Prediction of student academic performance using machine learning algorithms

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Abstract

Educational data mining (EDM) can be used to identify students' activities, progress, achievements, and overall success in learning. EDM has become very popular in recent years as a convergence of learning, analysis, visualization, and recommendation which makes the learning process persistent and visible. In this paper, an EDM approach was conducted in order to classify and predict student performance with machine learning techniques. Based on the history educational dataset collected in Learning Management System (LMS) and Educational Management System (EMS), a model for the classification of student performance was conducted. A model is trained and evaluated on data from four different courses. Machine learning algorithms such as Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN), Decision Trees (DT), Naive Bayes (NB), and Support Vector Machine (SVM) are analyzed. Support Vector Machine (SVM) classifier was finally selected for model training and evaluation. Although the proposed model gave quite good results, there is room for improvement in future work, which is discussed in the paper

Keywords

elearning, student academic performance prediction, educational data mining, machine learning

1. Introduction

Wide usage of online educational learning and management systems led to a large amount of stored data. The educational experience such as students' interactions with forums, lectures, and online assessments in the form of homework, projects, tests, etc. provide the possibility to discover valuable and significant knowledge about student specifics and their further achievements [1].

Students' performance is a term used for measuring not only students' achievements but also the quality of educational institutions. While some authors define student performance as a value obtained from measuring a particular student learning assessment compared with study curriculum, grade point average (GPA), or final grades, others define student academic performance only as the possibility of gaining a long-term goal such as graduation or potential for future job prospects [2]–[4].

Analyzing collected data and predicting student performance has great importance for the efficiency of educational institutions and can help in identifying students with low academic achievements at the early stages of studying, tackling academic underachievement, increased university dropout rates, graduation delays, etc.[5]. For educational institutions, it is very important to understand the potential of using collected data in order to improve learning efficacy and academic achievements of individuals and institutions [6].

Proceedings 13th International Conference on eLearning (eLearning-2022), September 29–30, 2022, Belgrade, Serbia
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Educational data mining (EDM) is one approach that educational organizations can use to uncover the patterns hidden in educational data, extend their knowledge or make predictions about further student achievements [6]. While EDM is used for discovering knowledge from data, machine learning (ML) algorithms provide tools for that purpose.

EDM uses a broad range of data features, metrics, and prediction methods. In order to make conclusions or predictions on students' academic performance, features like cumulative grade point average (CGPA) and performance on online assessments (i.e. assessment scores, quizzes, attendance) have been used most frequently [7]–[10]. A prior academic achievement (i.e. high school data) can also help in understanding students' performance [11]–[14]. Some authors include university entrance tests as an important attribute as well [11]. Additionally, students' demographics such as gender, age, socioeconomic status, family background, and disability can also have an impact on students' success [8], [15], [16]. Learning in online learning environments means that the data recorded in the system, such as the number of access to lessons, time spent in learning, and participation in forums, play an important role and represent significant attributes in researching adequate metrics for addressing student performance [8]. Psychological attributes such as motivation, student interests, and personality type are usually interesting for research and are listed as important, but their qualitative nature sometimes makes them difficult for analysis [17], [18].

The large number of features that have been found in different research bring with them different prediction models to discover students' performance. The prediction of students' academic performance consists in estimating the unknown score or grade usually obtained by using different classification and regression techniques such as Decision Trees, Artificial Neural Networks, Naive Bayes, K-Nearest Neighbor, and Support Vector Machines [19]. Object Oriented Programming course data obtained from Politehnica University Timisoara was used for developing a model that could help in the identification of students at risk by predicting student academic performance. Their dataset included attributes such as student membership to the advanced study groups, number of credits earned in the previous year, average activity mark, number of attendances in practical activity meetings, average examination mark, and number of final exam attempts, with the conclusion that the Logistic Regression (LR) classifier produced the best accuracy for prediction students' academic performance [20]. In training small dataset size in order to predict students' academic performance, Support Vector Machine (SVM) and Learning Discriminant Analysis (LDA) algorithms showed the best accuracy [21]. A dataset from the University of Minho in Portugal with 395 samples was used to predict students' academic success using SVM and KNN. The performance of both algorithms was compared, and it was discovered that SVM performed better than KNN [22]. Review papers on machine learning-based student academic performance prediction show that Neural Network has the highest prediction accuracy (98%), followed by Decision Tree (91%), Support Vector Machine (83%), K-Nearest Neighbor (83%), and Naive Bayes (76%) [7].

