Predicting Final Exam Success Based on Learning Material Usage extracted from Moodle Logs

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*Abstract*—This paper presents the use of data mining with the aim of predicting the results of the final exam. The data were collected from the Moodle platform of the IT course within the University of Split. In this paper, we used and compared six classification methods and those are Decision Tree Classification, k-Nearest Neighbor Classifier, Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machine. Using Moodle Logs and previously mentioned methods, we are aiming to predict the ultimate success in the chosen course. For achieving greater accuracy, the algorithms were evaluated on all available and filtered data to determine which of the algorithms used were the most accurate.

Keywords— educational data mining, predicting final marks, predicting passing the class, online learning materials

# Introduction

The world is changing because of persistent technological development which consequently requires the adaption of humankind and their activities in all spheres of life. Education cannot resist technology and is increasingly relying on technological assistance to establish to what extent it contributes to education. During the pandemic, technology saved education around the world. Great support to the educational system were various e-learning platforms. In Croatia, the most used is a learning management system Modular Object-Oriented Dynamic Learning Environment (Moodle).

A learning management system enables the administration of the learning and teaching process. Moodle, for example, provides communication between teachers and students, creating student profiles and enabling the transfer and use of learning materials [9]. According to Chicioreanu and Cosma [11], there are many advantages of using Moodle inside a school. It is easy to manage and edit documents, and the creation of backup copies is simple as well as their restoration. Moodle allows downloading grades and other data into spreadsheets, and access to information that has been archived is easy for other academic staff. Due to the possibility of documenting student activities, teachers are provided with useful data about each student within the course [11].

Owing to its advantages, the Moodle is gladly used as a support in face-to-face teaching. Despite its growing presence in online courses and online study programs, Chicioreanu and Cosma highlight its shortcomings. Solving tasks and tests is possible by copying and pasting the answers. Therefore, no one can guarantee that the result represents true student knowledge. Also, regardless of clicks, it does not mean that students have learned the material. Besides, such systems do not allow us insight into the creativity and critical thinking of students [11].

As already mentioned, the Moodle collects students’ data, but it is not adequately developed and is providing teachers only with superficial insight into what is collected. In other words, the Moodle cannot perform data classification by itself and that is why we are deprived of insight into possible interesting relationships between data. To examine the obtained analytics, data mining is used.

“Data mining is the process of discovering interesting patterns and knowledge from large amounts of data.” (p. 8, [10]). In other words, it sorts through data sets with the goal to identify relationships and patterns between them. The main task is the classification of data that results in new findings and correlations. By grouping data in this way, we notice unknown relationships. Therefore, based on the previous research results, predict the future ones. Data mining can be applied to all types of data if there is a meaning to their application. Most used are database data, transactional data, and warehouse data. In addition to the above, it is possible to apply data mining to other forms such as spatial data, data streams, text data, graph or networked data, and many others [10].

Therefore, data mining is increasingly applied in education, through data obtained from various simulations, games, and intelligent tutoring systems. There are many learning tasks and problems that data mining solves and those are: evaluation of learning materials, detection of atypical student behaviors, assessments of students' learning performance, predicting the passing of exams, and finishing online courses, and more [2]. An Educational Data Mining (EDM) is a research area that uses data mining, machine learning, and psychological methods for understanding how students learn. Hypotheses are set and research is conducted to predict new outcomes, identify new knowledge, and contribute to the improvement of educational systems [12]. In order to make all this possible, the already mentioned classification of data must be used.

In this paper, we are interested in whether it is possible to predict the academic success of students by using classification and data mining and how the success is changing by the influence of individual variables. The main goal is to classify student data collected via the Moodle as a part of the introductory programming course and predict their final exam success.

The second section of this paper includes a brief overview of previous research that have used the learning analytics and data mining on the Moodle data to generate new insights. Furthermore, a sample of students, used data and methods used in our research are described. Finally, in the last section, the results are presented and the answers to the research questions given.

# RELATED WORK

This section presents an overview of previous work on predicting student learning outcomes both in general and more specifically in the context of programming education. Over the last couple of years, mainly since the last pandemic, the number of online learning environments has grown. As a result, their use has grown, and the amount of data they generate is growing exponentially, allowing scientists to do more relevant research.

Leppänen et al. [1] did research on predicting academic success based on learning material usage, in which they investigated students’ utilization of online learning material as a predictor of academic success. They have collected the data on how much some paragraphs have been visible on students' screens and applied machine learning methods to it. More specifically, they have used Support Vector Classifiers (SVC) and ε-insensitive Support Vector Regressors (ε-SVR) to conclude that the time spent with each section of the online learning material is a moderate predictor of student success.

