1. **Introducere**- din fiecare articol parcurs ar trebui să extrageți scopul, abordarea, concluziile și probleme rămase nerezolvate. Puteți structura articolele pe categorii.

[1]

Scop:

This paper proposes a more flexible framework to predict the students’ academic performance. In this framework, the raw data is used directly to construct the prediction model without the feature engineering step.

Abordare:

The feature selection is instead based on model interpretability. The framework is applied to the open university learning analytics dataset (OULAD) with two different type of classifiers: random forest and artificial neural networks.

This study details three main contributions to improve the flexibility and automation of prediction models: 1) a framework that reduces the complexity of the approaches available in the literature by eliminating the feature engineering step is proposed; 2) model interpretation methods to automate the feature selection for different prediction scenarios is introduced; 3) the proposed framework is verified with two popular prediction models available in the literature: artificial neural networks and random forests. This work uses the manylearners’ records that are available in the Open University Learning Analytics Dataset (OULAD) (Kuzilek, Hlosta, and Zdrahal (2017)). These records contain students’ demographics and their interactions with a virtual learning environment.

In this work, the Open UniversityLearning Analytics dataset (OULAD) (Kuzilek et al. (2017)) is selected as it contains a mixture of students’ interactions with the virtual learning environments and their demographics. Also, a sufficient number of research results were published using this dataset, making it an excellent choice for comparing our work with state of the art methods.

The target of predictions in this work is the students ’ academic performance. In OULAD, this target is expressed by four different categories: Distinction, Pass, Fail, and Withdrawn. The distribution of the 32,593 students based on the final result is the following: Distinction (3,024), Pass (12,361), Fail (7,052), and Withdrawn (10,156). Following the approach of (Waheed et al. (2020)), the given students’ academic performances are split into four different categories, where each category is a binary classification problem.

In (Zheng and Casari (2018)), feature engineering is described as “the act of extracting features from raw data and transforming them into formats that are suitable for the machine learning model”. This work ’s main contribution introduces eliminating the feature engineering steps contrary to the other researchers’ approaches. For example, in (Waheed et al. (2020) ), 54 features were engineered and fixed in the pre-processing stage. Our work only considers the features present in the raw data of OULAD. These features can be categorized into three types: students’ information and demographics, courses information, and interactions with the virtual learning environment, described in Table 1, Table 2, and Table 3 respectively. All the features sum up to a total of 32. Regarding demographic features, the work of (Al-Zawqari and Van dersteen (2022)) investigated the role of students ’ background information in the performance of prediction models. However, to draw a fair comparison between the flexible feature selection approach and other work in the literature, we are considering all the raw data.

Still, for simplicity, it is decided to divide the course timeline into four moments of pre diction distributed evenly over the course duration. The length of the courses varies between 234 and 269 days. So, each class has different moments of predictions. The first quarter contains all the student interactions until the last day of the quarter. These interactions alongside the static featuresare used to constructthe prediction model. The second quarter data adds the newlyrecorded interactions until the middleof the course to what we had in the first quarter.The same reasoningis applied for the third and the fourth quarters. As no one is interested in having prediction moments on the last day of the course, the end of the fourth quarter is shifted two weeks before the course’s last day. In other words, the fourth quarter has the recordedstudent’s interactions available from the first quarter, second quarter, third quarter, and the recorded interactions until 14 days before the last day of the course.

The main motivation for this work is the observation that con structing a fixed set of features to predict the students’ academic performance is not straightforward. In addition, feature engineering adds a series of pre-processing steps and prevents the framework from being adaptable based on the changes in students ’ records at different moments of prediction. This section rationalizes the reason for removing the feature engineering step in the proposed framework, followed by a description of two different types of prediction models used in the experiments, namely, artificial neural networks and random forests. The choice of these prediction models is based on two criteria: 1) their frequent use in the literature; 2) the fact that they originate from two distinct families of machine learning algorithms. Finally, the possibility of linking a flexible feature selection/reduction step to the proposed model is explained.

