. When we put batch Size is set to 250, Supervised Discretization parameter as true, numDecimalPlaces value as 3, unfolds value as 5 and we choose only ten most significant attributes the accuracy in this algorithm increased to 82.8% that means the accuracy increased up to 6.1%. In implementation **Bagging Classification Algorithm**, when we experimented with the whole 35 attributes, this algorithm showed 89.5% as the highest accuracy and 59.9% as the lowest accuracy as shown in Table 2. When we put the Kernel Estimator parameter as false and Upervised Discretization parameter as true and we choose only the ten most significant attributes the accuracy in this algorithm increased to 92.8% that meaning the accuracy increased up to 3.3%. In implementation **KNN Classification Algorithm** when we experimented with the whole 35 attributes, this Algorithm showed 96.8% as the highest Accuracy and 77% as the lowest Accuracy as shown in Table 2. Previous studies(Narimani, Zamani, & Asemi, 2015) (Narimani et al., 2015) from 2012 to 2015 proved the reliability and accuracy of prediction based on an algorithm KNN which reached 100%. These algorithms when improving the prediction accuracy, it reached the highest value100%. Figure3 shows the accuracy of prediction student performance using a classification technique categorized by algorithms in data mining.

Table 4 The accuracy of classification algorithms with change parameter in E-learning

Data Mining Techniques taken for implementation	Decision Tree	Random Tree	Naive Bayes	Random Forest	REP Tree	Bagging	KNN
New Accuracy	90.8%	88.9%	92.8%	80.8%	82.8%	92.8%	100%

We may conclude from the above depiction of all implemented algorithms in table 4 that all classification algorithms perform well with a little margin in overall prediction accuracy. From the seven algorithms, four classification algorithms for predicting student results the accuracy increased more than 90% and it is working very well unlike the rest of the algorithms. From our implementation result, the KNN classification algorithms performed fully and best than the other classification algorithms, and accuracy for these algorithms which is reached 100%. As we mentioned before, we depend on the WEKA tool to implement all algorithms.

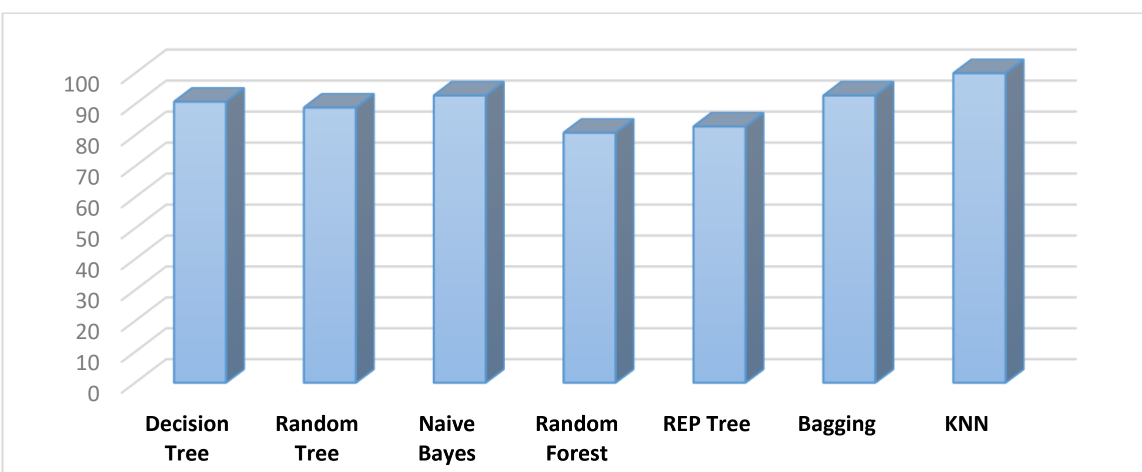

Figure 3 The accuracy of prediction student performance using a classification technique