In this paper, we focus on predicting students' academic performance by using historical data collected at Belgrade Metropolitan University with the aim to identify a model suitable to predict students' success in a course. Data used in this work represent educational data collected in two Object-oriented programming courses and two Information Technology based courses, gathered from academic year 2017/18 to 2021/22. The collected data set contains students' high school average grade, grades on tests, homework, projects, and class participation, as well as student class attendance, number of failed attempts to pass the final exam and final grade. Final grades are classified in two categories – those who passed the course and those who failed it. This work provides comparative analysis on different machine learning algorithms such as Logistic Regression (LR)[23], Linear Discriminant Analysis (LDA) [24], K-Nearest Neighbor (KNN) [25], Decision Trees (DT) [26], Naive Bayes (NB) [27], and Support Vector Machine (SVM) [28].

This paper is organized as follows. Section 2 presents short overview of the Educational Data Mining techniques. Section 3 describes used methodology for data collection and analyses. Section 4 presents and discusses obtained results. Finally, Section 5 concludes the paper.

2. Educational data mining

EDM develops and adopts different methods that are used in order to gain valuable knowledge hidden in educational data from educational settings. EDM uses different statistical, machine learning, and data-mining methods with the aim to better understand students and to try to predict patterns that characterize students' behaviors and performances [29], [30]. Education, statistics, and informatics represent the main areas of EDM where overlaps of these areas lead to coupling of EDM with machine learning, data mining, learning analytics, and computer-based education [31]. The goal of the EDM is to transform raw data with a large number of attributes into meaningful data-driven decisions. EDM can also lead to more accurate predictions of student knowledge, dropouts, and student motivational state as it is based on different data, which in return provides a broader understanding of specific groups of students [32], [33]. EDM can be classified in five main categories: (i) prediction, (ii) clustering, (iii) relationship mining, (iv) distillation of data for human judgment, and (v) discovery with models [34]

Prediction - Develops a model that calculates assumptions for certain events and are made based on available processed data. In data mining, independent variables are attributes that are already known, and response factors are what needs to be predicted. Three main categories of prediction are classification, regression, and density estimation [35].

Clustering - Identifies data that grouped together, respond to a similar logic and observations. In online learning, an example of clustering would be grouping students based on their learning patterns which allows one to further gain meaningful conclusions [36].

Relationship mining - Discovers relationships between numerous variables in a dataset and can provide information on variables that are strongly associated with another variable. Additionally, relationship mining can discover the strongest relationships between some variables. Four main categories of relationship mining are: (i) association rule mining, (ii) correlation mining, (iii) sequential pattern mining, and (iv) causal data mining [30].

Distillation of data for human judgment - Develops methods for appropriate presentation and visualization of data for easier human judgment [37]. Presenting the data in different ways can help in discovering new knowledge in order to achieve classification and/or identification. Data distillation for classification can be used as a preparation stage for further prediction, while identification aims to display data such that it is easily identifiable via well-known patterns [38].

Discovery with models - entails using previously defined models based on clustering, prediction, or knowledge engineering using human reasoning rather than automated methods [34].

ML uses techniques that allow machines to learn and make accurate predictions from past observations. In recent years coupling of ML with EDM has received high attention in research. Various techniques and algorithms such as Clustering, Classification, Regression, Neural Networks, Association Rules, Genetic Algorithms, Decision tree, etc. are used for knowledge discovery from databases [31].

3. Methodology

Methodology used to build a student performance prediction model is presented in Figure 1. Methodology consists of three stages: (i) Data collection and integration, (ii) Data preprocessing, and (iii) Model building and evaluation. In the *Data collection and integration* stage data is collected during the student learning process. *Data preprocessing* stage includes tasks such as: (i) handling missing values, (ii) solving inconsistency, (iii) removing redundancy, (iv) feature selection, and (v) normalization. An output from this stage is a transformed dataset which is converted into a normalized dataset. In the *Model building and evaluation* stage normalized data is divided into two sets: training dataset (consists of 80% of received normalized data) and testing dataset (20%).