From CHPATER 4.1 ALMOST ALL

Concluzii:

Obtained results show that the feature engineering step can be abandoned without affecting the models’ prediction performance. The prediction results of the flexible feature selection framework either outperform or have a difference of less than 1% accuracy compared to other work in the literature that relies on a manual feature engineering step. Both random forest and artificial neural networks without feature engineering accomplish a high prediction accuracy for the case of students at risk of failing with 86% and 88% compared to all students with pass grades and students with distinction grades, respectively. Also, the prediction models have the highest accuracy rate of 93% in predicting drop-out students. Yet, the prediction models in the proposed framework and previous research work perform poorly in predicting high achieving students with maximum accuracy of 81%, a precision of 69%, and a recall of 57%.

Each model has been investigated against 16 prediction moments, four quarters for each of the four binary classification problems. The results obtained from the prediction models show three important conclusions: 1) feature engineering steps do not add significantly to the accuracy of the prediction models so that they can be eliminated;2) a randomforest classifier is as competent as a deep learning classifier for predicting students’ academic performance; 3) random forest or other tree-based classifiers have the advantage of explainability when compared to deep learning classifiers. The prediction models in the proposed framework are evaluated at the fourth quarter with an accuracy of 85.83%, 88.15%, 81.26%, and 92.91%, for Pass-Fail, Distinction-Fail, Distinction-Pass, and Withdrawn-Pass, respectively. These results either outperform or have a difference of less than 1% compared with the state of the art accuracy,which relies on a manual feature engineering step. Our study also reveals that both the proposed framework and the available literature perform poorly in classifying students with distinction grades against students with pass grades.

Probleme ramase nerezolvate:

Future work will focus on solving this problem in addition to developing an algorithm/framework that can deal with a small dataset. Moreover, the students ’ demographic information helps predict their performance, but their misuse -e.g., using them for profiling-can lead to unexpected negative consequences. Therefore, future work will additionally focus on avoiding this demographic information as it might have a historical bias. Furthermore, an investigation of the proposed framework in different educational set-ups is needed, e.g., using this framework with a dataset generated from a physical classroom.

[2]

Scop:

In the present paper, five single supervised machine learning techniques have been used, including Decision Tree, Naïve Bayes, k-Nearest-Neighbor, Support Vector Machine, and Logistic Regression. To analyze the effect of an imbalanced dataset, the performance of these algorithms has been checked with and without various resampling methods such as Synthetic Minority Oversampling Technique (SMOTE), Borderline SMOTE, SVM-SMOTE, and Adaptive Synthetic (ADASYN). The Random hold-out method and GridSearchCV were used as model validation techniques and hyper-parameter tuning respectively.

Thus, it is quite important to predict low-performing students at an early stage with higher accuracy, along with the important factors that may affect their performance. To achieve this goal, the present study has three important research objectives: (i) to identify the influential features by using a filter-based feature selection technique. (ii) to identify the best performing classifier by comparing various singlesupervised machine learning techniques, viz., decision trees, Naïve Bayes, k-Nearest Neighbor, Logistic Regression, and Support Vector Machine with various resampling techniques such as random oversampling, SMOTE, Borderline SMOTE, SVM-SMOTE, and ADASYN. (iii) to enhance the prediction rate of the students at-risk by using an ensemble model that integrates the most suitable data mining technique.

Although there are several studies to predict the students‟ academic performance, the study which considers all categories of variables, i.e., background, academic, social, and psychological, and predicts students at-risk at an early stage with adequate accuracy is lacking. Also, a single classifierbased prediction is not suitable from one perspective to another. Moreover, a classifier giving the highest prediction accuracy for a particular dataset may not be valid for a different dataset. Thus, the aim of the present study is to identify low performers at an early stage with a higher prediction rate by using a scalable approach.

Abordare:

To make the data versatile, it is collected from the two different engineering colleges situated in different regions (the north and south of India). In the present paper, the sample size comprises 550 engineering students from two different engineering colleges in India, i.e., Bipin Tripathi Kumaon Institute of Technology, Dwarahat, Uttarakhand, and Cochin University of Science & Technology, Trivandrum, Kerala. The dataset includes information regarding background, past academic, social, and psychological factors with 30 different attributes, of which three attributes (roll-number, name, and branch) are used for identification purposes only and do not play any role in the prediction of low-performers. So, only 27 attributes were used for the present work, with first semester GPA as the output variable. For these attributes, data was collected online with the help of a multiple choice questionnaire created via outsourced technology, i.e., Google Form. As the aim of the paper is to identify the students having the highest risk of dropping out of college, the information about the output attribute for the dataset is divided only into two categories, i.e., low performers and high performers, based on the first-semester grade point of the students.