While conducting statistics to evaluate the effectiveness of education, a great discrepancy was found in the differences in the statistical population for research and use of different tools, the reason for this discrepancy, Females consent to e-learning since their limitations do not hinder them from accessing many sciences. Furthermore, the findings indicated that 39% of them were dissatisfied. At the time of Covid-19, the use of online classes was effective in terms of communication, assisting in the development of skills and knowledge, and providing a better understanding through recorded classes, sending assignments and Q&A sessions, but had little effect on other parameters, indicating dissatisfaction with e-learning participation. There are several factors such as a lack of various types of e-learning, instructors' lack of knowledge with e-learning technology, insufficient facilities, including insufficiency of the number of students with hardware facilities, and a lack of a suitable atmosphere to utilize the virtual courses, as a result, Incomplete presentations and, ultimately, students' lack of familiarity with computers and the internet, particularly among lower-semester students, might contribute to student discontent. Moreover, the students' mean satisfaction with e-learning was 61%, according to the findings. Furthermore, 610 students (61%) expressed positive satisfaction, whereas 390 students (39%) undesirable satisfaction and is not a small percentage. By using the WEKA tool to find out the most important factors that affect the student's performance among the 35 proposed factors according to Table 1, it is very much apparent that attributes (4,5,8,10,13,14,16,19,22,23,26,27,29,30 and 35) are the most significant attributes. The current study's findings revealed students' dissatisfaction with e-learning during the Covid-19 era.

At present, in addition to students' satisfaction and dissatisfaction with e-learning, the scientific community is very interested in educational data mining. Because it is most beneficial for educators, management, and educational policymakers to forecast student academic achievement, educational dropout in the future, and institute placement and admission in a new academic year. It is also utilized at the institution to improve the teaching-learning process. This paper looked at a number of research articles, including one on forecasting student academic achievement using a specified characteristic and an analytical method. In most situations, the student's internal academic grades are key factors in predicting the outcome. In one of the study papers, they can predict with 100% accuracy, the authors found that using a combination of diverse variables such as age, gender, marital status, occupation, bachelor, computer-related job, computer literacy, and bachelor in informatics. When it case to data mining prediction, classification is a common method. Finally, we conclude that the meta-analysis on predicting student academic achievement inspired us to do more study in our educational setting. It would greatly aid in the improvement of our educational system by allowing us to monitor student performance regularly.

Conclusion

The world recently witnessed an outbreak of Covid-19 disease, which led to a major crisis worldwide. Among the groups affected by the restrictions imposed by the Covid-19 virus are students, with the development of information technology, most educational institutions and universities have published courses on the use of e-learning and how to help students to obtain the best level of education. In this study, data mining algorithms were relied on to build e-learning classification models for a "student performance" data set, the proposed model includes 1000 instances with 35 attributes. Data mining algorithms have been implemented on the student performance data set in E-learning. Three types of questionnaires were used to collect data and we used the WEKA toolset for the analysis of this dataset.

The students' mean satisfaction with e-learning was 61%, according to the findings. Furthermore, 610 students (61%) expressed positive satisfaction, whereas 390 students (39%) undesirable satisfaction, the most important factors that affect the student's performance among the 35 proposed factors according to Table 1, it is very much apparent that attributes (4,5,8,10,13,14,16,19,22,23,26,27,29,30 and 35) are the most significant attributes. Because of the ubiquity of Covid-19, distant education may be held for a long period, efforts should be made to improve the quality of e-learning and the variables impacting it. The quality of education and the degree of knowledge of pupils might be harmed if these instances are not addressed. As a result, they are less satisfied with e-learning in general and with the e-learning system in particular. As a result of the poor satisfaction with e-learning, the ideal training technique is combination training, which should be begun as soon as the situation returns to normal because it will lead to the development of professional skills and an improvement in training quality. The need for efforts to increase the level of knowledge of students in this sector depends on their wants and aspirations is felt in order to provide a suitable platform for the creation and growth of e-learning. Designing training programs, such as workshops, to improve awareness and the capacity to use e-learning as an effective training tool, as well as increasing the quality of hardware, are proposed as ways to do this.

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