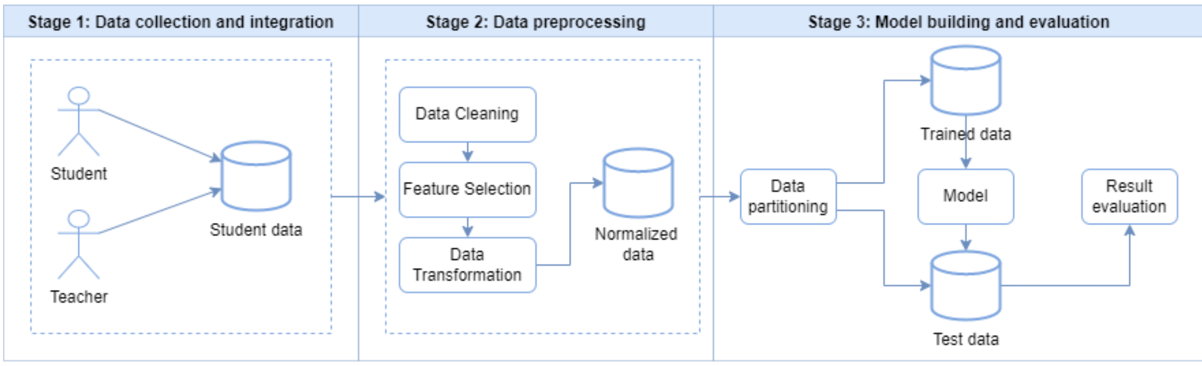


Figure 1. Student performance prediction methodology

In this study, the data were taken from Belgrade Metropolitan University's EMS and LMS, where all student records are stored. This dataset includes data collection from academic year 2017/18 to 2021/22. Data were narrowed down to four courses: (i) Introduction to object oriented programming (ii) Objects and data abstraction, (iii) Introduction to information technologies, and (iv) Information technology systems. The dataset included records for 1696 students.

In the first stage, the raw dataset was collected and after that dataset was preprocessed by removing outliers, missing and noise values. Null, empty or negative values were removed from the dataset. Students' data used in this work includes: (i) homework assignments grades, (ii) online test grades, (iii) project assignments grades, (iv) class participation grade, (v) number of failed attempts to pass the final exam, (vi) class attendance, and (vii) high school average grade. In the selected courses, students had assigned with weekly homework assignments, online assessments every three weeks, and one project assignment per course. Student class attendance was taken each week. Besides the assigned grades, EMS and LMS collected additional data about student learning such as time spent on the LMS, forum participation, time when students submitted their assignments, etc.

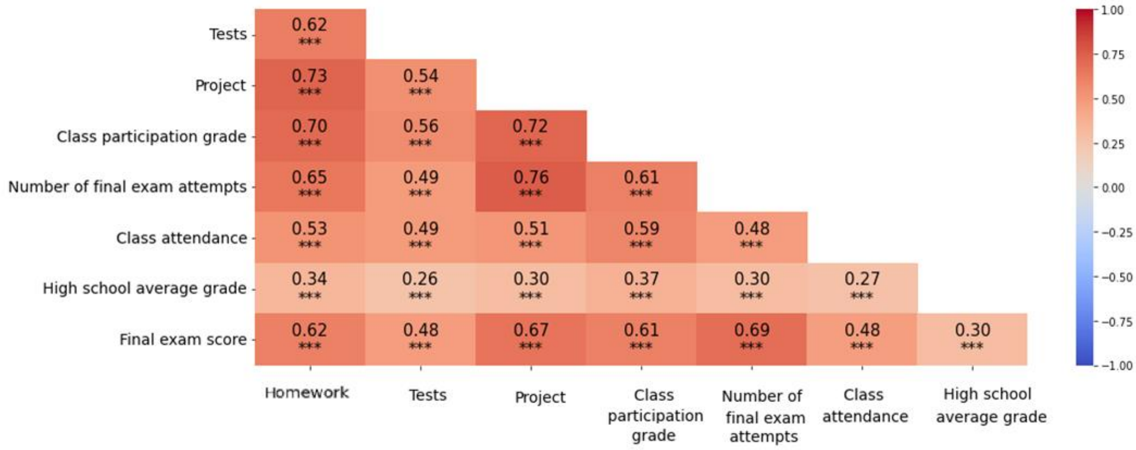
The syllabus of each course defines a different number of assignments and their portion of the final grade. Homework assignments, tests, projects and class participation grades represent 70% of the final grade for the course. Final exam represents 30% of the grade.

The collected dataset was normalized using min-max normalization which performs a linear transformation on the original data and scales the data in the range (0, 1). The numeric values of the final exam score are classified into the categorical variables fail/pass (946 were classified with *fail* and 750 with *pass*). The *fail* class includes students who earned less than 50% of the exam score, while the *pass* class includes those who successfully passed the exam and achieved 50% or more on the exam score.

Exploratory data analysis was conducted in order to select suitable features. Correctness of feature selection was ensured with Pearson's correlation finding and correlation between the variables in data set was explored. Six machine learning algorithms were applied for model validation. Selected ML techniques were utilized for this purpose: (i) Logistic Regression (LR), (ii) Linear Discriminant Analysis (LDA), (iii) K-Nearest Neighbor (KNN), (iv) Decision Trees (DT), (v) Naive Bayes (NB) and (vi) Support Vector Machine (SVM). Evaluation of the built model was done on testing dataset with SVM classifier. To undertake the classification of ML techniques Python programming language and Google Colab Environment were used. Obtained results are presented using accuracy and confusion matrix as metrics.