Feature selection: Feature selection is an important part of the students‟ performance prediction model for two main reasons:  The main purpose of the prediction of students‟ academic performance is to provide timely support to the low-performing students in the area where they are lacking. Only after identifying the attributes that have a significant impact on the output variable, i.e., students‟ academic performance, suitable corrective measures may be taken to provide support to the lowperforming students.  With the help of feature selection, irrelevant attributes may be removed from the data without losing reliability in classification. Thus, the dimensionality reduction raises the processing speed, and hence the classifier can learn faster. There are three main feature selection techniques: manual selection based on pedagogical theories or expert experience; filter-based selection; and wrapper feature selection [19]. In the present study, as all the attributes were categorical, a filterbased feature selection technique, namely “chi-square”, was used by which p-values were calculated for each attribute [8]. The attributes having a p-value of less than 0.01 show a highly significant correlation with the student's grades.

There are different types of classification machine learning models that may be used to predict the students‟ academic performance. In the present study, five single supervised machine learning models have been applied, including Decision Tree [25], Naïve Bayes [9, 26], k-Nearest-Neighbor [27], Support Vector Machine [28], and Logistic Regression [29]. To achieve the best performance of these machine learning models, the passing parameters for these models were set with the help of an algorithm called "GridSearchCV" which gives the best combination of passing parameters [30]. These combinations of passing parameters are listed in Table I.

Concluzii:

From this table, it is depicted that after applying the feature selection technique, the following 11 features are selected as influential features that affect students‟ academic performance: percentage in 10th standard, percentage in 12th standard, confidence, mathematics % in 12th standard, punctuality, curiosity, medium/language of previous study, category, father‟s highest qualification, mother‟s highest qualification, and mental stress. After selecting the most influential attributes, Decision Tree, Naïve Bayes, k-Nearest-Neighbor, Support Vector Machine, and Logistic Regression algorithms have been applied to the dataset, which contains only the 11 selected most influential attributes. The results obtained for accuracy, precision, recall, and f1-score of these algorithms are represented in Table III.

From the present work, it may be concluded that students‟ past academic performance (10th standard %, 12th standard %, and Math‟s % in the 12th standard), their background (category, parents‟ qualification, and medium of the previous study), and their psychological features (mental stress, confidence, curiosity, and punctuality) were the relevant attributes. Thus, to increase the academic performance of the students, these factors may be considered as the focus points. In the present study, all the used classifiers were able to predict students‟ outcomes with reasonable accuracy of more than 80%. Among all the used classifiers, Logistic Regression was the best performing algorithm with a balanced as well as an imbalanced dataset. Further, the accuracy and prediction rate for identifying low performers as well as for high performers were improved when the Logistic Regression was applied to the balanced dataset. The prediction accuracy was further enhanced with the use of an ensemble classifier in which three Logistic Regression classifiers (because of its highest performance) were integrated with the help of bootstrap aggregation. The proposed integrated model has achieved the highest accuracy of 95.45% and the highest precision and recall for low performers with the balanced dataset formulated with the help of the resampling technique SMOTE. It should be noted that with different datasets, the different classifiers may give the highest prediction accuracy, and hence there is a need for the methodology to be scalable for every situation. Thus, the main advantage of the present approach is its scalability for different datasets.

The results of the present study indicated that Logistic Regression is the best performing classifier with every balanced dataset generated using all of the four resampling techniques and also achieved the highest accuracy of 94.54% with SMOTE. Furthermore, to improve the prediction results and to make the model scalable, the most suitable classifier was integrated with the help of bagging, and a well-accepted accuracy of 95.45% was achieved.