Which statistical methods, decision trees, rules, fuzzy rule induction methods, and neural networks can be used in final marks predictions for students using the Moodle is described in a paper by Romero et al. [2]. They have concluded that the classifier model appropriate for an educational environment must be both accurate and understandable for teachers to be able to use it for decision making.

Decision tree classification gives the best accuracy while predicting student success through analysis of the Moodle logs, as concluded by Ademi et al. [3] They have trained the model with a one-year course activity data and then used that model to predict the next year's grades. As stated earlier, they have used a decision tree in comparison to Bayesian Network (BN) and Support Vector Machine (SVM) algorithms.

With 60.5% accuracy and 0.43 kappa, Quin and Gray managed to predict students' grades based on the Moodle data in a blended learning further education environment [4]. Also, the model predicts whether a student would pass or fail with an accuracy of 92.2% and a kappa of 0.79. They have compared Random Forest, Gradient Boosting, k Nearest Neighbors, and Linear Discriminant Analysis. Random forest had the best accuracy, but it turned out that others were almost equivalent.

How the Moodle plugins for data extraction, analysis and interpretation can be used for better understanding and more accurate analyses of student behavior and success is described in a paper by Kadoić and Oreški [9]. In that paper, a few plugins are described, and the Moodle logs are analyzed. Before any model is made, it is certainly desirable to make analyses of the data, and the Moodle plugins have shown to be helpful. Also, the authors have concluded that just by an analysis, their results are potentially beneficial in the early detection of students experiencing difficulties in a course.

# METHODS

The purpose of our research was to predict final exam success based on learning material usage. The following was selected from the Moodle logs: how many times an individual student clicked on a video of a particular lesson, how many times an individual student started a particular lesson, how much time an individual student spent on a particular lesson, how many points each student scored in a particular lesson, the number of points the student earned on the test and the time each student spent solving the test.

## Research Questions

RQ1: Is it possible to predict student academic performance on the course using variables created from course data?

RQ2: How do individual variables in course data affect the prediction of student success in the course?

## Participants

A total of 166 students participating in the introductory programming course at the Faculty of Science, University of Split participated in this research. Out of the total number of students, 36.1% students are enrolled in an Informatics study program, 35.5% Informatics and Technics, 22.2% Mathematics and 0.05% of Mathematics and Informatics.

## Study Design and Procedure

During this research, student work was monitored throughout the semester, from the number of clicks on a particular video lesson to the number of points achieved on the test.

## Data Collection and Processing

Six log files from the Moodle, which have already been mentioned, were taken for this research. In the introductory programming course, the Moodle was used to distribute teaching materials to students in the form of textual lessons and video lessons, it was also used to administer the tests for each lesson. The fields retrieved in the log files are study program, the fact whether the student has enrolled the course for the second time, the fact whether the student has passed the practical part of the exam, the oral part of the exam, the student’s final grade, and information about each lesson and test.

## Feature Selection

Feature Selection reduces the number of variables in the model. The goal is to remove redundant or irrelevant variables and choose only those variables that increase the model’s predictive strength and generalizing ability. In our research, we used two feature selection methods: Regression Feature Selection [7] and the Correlation-based Feature Selection [8].

## Data Analysis

The algorithms used in this research were Decision Tree Classification, Random Forest, k-Nearest Neighbor Classifier, Logistic Regression, Support Vector Machine and Naive Bayes.

Decision Tree Classifier is probably the best-known classification paradigm. The decision trees are learned from data. On the one hand, decision trees have many advantages. They are simple and easy to understand. But on the other hand, the assumption that all data points in the domain may be categorized deterministically into exactly one class is the basic constraint of decision trees [5].

Random Forest Classifier trains several trees using slightly different subsets of data, with each subset including a case containing a random selection from each variable’s range. This collection of trees resembles an ensemble. Each decision tree is the ensemble votes on how each input case should be classified [6].

The k-NN classifiers do not create an explicit global model, instead, they just approximate it locally and implicitly. The fundamental idea is to categorize a new item by looking at the class values of the K data points that are the most similar. In k-NN classifiers, the only learning task is to choose two crucial parameters: the number of neighbors K and the distance metric d [5].

Logistic Regression is a type of classification that models binary outcomes with only one of two possible values. It is used to model the nonlinear relationship between Y and the combined effects of the independent variables [6].