4. Results and Discussion

In order to perform feature selection and analyze correlation between variables, correlation matrix with Pearson's coefficient was calculated. Figure 2 illustrates the correlation heatmap graph of the input dataset provided by using the Python Pandas library. Correlation degree was classified as follows: low (below 0.29), moderate (from 0.3 to 0.49) and high (from 0.5 to 1). Based on the obtained results, we can see the presence of moderate and high correlation degrees among all variables.



*** - p < 0.001, ** - p < 0.01, * - p < 0.05

Figure 2. Correlation HeatMap

It was of interest to analyze whether the correlation exists between all of the parameters. For instance, it is interesting to see that homework is in high correlation with tests (0.62), projects (0.73), class participation grade (0.70), number of final exam attempts (0.65), and class attendance (0.53). One of the possible explanations is that attending class regularly helps with completing homework successfully, and in return being ready for the project. Similarly, the project has a high correlation with class participation grade (0.72), number of final exam attempts (0.76), and final exam scores (0.67). However, the focus was placed on the correlation between the final exam grade and other parameters.
Based on the correlation matrix, it can be seen that the highest correlation is between the project and number of attempts the final exam was taken (0.76). Additionally, a high level of correlation is shown between the final exam score and projects' grade (0.67) and homework (0.62).

Courses that were taken into consideration for our dataset, are similar not only in the structure of the final grade, but also in the type of assessments. For instance, all of the courses are part of the computing curricula, and have a high degree of practical assignments, and even assessments are based on problem solving that is mainly relating to programming or some sort of technology (hands on) assignment. Hence, this is the reason why it is expected to see correlation between the final exam scores and homework and projects, as the final exam questions are similar to homework and project assignments. It should also be noted that students' class participation grade have a high correlation with the final exam score (0.61) because that grade in itself carries information about how actively and regularly the student studied during the semester, which indicates student's preparation for the exam. Poor correlation is found between high school average grades and final score exams (0.3). That shows that differences in high schools from which the students come do not have a great influence on the passing of the course. This value reflects differences in the type of high schools the students attended or the level of knowledge they acquired there. Moderate correlation is shown for the correlation with class attendance and tests. Being present in the class does not necessarily mean that the student is active and participating. This is the reason why there is a high correlation between the final exam scores and class participation grade (0.61), but only moderate correlation between the final exam scores and class attendance (0.48). Similarly, there is a moderate correlation between the final exam scores and grades received on tests (0.48). This is interesting, as most of the tests are multiple choice questions, including the covered theoretical work, where the class final exam questions contain both theoretical and practical problems. Also, we can see moderate and high correlation degree levels between features and the target variables (final exam score), so all features are kept in the dataset.

In order to choose a classifier for predicting the final exam outcome (whether the course was passed or failed), a 10-fold cross-validation approach was conducted. Cross validation approach splits the training dataset into 10 groups of approximately equal size, trains the model on nine groups and tests the model on the tenth group in ten iterations. The outcomes of the experiments are summarized using classifier accuracy that was calculated as the average accuracy after ten cross validation iterations. Six

ML algorithms were applied for validation of the model. Classifier accuracy for all ten iterations is presented with boxplots in Figure 3.

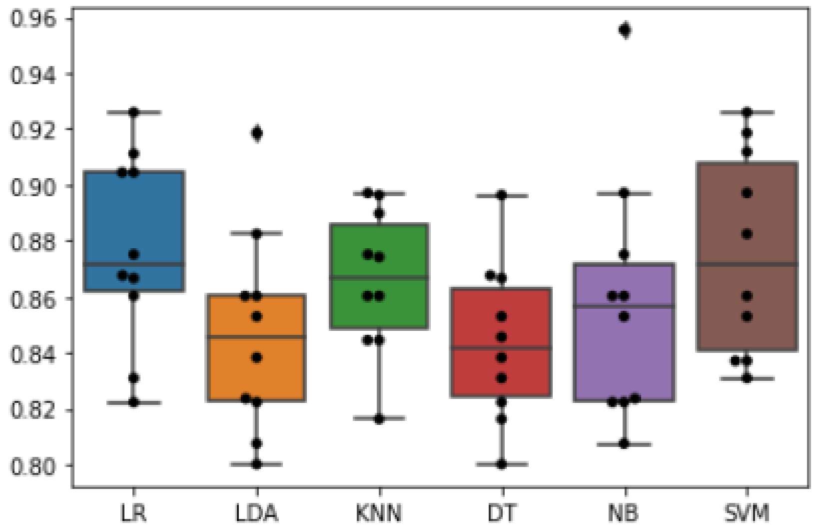


Figure 3. Boxplots with accuracy after 10 iterations of cross validation for six different classifiers

