A prediction system using AI techniques to predict Students' learning difficulties using LMS for sustainable development at KFU

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Abstract

With the emergence of the covid 19 pandemic, E-learning usage was the only way to solve the problem of study interruption in educational institutions and universities. Therefore, this field reserved significant attention in current times. In this paper, we used ten Machine Learning (ML) algorithms: Decision Tree(DT), Random Forest(RF), Logistic Regression(LR), SGD Classifier, Multinomial NB, K- Nearest Neighbors Classifier(KNN), Ridge Classifier, Nearest Centroid, Complement NB and Bernoulli NB) to build a prediction system based on artificial intelligence techniques to predict the difficulties students face in using the e-learning management system, to support related decision-making. Which, in turn, contributes supporting the sustainable development of technology at the university. From the results obtained, we detect the important factors that affect the use of E-learning to solve students' learning difficulties using LMS by building a prediction system based on AI techniques.

Practitioner Notes

What is already known about this topic?

- E-learning and its systems (learning management systems LMS), have become standard tools in universities, and the fast development of information and communications technologies (ICTs) and their application to education has support this possible.
- Despite the great benefits of using LMS, there are many problems encountered in achieving learning goals, the most important of which is increasing student performance rates.
- Prediction of student's performance by classifying their data is an important topic in the education field, by using Machine learning algorithms to recognize learners’ learning is common in the environment of education.

What this paper adds:

- There is a small but steadily increasing contribution to the field from authors affiliated to apply machine learning researches in their institutions.
- With the emergence of the Covid-19 pandemic and the need to adhere to precautionary measures and social distancing, the use of e-learning has become the best option to ensure the continuity of study. Therefore, this field has recently reserved significant attention.
- This paper aims to build a prediction model to determine the difficulties students might face in using the e-learning management system. Ten well defined machine leaning (ML) algorithms are used in this paper. These algorithm namely are (Decision Tree (DT), Random Forest (RF), Logistic Regression(LR), SGD Classifier, Multinomial NB, K-Neighbors Classifier, Ridge Classifier, Nearest Centroid, Complement NB and Bernoulli NB).
- The experimental investigations are conducted using data set of students who studied fully online at King Faisal University during Covid-19 pandemic.

Implications for practice and/or policy:

- The field does have a beginning but significant research output. This could be proof that Learning Analytics should be acknowledged as a study line by research support institutions in Arab countries.
- Educational institutions and universities should provide data to data analysis experts with easy restrictions and expand the application of expert systems in analyzing their data to benefit from them in decision-making.
- Courses related to data science analysis, artificial intelligence techniques, and machine learning should be taught within the curriculum.

Introduction

Many students, particularly university students, have problems with learning as a result of numerous causes, the most prominent of which is difficulty in using the tools of LMS, which has resulted in a marked deficiency in their academic performance. This motivated us in this research to use AI techniques to reach a prediction for the difficulties that students may face in their use of the tools of LMS, and to help decision-makers to take the appropriate decision to avoid these difficulties from occurring early.

A long time ago, researchers have used applications of Artificial Intelligence (AI) to solve many problems of learning environments and teaching. AI, some defined it as machine intelligence, is one of the famous computer science branches that aims to provide software with the capability to make analyzing of its environment, by using both specific rules and algorithms of search, or style of recognizing ML models, and then support decision maker to take decisions according to those analyses. (B.J. Copeland, 2019).

E-learning and its systems (learning management systems LMS), have become standard tools in universities, and the fast development of information and communications technologies (ICTs) and their application to education has support this possible. Despite the great benefits of using LMS, there are many problems encountered in achieving learning goals, the most important of which is increasing student performance rates. Prediction of student's performance by classifying their data is an important topic in the education field, by using ML algorithms to recognize learners' learning is common in the environment of education. (Ko & Leu, 2020).

Educational Data Mining defined as a process of classification and analyzing educational data by using data mining methods, such as ML algorithms, to reach results that support educational institutions to make a decision.(Ghorbani & Ghousi, 2020).