Probleme ramase nerezolvate:

Further, this study may also be applied to the different domains of data mining and machine learning applications for enhancing prediction accuracy. The limitation of the present study is that the examined dataset has a small sample size and slightly imbalanced data, so in the future, the proposed methodology should be used with large sample sizes and highly imbalanced data for the prediction of students‟ academic performance.

[3]

Scop:

The objective of this paper is to propose an enhanced predictive model for students’ performance prediction. Selecting the most important features is a crucial indicator for the academic institutions to make an appropriate intervention to help students with poor performance and the top influencing features were selected in feature selection step besides the dimensionality reduction and build an efficient predictive model. DB-Scan clustering technique is applied to enhance the proposed predictive model performance in the preprocessing step. Various classification techniques are used such as Decision Tree, Logistic regression, Naive Bayes, Random Forest, and Multilayer Perceptron. Moreover ensemble method is used to solve the trade-off between the bias and the variance and there are two proposed ensemble methods through the experiments to be compared.

Therefore, the objective of this paper is to propose an enhanced predictive model for accurate prediction of students’ performance. Various machine learning techniques were experimented. For enhancing the predictive model, we applied DB-Scan clustering technique and feature selection approach. Experimental results proved the effectiveness of the proposed model.

Abordare:

The purpose of this paper is to propose a predictive model for students’ performance prediction. This is achieved by exploring various classification techniques, besides the ensemble method that solves the trade-off between the bias and variance, to investigate which one would achieve the best performance. Moreover, DB-Scan was used in preprocessing for outlier detection and features selection was used to enhance the predictive model of students’ performance.

Pre-processing is an essential process for any data set. It includes data cleaning and transformation. We pre-processed the dataset through three steps. Firstly, data was converted from nominal to numerical values. Secondly, some features were reshaped to be within a certain range using standardization method. Finally, DB-Scan clustering methodology was applied for outlier detection, as it had a great efficiency in [16]. B. Feature Selection Feature selection aims to select the most important and influencing features in the dataset. Also, it is very important for dimensions’ reduction before implementing the prediction and classification methods. It works by selecting the best features that contribute most to the target variable based on univariate statistical tests. We used the SelectKBest technique [15]. SelectKBest technique selects the first k features with the highest score values based on the Chi-Square test, for comparing the actual and predicted results, as a score function [14] using equation (1). X2 = P(Oi–Ei)2/Ei (1) where Oi and Ei are the actual and expected values, respectively. C. Classification For classification, we designed two different Ensemble models. One consists of Multilayer Perceptron (MLP), Random Forest (RF) and Decision Tree (DT), the other consists of RF, Logistic regression (LR) and DT.

The dataset is collected from a Learning Management System (LMS) [24]. It contains 480 records of students’ data in various educational levels with 16 features. The features were categorized as follows: • Academic features: Section id, Semester, Educational stages, Viewing announcements, Grade levels, Topic, Discussion groups, Visited resources, Raised hand, and Student absence days. • Personal features: Gender, Parent responsible for student, Parent answering survey, and Parent school satisfaction. • Demographic features: Nationality and Place of birth. We pre-processed the dataset through two steps. Firstly, we converted the data from nominal to numerical values for the features: Section Id, Semester, Educational stages, Grade levels, Topic, Discussion groups, Gender, Parent responsible for student, Parent answering survey, Parent school satisfaction, Nationality, Place of birth, and Student absence days. Secondly, the following features: Viewing announcements, Discussion, Visited resources, and Raised hand, were reshaped to be within a certain range using standardization method. Fig. 2 shows a sample of the dataset’s features and instances.

FROM C EVALUATION MEASURE -> ALMOST EVERYTHING

Concluzii:

The proposed model is an ensemble classifier of Multilayer Perceptron, Decision Tree, and Random Forest classifiers. The proposed model achieves an accuracy of 83.16%.

In this paper, we proposed an enhanced predictive model for students’ performance to improve the prediction accuracy. We applied various machine learning techniques for predicting the students’ performance. Additionally, DB-Scan clustering algorithm and feature selection steps have been exploited, for choosing the significant features. Our first ensemble method has achieved an accuracy of 83.16%, 78.95%, and 65.26% using all the features, the top 10 influencing features, and the top 5 influencing features, respectively. The proposed predictive model outperformed previous work using the same dataset from the learning management system. Applying DB-Scan clustering technique as a preprocessing step has a great effect on enhancing the predictive model performance and the distribution of results as seen in the confusion matrix of each predictive model.

