**IAES International Journal of Artificial Intelligence (IJ-AI)**
Vol. 12, No. 2, June 2023, pp. 831∼839
ISSN: 2252-8938, DOI: 10.11591/ijai.v12.i2.pp831-839 

# Predicting students' academic performance using e-learning logs

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**Article Info**

***Article history:***

Received Oct 19, 2021
Revised Sep 25, 2022
Accepted Oct 25, 2022

***Keywords:***

Coronavirus disease 2019
Correlation
E-learning
Jordan University of Science and Technology
Machine learning

**ABSTRACT**

The outbreak of coronavirus disease 2019 (COVID-19) drives most higher education systems in many countries to stop face-to-face learning. Accordingly, many universities, including Jordan University of Science and Technology (JUST), changed the teaching method from face-to-face education to electronic learning from a distance. This research paper investigated the impact of the e-learning experience on the students during the spring semester of 2020 at JUST. It also explored how to predict students' academic performances using e-learning data. Consequently, we collected students' datasets from two resources: the center for e-learning and open educational resources and the admission and registration unit at the university. Five courses in the spring semester of 2020 were targeted. In addition, four regression machine learning algorithms had been used in this study to generate the predictions: random forest (RF), Bayesian ridge (BR), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost). The results showed that the ensemble model for RF and XGBoost yielded the best performance. Finally, it is worth mentioning that among all the e-learning components and events, quiz events had a significant impact on predicting the student's academic performance. Moreover, the paper shows that the activities between weeks 9 and 12 influenced students' performances during the semester.



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## 1. INTRODUCTION

Electronic learning (e-learning) uses digital technologies, such as computers and smartphones, to empower people to access and learn information anywhere and anytime, depending mainly on the internet [1], [2]. Thus, e-learning helped educational institutions' users (i.e., teachers and students) to acquire various skills and valuable knowledge. During the coronavirus disease 2019 (COVID-19) pandemic, traditional education (face-to-face) was switched to online and distance learning by many educational institutions worldwide [3]. The e-learning system facilitated the educational process by providing a set of electronic educational materials and the possibility of sharing them in various formats (i.e., pdf, power point slides, word document, audios, videos, and images) [2]. It also allows, improves, and increases the interaction between teachers and students [3]. Teachers can perform several activities, including writing quizzes, exams, assignments, uploading several materials for a specific course, and asking specific questions to be discussed [1].

Several researchers and educators in academic institutions in different countries are interested in exploring the prediction methods of students' academic performances based on the previous records [4]–[7]. They are also motivated to determine the relationship between e-learning system usage and students' performances. This relationship can help the academic institutions to identify the various crucial activities that affect the educational process [8]–[10]. This research paper examines the e-learning system datasets in Jordan University of Science and Technology (JUST) during the spring semester of 2021. We have collected the data from five courses at the JUST in the spring semester of 2019/2020. We have selected the courses with the most significant number of students representing different faculties. The datasets include files related to students' performances: log, grades, and user files. The total number of students in this study is 4,874. The data are manually filtered and analyzed to determine the significant features. This study aims to: i) provide an e-learning dataset to tackle the lack of dataset availability; ii) predict students' performances in different courses using different machine learning algorithms (RF, BR, AdaBoost, and XGBoost); iii) expose the relationship between e-learning usage and students' performances; and iv) analyze the error in the mentioned models for each course.

The research paper's reminder sections proceed: section 2 provides insights into the proposed methodology used in this paper in terms of dataset collection, dataset description, pre-processing, feature extraction, and the used regression models. Next, section 3 discusses the experimental results and analyzes the error for the best ensemble regression model, and sheds light on the feature importance. Finally, section 4 shows the conclusion of the research study.

## 2. RESEARCH METHOD

This section presents the architecture of the proposed methodology used in this paper to predict the students' performance using e-learning data at the appearance time of COVID-19. The architecture of this paper methodology includes collecting the data from the "Center for E-Learning and Open Educational Resources" and the "Admission and Registration Unit" at JUST, then analyzing and filtering the data. It also includes extracting the essential features and using the regression machine learning algorithms to predict the students' performance. Finally, another crucial step in this study is to find the correlation between e-learning events and grades to find the most dramatic events on the students' performance. The following subsection explains each of the architecture components in detail.