Support Vector Machine (SVM) simply focuses on class borders, excluding points that are easily categorized in any way. The central concept is when data is mapped to a higher dimension, the classification becomes linearly separable. The mapping is only done implicitly in practice, utilizing kernel functions [5].

In Naïve Bayesian Classifier the predictor variables are assumed to have independent impacts on the classification. This assumption is naïve in the face of reality, which is where the name comes from. Despite this overly strong assumption, it performs admirably with a variety of data types [6].

# RESULTS

## Prediction using course data with variables selected using feature selection

### Prediction of Written Exam Passed

As we mentioned before we used two methods to do the feature selection. The one that made our model get better prediction results was Regression Feature Selection. From the 20 selected features as seen in Figure 1. Those features were selected and used because their feature selection scores were higher than 0.0. For the training and testing set, we dropped two features called: Written Exam Passed and Final Grade. Both features are the ones we were trying to predict so we needed to remove them from the dataset.

Here we wanted to see how well our model would predict Written Exam Passed – a variable with two outputs, and we got results as shown in Table 1.

Table 1. Accuracy and Kappa score of each Algorithm on Test Set – Written Exam Passed Prediction with Feature Selection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **MODEL** | **ACCURACY** | **ACCURACY**  **KFOLD** | **KAPPA** | **KAPPA**  **KFOLD** |
| Decision Tree | 0.941 | 0.880 | 0.77 | 0.74 |
| SVM | 0.900 | 0.900 | 0.79 | 0.79 |
| Gaussian Naive Bayes | 0.900 | 0.890 | 0.79 | 0.76 |
| Random Forest | 0.875 | 0.875 | 0.74 | 0.71 |
| KNN | 0.810 | 0.870 | 0.71 | 0.73 |
| Logistic Regression | 0.750 | 0.900 | 0.73 | 0.79 |

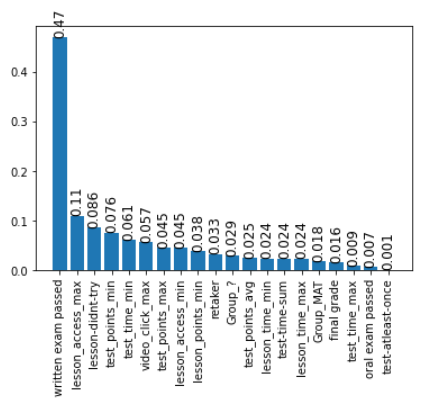


Figure 1. Selected Features

Decision tree was the best performing algorithm with an accuracy of just over 94%, if we are looking at the results obtained without K-fold procedure. The results of the other classifiers were in the range of 87% to 90%. On the other hand, from the results that were obtained with the help of the K-fold procedure, we can see that both Logistic Regression and Support Vector Machine gave the best results with an accuracy of 90%. Others, in this case, had resulted in the interval of 87% to 89%. For Cohen Kappa score, the Kappa result falls in the interval of 0.61–0.80 so we can say that our model shows substantial agreement. Best kappa score, in the case without using K-fold, have Support Vector Machine and Gaussian Naïve Bayes with the score being 79%. In the case where the results were obtained with the help of K-fold, Logistic Regression and Support Vector Machine gave the best results of 79%.

Therefore, looking at the accuracy scores (K-fold procedure used or not) we can see that Decision tree algorithm without the use of K-fold gave the best performance of 94%. But if we are looking at both the accuracy score and the Kappa score, we can see that the best results were given by Logistic Regression and Support Vector Machine, and those results were obtained with the help of K-fold, and they were 90% for accuracy and 79% for Kappa score.

### Prediction of Final Grade

Since the feature Final Grade has five categories to predict (marks 1, 2, 3, 4, and 5), we had to use multiple classification. Here we are still using the dataset that has only selected features.

Table 2. Accuracy and Kappa score of each Algorithm on Test Set – Final Grade Prediction with Feature Selection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **MODEL** | **ACCURACY** | **ACCURACY**  **KFOLD** | **KAPPA** | **KAPPA**  **KFOLD** |
| KNN | 0.875 | 0.670 | 0.52 | 0.47 |
| Random Forest | 0.813 | 0.813 | 0.52 | 0.50 |
| Decision Tree | 0.794 | 0.700 | 0.74 | 0.52 |
| Gaussian Naïve Bayes | 0.690 | 0.650 | 0.48 | 0.44 |
| SVM | 0.680 | 0.690 | 0.46 | 0.49 |
| Logistic Regression | 0.670 | 0.680 | 0.47 | 0.46 |