In this paper, we used educational data from Deanship of E-learning and Distance Education of King Faisal University (KFU) in Saudi Aribia to provide datasets for prediction. The list of data resources for our research as follows, the dataset of students who studied full Online and used Blackboard (LSM) to learn. Then we compared the performance of ten ML algorithms, which are DT, RF, LR, SGD Classifier, Multinomial NB, KNN-Neighbors Classifier, Ridge Classifier, Nearest Centroid, Complement NB and Bernoulli NB, to reach the best technique for prediction, and then we extracted the most important features affecting students' performance.

This paper is organized as follows: section ii shows a related work study, section iii explains the machine learning algorithms used in this paper, section iv the dataset description is introduced, in section v we describe our methodology, in section vii data engineerineg partitioning and cleaning is explained, section viii shows the performance evaluation techniques uesed, section ix shows the expermental results and finally in setion x we introduce the conclusion.

Related Work

The research used ML algorithms to predict Students' learning difficulties using LMS, while many researches used it to predict students's performance. (Jayaprakash et al., 2020), concentrate on the students which fall in risk, built a model used Random Forest, Naïve Bayes and other algorithms, which sorted the attributes, to use as a temporary or the mechanism of early warning which helpe to improve the performance of students. They concluded that personal attributes like family size, parental status, gender, parents upbringing, maternal and paternal function, are the basic factors that can make negative affect of student performance. (Kime et al., 2019), used Interactive machine learning to classify students 'skills in calculus. They reached to use machine techniques by classifying skills and predicting the skills which added by expert teacher to improve the performance of his students.

(Bajpai et al., 2019), compared several machine learning algorithms to choose the most appropriate and efficient algorithm to predict researchers' academic performance. They reached to there are some ML algorithms were easy to understand, another were weighty, and another may take long time in computation. (Hussain et al., 2018), used some of the machine learning algorithms to predict the most beneficial e-learning sessions for students. They found that the DL and Random Forest algorithms are proper for predicting useful sessions through e learning, and they reached from the prediction results to factors that affect the effectiveness of sessions like environment of study, commitment of family, and style of teach.

(Athani et al., 2017), proposed prediction system using SVM algorithm. The results showed that SVM algorithm predicted students performance and provide departments of institution, information of student status, and thus supply students with appropriate additional educational tasks that help them to improve their academic performance. (Sorour et al., 2014), used SVM algorithm and

ANN algorithm to predict students' scores according to their comments, and the results showed that prediction accuracy when using SVM was higher than prediction accuracy when using ANN.

Machine Learning

There are many Data Mining classification algorithms(classifier), however, our choices in this paper are these 10 well-known ones because of their critical features, which we briefly describe in the next paragraphs:

1-Logistics Regression (LR)

LR is a statistical analysis approach for predicting a data value based on previous data set observations. The method allows a machine learning application's algorithm to classify incoming input using previous data.

LR model forecasts a dependent data variable by examining the relationship between one or more pre-existing independent variables. The resulting analytical model can take into account a variety of input criteria. Based on historical data about earlier outcomes involving the same input criteria, it then scores new cases on their probability of falling into a particular outcome category. LR is a supervised algorithm that involve more dependent features, LR is a linear model which is used to approximate the relationship between variables by using a logistic function(Peng et al., 2002).

2-K-Nearest Neighbor (KNN)

KNN algorithm is a data classification algorithm that looks at the data points around it to determine which group a data point belongs to. The range is arbitrary, but the goal is to take a sample of the data. This makes k-nn very easy to implement for data mining. KNN select the nearest K neighbors of x_0 and uses a plurality vote to decide the class mark of x_0 , Euclidean distances is applied as a distance metric, without prior knowledge and classes importance are equal (Song et al., 2007).