### 2.1. Data collection and feature extraction

The five courses data was collected from two units at the Jordan University of Science and Technology in the spring semester of 2019/2020. We have selected the courses with the most significant number of students representing different faculties. The total number of students is 4,874. Each course has i) logs file that contains entry time for e-learning, events performed using specific e-learning components, description of what the users are doing in each entry, how to access the system, and the internet protocol (IP) address of the device; ii) users file that contains information about the students and teachers in terms of student ID, teacher ID, and e-mails; and iii) grades file for the students regarding quizzes, assignments, first exam, second exam, mid-exam, final exam, and final grades. The first two files are obtained from the Center for E-Learning and Open Educational Resources, while the last one is obtained from the Admission and Registration Unit. Table 1 shows the course name, course id, and the number of students in each course in the Spring semester 2020. It is worth mentioning that the registered students are from eleven faculties.

Table 1. Five courses at spring semester 2019/2020

| Course name | Course id | No. students | No. of entries | No. components | No. event |
|---|---|---|---|---|---|
| General biology laboratory | BT107 | 1,002 | 79,874 | 6 | 8 |
| Biochemistry | CHEM262 | 612 | 79,877 | 7 | 9 |
| Computer skills | CIS099 | 876 | 97,195 | 7 | 7 |
| General skills | HSS129 | 1,784 | 234,554 | 6 | 8 |
| General physics | PHY103 | 600 | 79,697 | 9 | 15 |
| Total number | | 4,874 | | | |

After collecting the dataset, the students' names and IDs were masked using a masking strategy in which each student had a unique number. Finally, the three files were merged by matching each student's logs with his information and grades. The students' logs files' main contents are components and events. The components are the group of features in e-Learning that include different resources to track students' progress. While the events are the activities performed by the users using the components. The data set was filtered based on the entries related to students only. Table 1 shows the number of entries, components, and events for only students in the spring semester 2020. This filtering extracts the components and events related only to students to predict their performance using the e-learning system at COVID-19 time.

After filtering the dataset, the features were extracted from log files of the five courses. These features are the student's faculty, what the way used to access the e-learning system, whether through their computer or phone, what the activities and resources viewed for a course, the number of discussions for each student, number of submitted, started, viewed and summary viewed of quizzes, number of message sent between teachers and students or among students, number of assignments' submissions, number of times that each student's view his grades or grades' reports, and number of times that each student has done different activities per week during the semester. The quiz component with its events had the highest impact on the student's performance in the five courses: the quiz attempt started, and quiz attempt submitted have the highest correlation values as : 0.49, and 0.51 in BT107, 0.47, 0.37 in CHEM262, 0.65, and 0.65 in CIS099, 0.73, and 0.72 in HSS129, 0.38 and 0.36 in PHY103. Therefore, we noticed that the quiz events have the most affected because it is done frequently and interested by the students during the semester. Furthermore, it is noticed that the activities of weeks between nine and thirteen have the highest correlation values than other weeks because it is the period for the student to prepare for the various semester works exams and final exams. In BT107, CHEM262, and PHY103 courses, the students did not conduct any activities on e-learning. This is because the nature of these courses is practical. Compared with CIS099 and HSS129 courses, the students need to open the e-Learning because these courses' nature is not practical.

### 2.2. Regression models

This study conducted experiments to predict students' performances based on the semester work grades (out of 50). The semester work contains activities based on the course's nature, such as quizzes, assignments, first exam, mid-exam, and second exam. Thus, the semester works grades are out of 50 based on activities accomplished in each course. This research paper experimented with four regression models to predict students' semester work out of 50. To train the machine learning models, we have divided the dataset of each course into 70% of the dataset as a training dataset and 30% as a testing dataset. Several regression and correlation metrics were used in the experiments to evaluate machine learning models. The root mean square error (RMSE) [11] is used as a standard popular regression metric in the prediction process. The RMSE is calculated as the difference between the predicted and actual continuous values. We have listed the RMSE with other metrics for our analysis, such as mean absolute error (MAE) [12], mean absolute percentage error (MAPE) [13], [14], R square ($R^2$) [15], scatter index (SI) [16], Pearson correlation, and Spearman correlation [17].