SVM shows the best results with choosing the classifier in all ten iterations with the average accuracy of 88.5%. Other examined algorithms show the average accuracy of LR (87.6%), LDA (84.6%), KNN (86.5%), DT (84.4%), and NB (85.7%). Obtained results are in accordance with conclusions in [20] that show that SVM performs well with small dataset size. As a supervised learning algorithm for classification problems, SVM has the best performances when the class boundaries are nonlinear because it is focused only on the class boundaries, while points that are anyway easily classified are skipped [39].

Once the model was trained, it was tested on the collected dataset. The proposed model for predicting students' academic performance based on SVM shows 90.3% accuracy after model evaluation on testing dataset. Chosen model performance was additionally assessed using a confusion matrix. The confusion matrix summarizes the selected model's overall performance as shown in Figure 4.

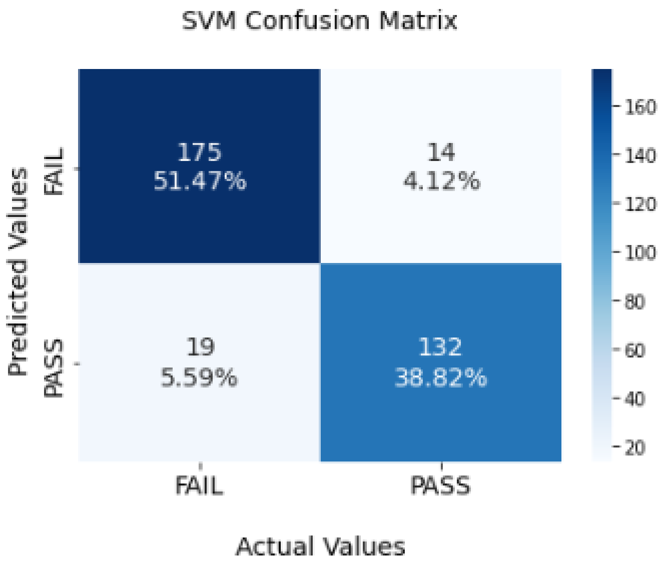


Figure 4. Confusion matrix of SVM proposed model

Based on Figure 4, we can conclude that the model predicts that 175 students from our dataset will fail the exam and that 132 students will pass the exam. This is compared to 189 students who actually failed the exam, and 151 students that passed. This means that model does not work perfectly and there are present type I and type II errors. Model classifies 14 students that passed the course in the failing group, and 19 students that failed the course are classified in the passing group. Also, the model predicts that 132 students will pass the exam, out of 151 students who actually passed the exam. The model does not work perfectly and there are present type I and type II errors. Model classifies 14 students that passed the course in the failing group, and 19 students that failed the course are classified in the passing group.

Evaluated SVM model performance is presented through precision and recall as shown in Table 1.

Table 1. Models performance

	Precision (%)	Recall (%)
FAIL	93%	93%
PASS	90%	87%

Based on the precision, we can see that from all "fail" predictions, 93% really failed the exam, while from all "pass" predictions, 90% passed the exam. On the other hand, based on recall we can see that from an overall number of students that actually failed the exam, the model predicted 93% successfully, and from an overall number of students that actually passed the exam the model predicted 87% successfully. These metrics confirmed that the chosen model gives very satisfactory results in predicting the final exam outcome. The results show that the selected model can be used to predict the final exam outcome (whether the course was passed or failed) with sufficiently high accuracy. This is important for early identification of at-risk students, which can help in addressing their problems and challenges early on.

5. Conclusion

Student academic performance is one of the important quality indicators for every university. Being able to anticipate identification of at risk students at an early stage of student academic life, provides an opportunity to improve the learning process and also reduce the dropout rates. In this work we have examined the accuracy of six different machine learning algorithms in order to predict students' passing or failing the final exam. The six ML algorithms that were investigated were NB, LDA, LR, DT, KNN, and SVM. For the analysis of the proposed model, dataset for four different courses was used. Algorithms were evaluated based on characteristics such as accuracy and precision rate. SVM showed as the most accurate in classifying a data set of student academic performance, and in predicting students' final exam outcome. Future work will analyze a larger number of ML algorithms and try to include additional features in order to gain more accurate model for the prediction of student academic performance and support the entire process of learning.

Acknowledgment

The work presented here was supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia *ref. no. 451-03-68/2022-14/200169.*

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