3-Decision Tree (DT)

DT is a supervised learning technique with a predefined target variable that is commonly used in classification problems. Each internal node represents a test of an attribute, each branch represents the result of that test, and each leaf node contains a class label. The root node is the node at the top of the tree. The dataset is split into smaller subsets.With the highest degree of accuracy, these smaller data sets can make prediction. Decision tree method includes C4.5, CART, conditional tree, and C5.0 (Sharma & Kumar, 2016).

4-Naive Bayes Algorithm (NB)

Spam filters, text analysis, and medical diagnosis are all common applications for Naive Bayes classifiers. To classify data, a Naive Bayes classifier employs probability theory. The Bayes theorem is used by naive Bayes classifier algorithms. The key insight of Bayes' theorem is that as new data is introduced, the probability of an event can be adjusted. The assumption that all attributes of a data point under consideration are independent of each other is what makes a naive Bayes classifier naive. A classifier sorting fruits into apples and oranges would recognise that apples are red, round, and of a certain size, but would not assume all of these characteristics at the same time.

NB is used to compute the probability using Bayesian theory, It provides simplest implementation and little training time with highest accuracy while computing the probabilities of noisy data. NB method includes Multinomial NB, Bernoulli NB, and Complement NB (Wu et al., 2015).

5-Random Forest (RF)

RF is a machine learning data construct that generates a large number of random decision trees by analysing sets of variables. Engineers build random decision trees in a random forest to more carefully isolate knowledge from data mining, using different variable arrays. For example, if five random trees from a subset provide information on the same variable and four of them agree, the machine learning algorithm may use that «majority vote» to build probabilistic models.

There are many decision trees in the random forest algorithm, each tree is built by samples with randomly sampled features. The decision is carried out by applying the majority voting on the decision trees, which is a successful method for merge unsteady learners with random tree selection variable (Breiman, 2001).

6-Stochastic Gradient Descent (SGD)

The method of stochastic gradient descent SGD is used to find the best parameter configuration for a machine learning algorithm. It iteratively makes small changes to a machine learning network configuration to reduce network error. Stochastic gradient descent seeks the global minimum by adjusting the network's configuration after each training point. Instead of reducing the error or determining the gradient for the entire data set, this method merely reduces the error by approximating the gradient for a randomly chosen batch.

SGD is an iterative technique for optimizing an objective function with appropriate (e.g. differentiable or sub-differentiable) smoothness properties, the method uses shuffled samples to evaluate the gradients, hence it can be considered as a stochastic approximation of gradient descent optimization (Sathyadevan & Chaitra, 2015).

7-Ridge Classifier

Ridge regression is a model tuning technique for multicollinear data analysis. This approach is used to accomplish L2 regularisation. When there is a multicollinearity problem, least-squares is unbiased, and variances are significant, resulting in projected values that are far from the actual values. This is a ridge regression-trained linear classifier: The scores are translated to estimated class labels using the winner-take-all approach, and the class labels (K) are encoded in a one-of-K scheme. (Peng et al., 2002).

8-Nearest Centroid

A nearest centroid classifier, also known as a nearest prototype classifier, is a machine learning classification model that assigns to observations the label of the class of training samples whose mean (centroid) is closest to the observation. A classification model that assigns the output label of the training samples' class to observations with the closest centroid (mean) to the observation (Kiranmayee et al., 2012).

Dataset Description

The dataset was collected from the Deanship of King Faisal University, and the data represents a sample of university students who used the e-learning system in the second semester of the acadmic year 2019/2020, and due to the Covid19 pandemic, the term was completely online. The dataset contains 500 records with 10 features for each student. Table 1 shows the feature name, values, and description.

Table 1. Dataset features description.