Probleme ramase nerezolvate:

For future work, we intend to apply the proposed predictive approach to various datasets, experiment different feature selection techniques, and implement alternatives for DB-Scan clustering technique.

[4]

Scop:

This study estimates pupils' success by analyzing secondary education data from two Portuguese schools, both of which included students with different levels of academic achievement [5].

The main goal of this study is to help educators identify pupils who are at risk and help them improve the educational outcomes for these individuals. Several data pre-processing techniques were used to boost the model's accuracy. A feature subset selection wrapper approach was used to locate the best feature subset. This study also explores the differences between using multiple and binary grading systems.

Abordare:

2.1 Dataset Description: This study used two openly available datasets to predict student performance. Students at two Portuguese secondary schools produced the two datasets. In addition to grades, the dataset includes information on students' demographics, socioeconomic status, and school. It was acquired through school reports and surveys. Data from a Portuguese language lesson is included in the second dataset, including a math class. There are 33 variables in total across both datasets.

2.2 Data Pre-processing: There are many possible final grades in this raw dataset, with 0 being the worst and 20 being the best, typical of European countries. There must be a grading criterion adjustment to categorize the data as it is currently in integer form, and the projected class should be in categorical values. Our research compared and contrasted two different grading systems: Binary and Multiple. There were two categories: "pass" and "fail" for the final grade. Because of this, we were able to compare the results. The range of 0 9 in table 1 is used to signal a failure. "Pass" is defined as a score between 10 and 20. To categorize the final grade, we first separated it into five groups. The ranges in question were calculated using the Erasmus methodology. It is the lowest grade, equivalent to the phrase "fail," as shown in Table 2. In terms of grade point average, the following class labels range from 10 11 to D, 12 13 to C, 14 15 to B, and 16 20 to A, respectively.

It was decided that three well-known classification algorithms would be employed to forecast student grades. These algorithms were the DT, the RF, the NB, the MLP, and the JRip [7].

A pre-processing operation categorizes the final grade attribute into two independent grading systems. There are now two different versions of both datasets. Numerous grading formats (including binary) were available for both the math and the Portuguese datasets. Because of this, we can compare the results of the many possibilities. Using the Portuguese dataset in its multiple grading and binary versions, the first experiment compared five algorithms. Table 3 shows the highest accuracy rate of 75.40% for this dataset's multiple grading version [8].

An improved accuracy rate was achieved using the Random Forest method with the binary grading. According to a dataset, where final grades are categorized as Pass/Fail, the accuracy percentage increased to 95.08%. The categorization results are shown in Table 4 on the set of mathematics datasets (Multiple and Binary Grading System). The Decision Tree algorithm delivered the best results for the multiple grading systems, with an accuracy rate of 85.62%. At 93.49%, the binary dataset version's most excellent accuracy rate was achieved by Random Forest.

After preprocessing the dataset or picking a feature subset in a second experiment, we carried out all comparisons. The wrapper subset method selected the most relevant attributes and increased accuracy rates. It is critical to choose the suitable characteristics for a model to succeed. Selecting appropriate qualities and removing redundant or superfluous ones is an easy two-step. First, attribute selection is made to develop a basic model, an easier-toread model, and decide which attributes are most relevant to the findings. Next, we used filters and wrappers to choose features. The wrapper method was used in this investigation because it consistently produces better results. This procedure uses a recursive structure. Invoking the algorithm on a subset is the first step in the process. Evaluation is based on the model's success. This examination has two possible outcomes. If you choose option one, you'll have to start again from scratch; chance two lets you use what you already have picked [9]. A comparison of accuracy rates for the Portuguese dataset for the multiple grade version is shown in Table 5 and Figure 1. The accuracy rate of a decision tree algorithm was increased from 70.80% to 80.56% by using the wrapper subset approach. The Random Forest algorithm's accuracy rate rose from 82.40% to 85.74%. There was an increase in accuracy from 77.79% to 84.56% using the Naïve Bayes approach. The accuracy rate of the Multilayer Perceptron approach, which delivers the findings, has increased from 73.60% to 78.45%. The JRip method's accuracy percentage has increased from 75.30% to 80.87%.