The regression models used in the current study are the RF, XGBoost, BR, and AdaBoost regressor models. RF regression model is a supervised ensemble model of several decision trees generated for both regression and classification tasks, in which each decision tree produces a prediction [18]. The XGBoost regression model is an ensemble model developed to solve classification and regression problems [19]. It contains several weak learners to generate a single strong learner. The weak learners are gradient boosting decision trees, in which each tree is performed individually, produces individual predictions, and then combines these predictions to form a final model' prediction. However, unlike AdaBoost, XGBoost used the gradient descent algorithm to minimize the error between actual and predicted results, increasing speed and performance [19]. The third model is AdaBoost regression model, which is one of the boosting algorithms that is developed for both classification and regression tasks [20]–[22]. It is an ensemble algorithm used to fit weak learners and produce a single strong learner. The predictions of weak learners are combined under final prediction whether weighted majority vote for classification tasks or average prediction for regression tasks [20]–[22]. The last model is BR regression model . The Bayes theorem uses the independence assumptions between the features in the inner work to predict the results. It computes the possibilities for each class label and determines each input data to which of the labels belongs to it based on the maximum possibilities [23]. The BR estimator proposed to solve the regression task from a Bayesian perspective [24]. Bayesian regression techniques can be used to include regularization parameters in the estimation procedure that are tuned to the data at hand. The BR regression model estimates a probabilistic model of the regression problem. We also applied voting regression model, which is an ensemble model that uses different types of machine learning models (classifiers or regressors) as base learners to produce the final results [25], [26]. The final prediction of the voting model follows the wisdom of experts' pattern, and the output is the class that has the most votes from all classifiers in classification tasks [25], [26].

## 3. RESULT AND DISCUSSION

This section presents the experimental setup of five models: AdaBoost, BR, RF, XGBoost and the proposed voting model. Also, it presents the experimental results of these models. The experimental setup of the machine learning regression models used for the targeted course courses are:

- AdaBoost regression model We have experimented with different parameters of AdaBoost. Table 2 shows the best results of the different parameters used for four AdaBoost experiments and related results for each courses in these experiments. It is clear that none of the models is considered the best model for all courses. For example, AdaBExp (1) has the best prediction results for the courses CHEM262, CIS099, and PHY103. However, it has the worst prediction results for BT107 course.
- Bayesian ridge regression model: Table 3 shows the different parameters used in best four BR experiments and related results for each courses in these experiments. It is obvious that there is no best model for all courses.
- Random forest regression model: Table 4 shows the different parameters used in four RF experiments and related results for each courses in these experiments. Once again, no best or worst model for all courses.
- XGBoost regression model Table 5 shows the different parameters used in four best XGBoost experiments and related results for each courses in these experiments. None of the experimented models can be considered the best or the worst model to predict the results for all courses.
- Voting regression model Table 6 shows the different parameters used in six proposed Voting experiments and related results for each courses in these experiments.

Table 2. Experimental setup and results for AdaBoost

| Experiments | Parameters | RMSE BT107 | RMSE CHEM262 | RMSE CIS099 | RMSE HSS129 | RMSE PHY103 |
|---|---|---|---|---|---|---|
| AdaBExp. (1) | learning_rate=0.01, n_estimators=50, random_state=42 | 5.36 | **2.71** | **6.36** | 2.54 | **6.42** |
| AdaBExp. (2) | learning_rate=0.0001, n_estimators=50, random_state=42 | **5.29** | **2.71** | 6.46 | 2.50 | 6.56 |
| AdaBExp. (3) | learning_rate=0.001, n_estimators=50, random_state=42 | 5.33 | 2.79 | 6.48 | **2.49** | 6.53 |
| AdaBExp. (4) | learning_rate=0.0001, n_estimators=500, random_state=42 | 5.30 | 2.76 | 6.41 | **2.49** | 6.56 |