	Feature	Values	Description
1	Gender	M/F	student's gender
2	Level	L-01, L-02, L-03, L-04	Level student belongs
3	Section	A,B,C	Section student belongs
4	Raised Hands	integer(0 : 100)	The number of times the student requested to speak in the lecture
5	Visited_Resources	integer(0 : 100)	The number of times a student access the contents of a course
6	Announcements_View	integer(0 : 100)	The number of times the student inspections the new announcements
7	Discussion	integer(0 : 100)	The number of times the student is participating in discussion groups
8	Acadimc_Adivsor_Satisfaction	good, bad	the Degree of Acadimc Adivsor satisfaction from student performance
9	Absence_Days	above-7, under-7	The number of days the student is absent
10	Topic	English, Programmimg, Calculus, Arabic, IT, Math, Chemistry, Biology, Physics, History, Quran, Geology	course topic

The predicted feature is the student level (class) which will be used to extract features representing learning difficulties, Table 2 shows the level distribution over the level High (H), Medium (M), and Low (L)

Table 2. Distribution of students to levels

	Frequency	Percent
Hight	152	30.4
Low	127	25.4
Midum	221	44.2
Total	**500**	**100.0**

Table 3 show a few sample from the collected dataset

Table 3 : sample from the collected datset.

Gender	Level	Section	Raised Hands	Visited Resources	Announcements View	Discussion	Acadimc_Adivsor Satisfaction	Absence Days	Class
M	L-01	A	5	1	0	11	Bad	Above-7	L
M	L-04	A	20	14	12	19	Bad	Above-7	L
F	L-04	A	62	70	44	60	Bad	Above-7	H
M	L-01	A	30	25	5	35	Bad	Above-7	L
M	L-01	A	40	50	12	50	Bad	Above-7	M
F	L-01	A	42	30	13	70	Bad	Above-7	M
F	L-03	A	33	33	30	90	Bad	Under-7	M
M	L-03	A	20	12	15	70	Good	Above-7	L
M	L-01	A	7	10	1	30	Bad	Above-7	L
F	L-04	A	70	4	39	90	Good	Under-7	H
F	L-04	A	13	80	40	88	Good	Under-7	H
F	L-02	A	49	70	19	75	Good	Under-7	H
M	L-04	A	12	50	8	30	Bad	Above-7	L
M	L-03	A	16	14	6	20	Good	Above-7	L
M	L-04	B	19	5	4	1	Good	Above-7	L

Methodology

The classification technique is applied to predict the performance of students as a tool commonly used in prediction, The classifiers used in this paper are based on the algorithms commonly used in the literature. The steps of the student performance prediction are summarized in Figure 1.

VI-DATA TRANSFORMATION

Data transformation is a critical step for eliminating inconsistencies in the dataset, this makes it more appropriate for data mining (Osborne, 2003).

Convert string to numeric variables: Most Data Mining algorithms work only on the numeric variable. Therefore, non-numerical data must be converted into numerical variables, the most common methods are encode string using a value between [0 and (N-1)] where N is the number of values. For example, the gender feature (F/M) is encoded to 0 and 1.

VII-DATA PARTITIONING

The dataset is to divide the data set into two sections of training data and test data. Test data represent the smallest portion of the dataset and used for classifier testing. The test data are used to assess the output of the classifier (Han et al., 2012), in our experiments we use 80% for training and 20 % for testing.

VIII-PERFORMANCE EVALUATION

In our experiments the performance of the classification algorithms is determined, four standanard evaluation metrics are used to evaluate the performance namely : accuracy, recall, precision, and f-score, and they are defined as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (2)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (3)$$

$$F1 = \frac{(2 \times Precision \times Recall)}{(Precision + Recall)} \quad (4)$$

where FN, FP ,TP,TN, and refer to False Negative respectively, False Positive, True Positive, and True Negative, and (Alyahyan & Düştegör, 2020).

Results

- **TEST CLASSIFIERS**

To determine the best classifier in predicting the student performance in the dataset, we examine 10 Machine learning classifier namely: Decision Tree, Logistic Regression, Random Forest, SGD Classifier, K-Neighbors Classifier, Ridge Classifier, Nearest Centroid, Complement NB, and BernoulliNB, the result is shown in table 4.