Concluzii:

According to this study's findings, it is possible to forecast students' final grades using historical data mining approaches. Three well-known classification algorithms, such as Decision Tree, Random Forest, Nave Bayes, Multilayer Perceptron, and JRip, were tested for their accuracy rates. The wrapper feature subset selection strategy was used to improve classification performance. Pre-processing measures on the dataset, such as classifying the final grade field into a fine and two groups, increased the percentage of accurate predictions in the categorization. The wrapper attribute selection methodology increased accuracy significantly across all methods. It was found that the binary class technique was more accurate in both mathematics and Portuguese datasets. In the future, different methods of feature selection may be employed. In addition, the datasets can be subjected to a variety of categorization methods.

This report suggests that students' final grades can be predicted using data mining techniques based on past research. On two educational datasets related to mathematics classes and Portuguese language lessons, three well-known data mining approaches, such as Decision Tree, JRip, Naive Bayes, Multilayer Perceptron, and Random Forest, were utilized in the experiments. As a result, using the employed data mining methods, student success might be predicted with reasonable accuracy.

Probleme ramase nerezolvate:

[5]

Scop:

In this study, we examined students’ behaviors in online self-assessment task and how it affects their learning performance.

Abordare:

A 6-week experiment was conducted in an accounting course. Students were instructed to complete online self-assessment in the form of formative quizzes after class. We performed clustering analysis, which revealed three behavioral patterns in online self assessment, and we compared the learning performance of students across different patterns.

3.1. Participants and context A 6-week experiment was conducted for students studying in an accounting course at the Accounting department of a Taiwanese university. The course is mandatory for fourth-year students in the Ac counting department, and they all have the same educational background and the same exposure to information technologies. The experiment was conducted from the beginning of the semester to the midterm examination. The course employed BookRoll, an e-book reading tool developed by Kyoto university, where the instructor uploads learning materials before each class and students can perform various activities during their reading. For an introductionto the e-book reading activities available on BookRoll, the studies of Ogata et al. (2015) and Flanagan and Ogata (2018) can be referred. In this course, the Moodle online learning environment was used together with face-to-face teaching. The activities in Moodle included accessing learning materials, discussing with peers or a teaching assistant, and taking assessments in the form of formative quizzes. Most students have used Moodle before, but none of them have experience with BookRoll and the assessment system employed in this study. Therefore, students were introduced to Moodle, BookRoll, and the assessmentsystem as well as how to use them at the beginning of the experiment. The assessments were generated every week and consisted of cloze items related to the content taught during that week. Since the assessment was designed to assess students’ ability to recall the concepts in the study materials, it mainly contained factual questions. The questions were generated by the online assessment system proposed in a previous study (Yang et al., 2021). The system extracts keywords from the text of relevant learning material and masks those words to form the cloze items. To ensure that the masked items reflect students’ knowledge level on the learned.