Table 3. Experimental setup and results for BR

| Experiments | Parameters | RMSE BT107 | RMSE CHEM262 | RMSE CIS099 | RMSE HSS129 | RMSE PHY103 |
|---|---|---|---|---|---|---|
| BRExp. (1) | alpha 1=4e-6, compute score=True, n iter=100, normalize=True, fit intercept=True | 5.49 | 3.18 | **6.54** | 3.48 | 7.78 |
| BRExp. (2) | alpha 1=4e-6, compute score=True, n iter=100, normalize=True, fit intercept=False | **6.36** | 3.54 | 7.31 | 6.02 | 7.79 |
| BRExp. (3) | alpha 1=4e-6, compute score=True, n iter=2, normalize=True, fit intercept=True | 5.47 | 3.16 | 6.55 | **3.47** | 7.10 |
| BRExp. (4) | alpha 1=4e-6, compute score=False, n iter=10, normalize=False, fit intercept=True | 5.45 | **3.14** | 6.57 | 3.8 | **6.89** |

Table 4. Experimental setup and results for RF

| Experiments | Parameters | RMSE BT107 | RMSE CHEM 262 | RMSE CIS099 | RMSE HSS129 | RMSE PHY103 |
|---|---|---|---|---|---|---|
| RFExp. (1) | random state=42, max features=log2, n estimators= 1000, max depth=None | **5.31** | 2.44 | **6.22** | 2.14 | 6.49 |
| RFExp. (2) | random state=42,max features=auto, n estimators= 1000,max depth=None | 5.41 | 2.61 | 6.25 | 2.15 | **6.48** |
| RFExp. (3) | random state=42,max features=sqrt, n estimators=1000,max depth=None | 5.33 | 2.40 | 6.23 | **2.11** | 6.49 |
| RFExp. (4) | random state=42,max features=auto, n estimators=50,max depth=2 | 5.38 | **2.26** | 6.49 | 2.49 | 6.74 |

Table 5. Experimental setup and results for XGBoost

| Experiments | Parameters | RMSE BT107 | RMSE CHEM262 | RMSE CIS099 | RMSE HSS129 | RMSE PHY103 |
|---|---|---|---|---|---|---|
| XGBExp. (1) | random state=42,colsample bytree=1.0, eta=0.30,max depth=2,subsample= 0.9 | 5.23 | 2.69 | 6.34 | **2.08** | 6.91 |
| XGBExp. (2) | random state=42,colsample bytree=0.9, eta=0.10 max depth=1,subsample= 0.9 | 5.20 | **2.34** | 6.26 | 2.20 | 6.61 |
| SGBExp. (3) | random state=42,colsample bytree=1.0, eta=0.05, max depth=2,subsample= 0.9 | 5.26 | 2.45 | **6.18** | 2.18 | 6.58 |
| XGBExp. (4) | random state=42,colsample bytree=0.9, eta=0.10,max depth=2,subsample= 0.9 | **5.16** | 2.50 | **6.18** | 2.11 | **6.55** |

Table 6. Experimental setup and results for voting models

| Experiments | Base regressors | RMSE Course BT107 | RMSE Course CHEM262 | RMSE Course CIS099 | RMSE Course HSS129 | RMSE Course PHY103 |
|---|---|---|---|---|---|---|
| VotExp. (1) | BRExp. (4) + AdaBExp. (4) | 5.28 | 2.77 | 6.33 | 2.58 | 6.50 |
| VotExp. (2) | RFExp. (1) + XGExp. (4) | 5.20 | 2.41 | 6.16 | 2.08 | 6.48 |
| VotExp. (3) | RFExp. (4) + XGExp. (2) | 5.21 | 2.27 | 6.33 | 2.30 | 6.64 |
| VotExp. (4) | RFExp. (3) + BRExp. (3) + AdaBExp. (1) | 5.29 | 2.59 | 6.25 | 2.33 | 6.48 |
| VotExp. (5) | XGBExp. (4) + RFExp. (4) + BRExp. (4) + AdaBExp. (2) | 5.21 | 2.48 | 6.27 | 2.29 | 6.45 |
| VotExp. (6) | XGBExp. (3) + RFExp. (3) + BRExp. (3) + AdaBExp. (3) | 5.26 | 2.55 | 6.24 | 2.23 | 6.48 |