As seen in Table 2, the best accuracy score, without using K-fold, was obtained by K Nearest Neighbors and it values 88%. Other results are around 67% to 82%. The best results for the Kappa score were obtained by Decision tree, which

had, the value of 74% and that score falls under the substantial agreement zone. Other results were in the moderate agreement zone, with them being in the range of 0.47 to 0.52. For the results obtained by using K-fold, for accuracy Random Forest gave the best results, with the score being 81%. Other results were around 65% to 70%. Once again, Decision tree gave the best Kappa score but this time it falls under the moderate agreement zone because its value is 52%. Others have scored in the range of 44% to 50%. Here it is a little bit harder to state which classifier was the best. Both the best Kappa score and accuracy score were obtained without using K-fold. Looking at only Kappa score we can say that the Decision tree was the best out of all classifiers. But, looking at the accuracy k-NN was the best.

## Prediction using all course data

### Prediction of Written Exam Passed

Here we wanted to see what the results would be if we did not do a specific feature selection, but instead, we used all the features in the dataset. In Table 3 we can see the accuracy and kappa scores of our model.

As shown in Table 3, we can see that the best accuracy score has both the Support Vector Machine and the Gaussian Naïve Bayes with the score being 90%, without the use of K-fold. The remaining results are around 75-82%. If we are looking at the Kappa score, best results were obtained by Support Vector Machine. It had the score of 0.79 which lays in the substantial agreement zone. Other results were in the range of 11% to 78%. Looking at the results obtained using K-fold, best accuracy score was obtained by Logistic Regression and Support Vector Machine with the score being 90%. The remaining results were in the range of 81% to 89%. Also, best Kappa scores were also obtained by the mentioned classifiers. Their Kappa score was 79%, while the scores of the others are in the interval of 60% to 76%. In this case we can conclude that the best results were obtained using K-fold, and once again Logistic Regression and Support Vector Machine were the ones that gave the best results.

Table 3. Accuracy and Kappa score of each Algorithm on Test Set – Written Exam Passed prediction without Feature Selection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **MODEL** | **ACCURACY** | **ACCURACY**  **KFOLD** | **KAPPA** | **KAPPA**  **KFOLD** |
| SVM | 0.900 | 0.900 | 0.79 | 0.79 |
| Gaussian Naïve Bayes | 0.900 | 0.890 | 0.78 | 0.76 |
| Decision Tree | 0.823 | 0.890 | 0.11 | 0.76 |
| Random Forest | 0.813 | 0.813 | 0.75 | 0.61 |
| Logistic Regression | 0.810 | 0.900 | 0.61 | 0.79 |
| KNN | 0.750 | 0.810 | 0.60 | 0.60 |

### Prediction of Final Grade

Since the feature Final Grade has five classes, to predict that we had to use multiple classification, but this time it was done by using all dataset features.

As seen in Table 4, the best accuracy score, without using K-fold, was obtained by K Nearest Neighbors and Random Forest with the value of 88%. Other results are around 66% to 74%. Best results for the Kappa score were obtained by Support Vector Machine, which had the value of 57% and that score falls under the moderate agreement zone. Other results were also in the moderate agreement zone, with them being in the range of 0.43 to 0.55. For the results obtained by using K-fold, for accuracy Random Forest gave the best results, with the score being 81%. Other results were around 66% to 74%. Here Logistic Regression gave the best Kappa score which falls under the moderate agreement zone because its value is 57%. Others have scores in the range of 42% to 54%. In this case best accuracy results were obtained without the help of K-fold. And the score was high, but Kappa score fell under the moderate agreement zone not depending on the usage of K-fold. The highest Kappa score was 57% in both instances. So here it is harder to conclude with classifier has done the best.

# DISCUSSION

To answer the first research question (RQ1: Is it possible to predict student academic performance on the course based using variables created using course data?), we collected data from first year college students with features engineered from the Moodle log data, and we used them to train our models. We performed regression and correlation-based feature selection. Both gave similar features, and the model accuracies were differing by a small percentage, so we continued with regression-based because of its simplicity. Regardless of the method, we verified that a feature whether a student has enrolled a course for the second time or not, makes a poor attribute to identify student performance. This may be partly explained by the fact that second timers were not actively using the Moodle and doing all the activities as the first-time students. Also, we confirmed that feature student study program also does not affect student performance, only there is a slight difference between students from Informatics major sand Mathematics majors. This can be explained by the fact that it is the first-year course, so every student has the same starting point, most of the students have no prior knowledge of programming. On the other hand, we confirmed that some Moodle data makes for especially useful attributes. One example is the minimal time spent on a test. Low values might suggest that students did not prepare for test, but the ones who had some knowledge tried and spent some time viewing and solving the given problems.