subjects, the questions were reviewed by the instructors before being presented to students. The instructor could modify the cloze items by adding additional masks or removing existing masks to ensure that the items fit the course objectives. Students were asked to take the assessments after classes. Fig. 1 shows a snapshot of using the online assessment system. After entering the system, students can click the green mask to type and submit their answer. The system will provide immediate feedback by showing the result of their answer. The mask is removed if the student provides the correct answer. Otherwise, a red “x” is displayed in the input field. Students can choose to see the hint by clicking the “Hint” button if they cannot recall the answer. To discourage students from finding answers from learning materials during the assessments for achieving high scores, they were informed that their performance in the assessments would not affect their final grade. Thus, students repeatedly took the assessments for review purposes. During the experiment, five assessments with distinct properties were generated. The number of questions in each assessment was 15, 11, 11, 13, and 8, respectively.Students could take the assessments through the Moodle anytime and anywhere. Student self-assessment behaviors were recorded in the database with timestamps. The actions that students can perform in the assessments are presented in Table 1. The relationship between students’ self-assessment behaviors and their learning performance was analyzed in this study. The midterm examination scores for the course were used as the indicator of learning performance. The midterm examination involved the topics covered in the five assess ments, but the contentwas presented through different questions. With a total score of 100, each topic consisted of 20%. A total of 73 students participated in this experiment. Seven students did not take the assessment at all and werethus excluded. All students were informed that their self-assessment behaviors and learning performance would be logged, and that their personal information would be anonymized for research analysis. All participants agreed to the policy. 3.2. Feature selection and data analysis A total of 88696 online self-assessment events were collected and analyzed. The features presented in Table 2 were extracted from the logs. The attempt count was used to measure how frequent a student took the assessment. Question views indicated the number of times a student clicked and viewed the questions during the assessment. A high number of question views indicated that the questions were likely reviewed multiple times. The submission rate measured how many attempts students required before obtaining the correct answer; that is, how easily they were able to recall the learning content. The hint rate was used to evaluate students’ reliance on hints. The average values of attempt count, question views, submission rate, and hint rate were6.79, 14.23, 2.47, and 1.76, respectively. We applied hierarchical clustering to identify specific patterns of online self-assessment behavior for answering RQ1. The number of cluster was determined with the help of dendrogram that shows the distance between each data point. Since each feature has a different scale, which may affect the performance of clustering algorithms, all features were standardized for clustering analysis. Next, the difference between the learning performance of students from the identified patterns were examined using statistical model for answering RQ2. Data analysis and data visualization were performed using Python. Specifically, clustering analysis was performed using hierarchical clustering through the Scikit-learn package. Statistical analysis was carried out using the SciPy package.

Because the distribution of each feature did not satisfy the requirement for performing ANOVA, we employed the Kruskal–Wallis H-test to examine whether the performance in each feature differed significantly between clusters. The number of features in each cluster is presented in Table 3. The resultsindicated a significant difference in the frequencyof using the test module (H = 25.18, p < .001), question views (H = 28.30, p < .001), submission rate (H = 34.26, p < .001), and hint rate (H = 18.78, p < .001) among the three clusters. Students in Cluster C (median [M] = 9, standard deviation [SD] = 2.47) and Cluster B (M = 7, SD = 2.31) used the assessment system significantly more often than did those in Cluster A (M = 5, SD = 2.28), and students in Cluster C also had more assessment attempts than did students in Cluster B. The Mann–Whitney post hoc test results indicated that Cluster B students (M = 21.5, SD = 5.54) viewed significantly more questions than did Cluster A (M = 9.7, SD = 5.09) and Cluster C (M = 13.9, SD = 3.95) students, and Cluster C students also viewed more questions than did Cluster A students. Moreover, Cluster B students (M = 4.31, SD = 1.27) exhibited a significantly higher submission rate than did Cluster A (M = 1.42, SD = 0.94) and Cluster C (M = 1.68, SD = 0.65) students. Finally, the post hoc test results indicated that Cluster B students (M = 3.03, SD = 1.46) viewed hints significantly more frequently than did Cluster A (M = 1.69, SD = 1.73) and Cluster C (M = 0.1, SD = 0.78) students, and Cluster A students also used hints more often than did Cluster C students. The findings showed significant differences in behavior within each cluster, suggesting that it is feasible to use hierarchical clustering to classify students’ self-assessed behavior. To understand how individual features affect learning performance, we performed Spearman correlation analysis to analyze the relationship between each behavior and the examination score. The attempt count was positively correlated with learning performance (r = 0.3, p < .05), whereas the feature of question views was not (r = 0.15, p > .05). This indicates that assessment taking attempts in itself can generate positive effects for learners, and the frequency of viewing questions is not as critical as assessment taking attempts. On the other hand, submission rate (r = 0.24, p < .05) and hint rate (r = 0.29, p < .05) had a negative impact on learning performance, indicating that high submissions and the frequent use of the hint function may hamper student learning.