The proposed voting model VotExp(2) shows the best results in terms of MAE for all courses (except for PHY103, it is the second best result). Also, The summation value for all the RMSE of all courses yield that VotExp(2) has the least summation value of the RMSE. Thus, our proposed model is the voting model for RFExp(1) and XGExp(4). Figure 1 shows the proposed voting model. Table 7 shows the results of the regression machine learning models for the five courses at the spring semester 2019/2020. Depending on the results in Table 7, the results of all courses are explained as:

- BT107 course: the best regression model that gives the least RMSE value in this course is XGBoost model with 5.16; however, the voting model VotExp(2) has a descent value of RMSE 5.20.
- CHEM262 course: the best regression model that gives the least value of RMSE in this course is the RFExp(4) with 2.26. The voting model VotExp(2)'s RMSE is 2.41.
- CIS099 course: the best regression model that has the least RMSE value in this course is the voting model VotExp(2) with 6.16.
- HSS129 course: the best regression model that provides the least value of RMSE is the voting model VotExp(2) 2.08.
- PHY103 course: the regression model that has the least RMSE value in this course is the voting model VotExp(8) with 6.35, and the voting model VotExp(2) is not even close 6.48.

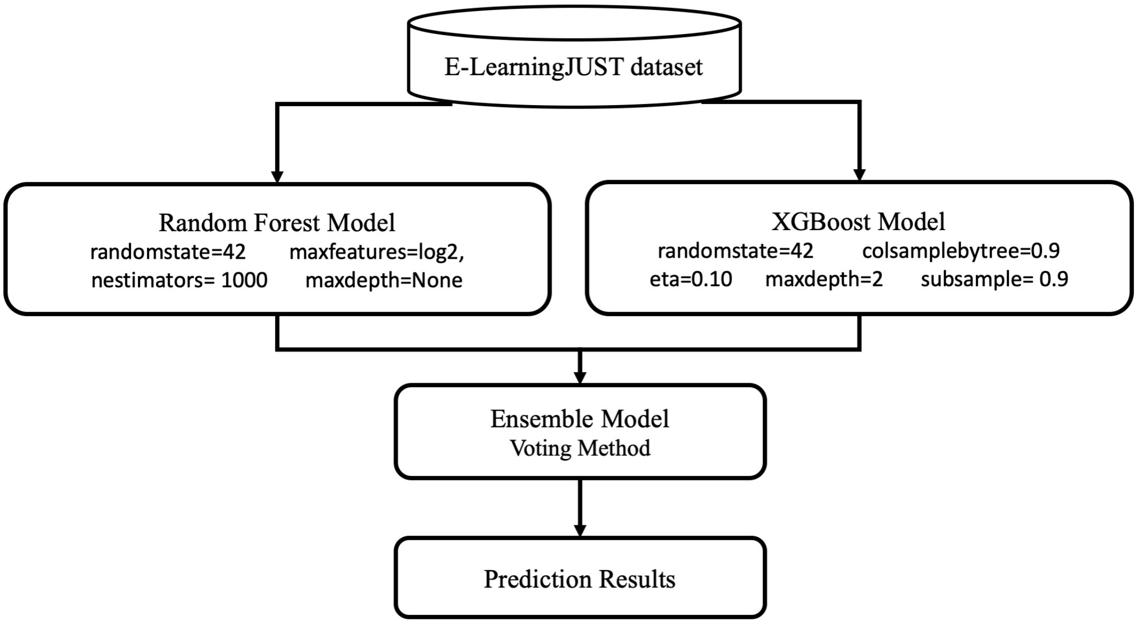


Figure 1. Proposed voting model VotExp(2)