Table 4: Classifiers performance comparisons

	Classifier	**Accuracy**	**F1_score**	**Recall**	**Precision**
1	Logistic Regression	0.719	0.716	0.719	0.726
2	Decision Tree	0.781	0.781	0.781	0.786
3	**Random Forest**	**0.844**	**0.842**	**0.844**	**0.842**
4	SGD Classifier	0.573	0.478	0.573	0.492
5	Multinomial NB	0.583	0.580	0.583	0.591
6	K-Neighbors Classifier	0.646	0.642	0.646	0.656
7	Ridge Classifier	0.677	0.667	0.677	0.686
8	Nearest Centroid	0.677	0.660	0.677	0.747
9	Complement NB	0.438	0.334	0.438	0.709
10	BernoulliNB	0.667	0.666	0.667	0.668

From the previous table, Random Forest gives the best performance with accuracy, F1_score, Recall, and Precision equal to 0.844, 0.842, 0.844, and 0.842, respectively.

- **PARAMETER TUNING**

Parameter tuning is important because default values cannot be suitable for all tasks and do not produce the best results(Smit & Eiben, 2009), so we will apply parameter tuning in the classifier with the best performance from the previous experiment(i.e. Random Forest) . Random Forest Hyperparameters we'll be looking at:

- Max depth
- Min sample split
- n_estimators
- Random state
- Min samples leaf

We employed the grid search method, which involves testing a set of hyperparameters to discover the best values for a given task based on validation accuracy. Utilizing the model's default parameter settings is less computationally complex than using this strategy. The effect of hyperparameter adjustment on prediction performance is shown in Table 5 and Figure 2. It is obvious that hyperparameter tweaking increases classifier performance.

Table 5: Performance comparison after tuning the parameters

Measure	Default parameters	Tuning Parameters
accuracy	0.844	0.864
f1_score	0.842	0.862
recall	0.844	0.864
precision	0.842	0.863

it is clear that the hyperparameter tuning improves the prediction performance.

And the best hyperparameters values were as follows:

N estimators	Min samples split	Min samples leaf	Max depth	Random state
300	2	1	None	0

FEATURE IMPORTANCE

As we mentioned earlier, the dataset contains 10 features, but are all features equally effective on the prediction process? To find out the importance of the features we compute the feature importance for each feature using the Random Forest Classifier, Table 6 shows the score of the top four features (score >0.5) and Figure 3 shows the weight of each feature in the dataset ordered descending.

Table 6: Top 4 Feature scores

Feature	Score
Visited Resources	0.28234
Student Absence Days	0.21433
Raised hand	0.17795
Viewing announcements	0.11615

From Figure 2 we can see that visited resources (How many times a student visits the contents of a course) is the most feature affecting the student performance, followed by student absence days (Total number of days the student is absent), the third feature in terms of importance is raised hands(The number of times the student requested to speak in the lecture), the fourth feature is announcements view(The number of times the student inspections the new announcements). The features that affect students ’performance are related to the students’ activities, their follow-up to academic content, and the regularity in attendance and follow-up.

Conclusion

Student performance prediction can help the educational institution to take timely actions, like planning for appropriate training to increase the success rate of students. Analyzing educational data can help in realize the desired educational goals. By applying the techniques of data mining, prediction models can be built to enhance student performance. In this paper, we collect a dataset respesnts a sample of student of King Faisal University, to study the possibility of predicting student performance. We applied data mining techniques to the dataset and tested 10 classification algorithms and gave the random forest the best results with an accuracy ratio of 0.844. We applied the parameter tuning technique to obtain the best parameter values that gave the best results. Indeed, the accuracy improved and became 0.864. Then we extracted the most important features affecting students' performance, and they were visited resources, absence days, raised hands, and announcements view.

Through the predictive model that has been built, there is an expectation of the performance and success of any student before taking the test and knowing whether the student's performance during the academic semester will ultimately lead to his success and thus an attempt to amend any defect in the student's performance before he fails or improve his academic level.