Table 4. Accuracy and Kappa score of each Algorithm on Test Set – Final Grade Prediction without Feature Selection

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **MODEL** | **ACCURACY** | **ACCURACY**  **KFOLD** | **KAPPA** | **KAPPA**  **KFOLD** |
| Random Forest | 0.875 | 0.813 | 0.53 | 0.47 |
| KNN | 0.875 | 0.660 | 0.49 | 0.42 |
| SVM | 0.740 | 0.720 | 0.57 | 0.54 |
| Gaussian Naïve Bayes | 0.720 | 0.660 | 0.55 | 0.47 |
| Decision tree | 0.676 | 0.700 | 0.44 | 0.52 |
| Logistic Regression | 0.660 | 0.740 | 0.43 | 0.57 |

To answer the second research question (RQ2: How do individual variables in course data affect the prediction of student success in the course?), six supervised models, using classification techniques were created each with and without K-fold, and with and without feature selection, giving twenty-four models in total. In Table 1, Table 2, Table 3, and Table 4 we can see performance scores of individual algorithms: Decision Tree Classification, Random Forest, k-Nearest Neighbor Classifier, Logistic Regression, Support Vector Machine, and Naive Bayes.

For prediction of the Written Exam Passed performing without using K-fold but with feature selection, Decision tree gave the best performance, if we are looking at the accuracy score alone which was 94%. But if we are looking at both the accuracy score and the Kappa score, the best results were given by Logistic Regression and Support Vector Machine, with an accuracy of 90% and 79% for Kappa score. Without feature selection, we can conclude that the best results were obtained using K-fold, and once again Logistic Regression and Support Vector Machine were the ones that gave the best results.

For prediction of the Final Grade, using K-fold and feature selection, it is harder to state which classifier was the best. Looking at only Kappa score, Decision tree was the best, but looking at the accuracy, k-NN was the best. Without feature selection, best accuracy results were obtained without the help of K-fold. And the score was high, but Kappa score fell under the moderate agreement zone, not depending on the usage of K-fold. The highest Kappa score was 57% in both instances. So here it is harder to conclude which classifier has done the best.

These results suggest that students' engagement in an online learning platform affects their performance. After that, however, new studies may be conducted, and a similar analysis could be performed to confirm the impact of students’ engagement throughout the course and how the engagement affects the success and Final Grade in the course.

We have decided to use the most common machine learning models; some of them are also briefly described in our related work section. Algorithms like Random Forest, k Nearest Neighbors, Logistic Regression, Gaussian Naïve Bayes, and Decision trees are proven to be indeed accurate in the Learning Analytics field. Since we made two predictions, prediction using course data selected feature selection and prediction using all course data, it is not easy to make comparisons with previous work in detail. But we can conclude that the above-mentioned algorithms, which have proven to be good in related research, also gave excellent results in our analysis as well.

# CONCLUSION

We conclude that there is no algorithm that achieves the best accuracy in all cases. Whether we tried to predict the passing of the Written Exam or the Final Grade of the course, no algorithm stood out as the most accurate. However, we noticed that the accuracy of algorithms increased in some cases.

Predicting the Final Grade without selecting features showed slightly higher accuracy of individual algorithms. However, in both cases, one of the algorithms showed an accuracy of 88%. The minimum accuracy was 66% which certainly indicates the difficulty of predicting the Final Grade. This indicates that the level of activity of the system does not help us to predict the Final Grade nor does the attribute that tells us whether tests have been passed or not. We need much more than that to be able to determine the Final Grade as accurately as possible. Data such as prior knowledge, habits and learning styles that make learning more successful would very much contribute to the assessment of the Final Grade.

On the other hand, when predicting the written exam pass, the algorithms gave greater accuracy with feature selection. In that case, accuracy ranged from 87% all the way up to 94%, while without feature selection it dropped to the range of 75% to 90%. Although the level of activity on the system did not help us in the previous prediction, it proved to be extremely useful in predicting the success of the written exam. Percentages increased when attributes that do not have a significant impact on taking the written exam were removed, one of them may be the fact of whether the student has enrolled the course for the second time or not.

This research confirmed that student performance in a course is affected by student behavior on online learning platforms. Although we use them more, they still do not provide us with enough information to predict students' future outcomes. As we proved, without additional attributes that still cannot be measured by such a system, the prediction will not always be at a high level.

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