Table 7. Results for VotExp(2)

| Courses | Models | RMSE | MAE | $R^2$ |
|---|---|---|---|---|
| | RF | 5.31 | 4.25 | 0.34 |
| BT107 | XGB | 5.16 | 4.14 | 0.37 |
| | Voting | 5.20 | 4.17 | 0.36 |
| | RF | 2.44 | 1.33 | 0.58 |
| CHEM262 | XGB | 2.50 | 1.37 | 0.55 |
| | Voting | 2.41 | 1.32 | 0.59 |
| | RF | 6.22 | 4.93 | 0.45 |
| CIS099 | XGB | 6.18 | 4.88 | 0.46 |
| | Voting | 6.16 | 4.88 | 0.46 |
| | RF | 2.14 | 1.25 | 0.81 |
| -HSS129 | XGB | 2.11 | 1.20 | 0.81 |
| | Voting | 2.08 | 1.20 | 0.82 |
| | RF | 6.49 | 5.19 | 0.41 |
| PYS103 | XGB | 6.55 | 5.16 | 0.40 |
| | Voting | 6.48 | 5.12 | 0.41 |

The current study relies on the semester works' grades. Thus, it is worth illustrating the grades' distribution for each course. The distribution is divided into four groups of ranges: [0, 24], [25, 37] [38, 41] , and [42, 50]. Table 8 shows the percentage of students in these groups of ranges. The key findings based on Table 8 is that the CHEM262 and HSS129 courses have the maximum percentage of students in the [42, 50] group and the lowest rate in the [0, 24] group. As a result, we can deduce why the RMSE values are better in CHEM262 and HSS129. Finally, the students who used e-learning intensively and frequently received high grades, as shown by the high correlation between the semester work and the total events in all courses.

Table 8. The percentages results of four groups for all courses

| Course ID | [42, 50] | [38 , 41] | [25 , 37] | [0, 24] |
|---|---|---|---|---|
| BT107 | 41.62% | 42.71% | 12.28% | 3.39% |
| CHEM262 | 93.46% | 3.43% | 1.8% | 1.31% |
| CIS099 | 28.77% | 42.35% | 19.41% | 9.47% |
| HSS129 | 91.31% | 5.89% | 1.40% | 1.40% |
| PHY103 | 30.50% | 40% | 22.17% | 7.33% |

## 4. CONCLUSION

This research paper provides a pilot study to predict students' performance using e-learning data in five courses (BT107, CHEM262, CIS099, HSS129, and PHY103) during the spring semester 2019/2020. We have chosen these courses from different departments with different faculties at JUST University. We have also selected the semester work grades because they included all the grades of activities and exams taken before presenting the final exam, and the students' performance will most affect it. To predict the students' performance, we used five machine learning algorithms with regression types: the RF, XGBoost, BR, AdaBoost, and voting models. The results shown in all courses, the voting regressor gave the higher values in three courses and the second-best results in two courses. We then studied the relationship between e-learning usage and the students' performance based on the most affected performance events. Based on the results achieved, there is a high correlation between e-learning usage and the students' performance using the linear regression algorithm. For example, the quiz with related events (quiz attempt started, quiz attempt submitted, quiz attempt summary viewed, quiz attempt viewed) gave a high correlation, which means that the students' performance was most affected with quiz. We have also studied the relationship between e-learning usage and student performance based on weeks' activities using a linear regression algorithm. The result showed that the period between week nine and week 12 most affected students' performance.

## ACKNOWLEDGEMENT

We gratefully acknowledge the Deanship of Research at the Jordan University of Science and Technology (JUST) for supporting this work via Grants #20200064 and #20210039.

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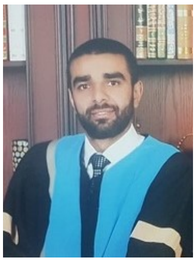

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