Discussion

We assessed what teachers and students need to know in order to apply machine learning effectively for their own learning and to comprehend the broader implications for society. Students must have opportunities to not only utilise and apply machine learning but also to generate their own instances in order to deepen their conceptual grasp of algorithms, models, and how machine learning works. Teachers will need to incorporate examples into their syllabi so that students build fundamental skills in leveraging machine learning's capabilities in the classroom while also developing a knowledge of how machine learning works and its potential applications in the real world.

Declarations

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ETHICAL STATEMENT: "All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards."

CONSENT STATEMENT: "Informed consent was obtained from all individual participants included in the study."

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Figures

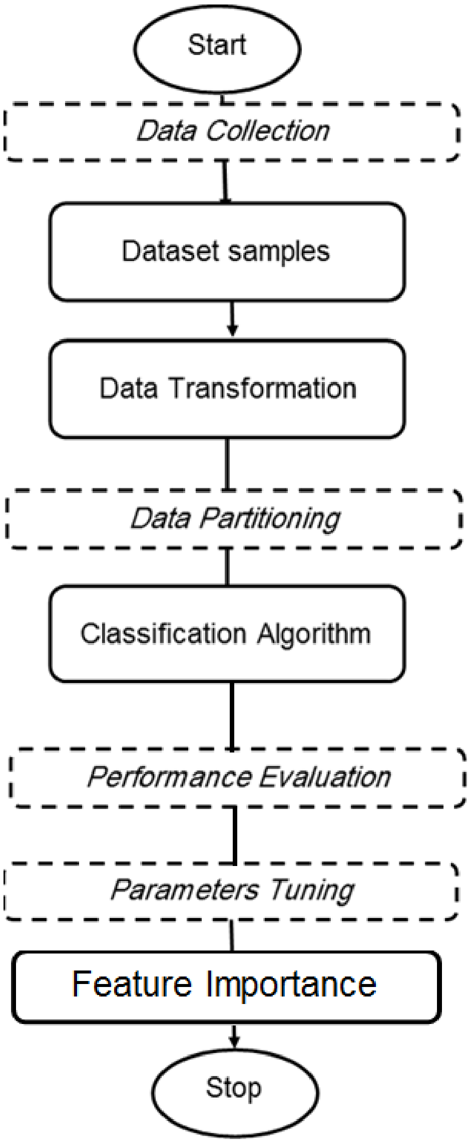

Figure 1

Student Performance prediction steps

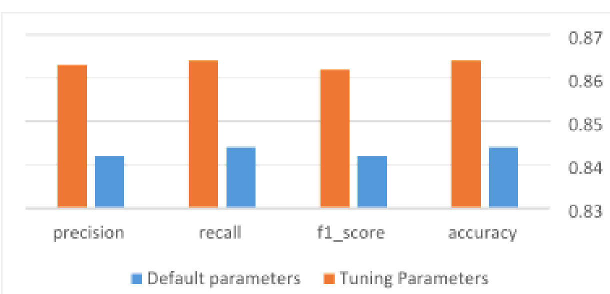

Figure 2

Performance comparison after tuning the parameters

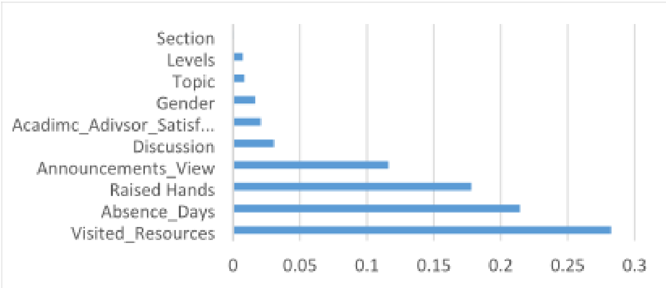

Figure 3

Feature Impotence