Concluzii:

Researchers can apply clustering analysis to examine students’ behavior in other online self-assessment systems that offer different features to identify more behavioral patterns. The results of the behavioral analysis can help software developers improve systems by designing features that prevent students from performing nonstandard behaviors. Additionally, teachers can provide personalized feedback to the individual student based on their behavioral patterns to help them maximize the benefit of self-assessment. In the future, we will conduct more detailed behavioral analysis of online self-assessment behaviors by using other approaches such as temporal analysis, which has been applied in other studies (Kokoç et al., 2021), to investigate whether the behaviors of students change over time.

The current study’s findings provide insights for researchers in related fields and educational practitioners. Researchers can optimize similar online assessment tools on the basis of our results; they can collect more features that reflect student behaviors and perhaps visualize behavioral analysis results on a dashboard for instructors to monitor students’ learning process. Our results may serve as a reference for instructors who wish to understand student behaviors and whether specific patterns exist during self-assessments. Instructors can also use our results to identify whether students demonstrate nonstandard behaviors during self-assessment. Finally, our results may prompt policy makers to facilitate the administration of online self-assessment. Our study has several limitations.

The results indicated that students who frequently took the online assessments after class tended to achieve a higher examination score than those who did not. However, the learning performance of students who demonstrated nonstandard behaviors did not necessarily improve, even though they actively took the assessments. Our results suggest that student behavior is a critical factor in improving learning through self-assessment. These findings provide insights for researchers in the learning analytics field as well as for practitioners who wish to adopt online self-assessment for learning.

Probleme ramase nerezolvate:

The small sample size (76 students) reduced the generalizability of our results. Similar results from large-scale experiments are required to confirm the relationship between students’ online self-assessment behaviors and learning performance. The addition of more features may also enable us to obtain more detailed and accurate insights into student behavior during online selfassessments. For example, recording the response time of each item may help us identify guessing behavior. Moreover, the current study analyzed students’ self-assessment behaviors using a frequency-based approach, which may neglect the detailed relation between features. For example, whether students view hints before they respond can result in two patterns. Therefore, another learning analytic approach, such as process mining, should be considered to explore other behavioral patterns of online self-assessment in future studies. Temporal analysis is another approach that can determine whether students follow the same pattern while taking the assessments throughout the experiment. Finally, comparison of SRL skills, testing strategies, and cognitive individual differences of students who exhibit similar behavioral patterns may reveal valuable insights. Future studies modeling online selfassessment behaviors should account for these indicators.

[6]

Scop:

The objective of this article is to show the implementation results of a predictive information system (IS) for the prevention of university dropout in a higher education institution. The system allows the calculation of the risk of dropout per student and uses an alert generation procedure to coordinate interventions.

Abordare:

This article aims to show the results obtained through the implementation of a predictive information system (IS) for the desertion of university students. The methodological design consisted of 3 phases: data collection, modeling, and implementation/validation. The resulting IS was implemented in a higher education institution with more than 15,000 students, provides a user interface for monitoring the main risk factors associated with student’s dropout, in a timely and personalized way.

The data was collected, consolidated, and complemented with information is obtained from the Colombian Ministry of National Education, and the Colombian Directorate of Social Development). 2.2. Phase 2: Modeling. 2.2.1. Variable Selection. Given that the students of each higher education institution have a specific set of characteristics, the dropout patterns may vary according to the institution. A “naive” approach was adopted, aiming to achieve an objective point of view at the time of analyzing the dropout phenomenon. All data were included in the analysis, without any of the variables being previously discarded. This selection process aims to reduce the number of variables that will be used to train the model, prioritizing those with the most significant predictive potential. 2.2.2. Classifier Selection: Instead of predefining a single model that works for most educational institutions, several methods were tested simultaneously, and finally, the method that best suits the reality of the institution was chosen. Thus, the predictive model will be specifically adapted to the dropout patterns observed in the students of the institution. The goal of this step was to determine the classification algorithm with the highest prediction efficiency on the dataset. The algorithms considered during this phase included: AdaBoost algorithms, Bayesian GLM, Decision Trees, Logit Boost algorithms, Random Forest, and Stochastic Gradient Boosting.

3. Results 3.1 Variable Selection The data collected in Phase 1 consisted of 44,031 records of 15,805 students, covering four academic periods (2016-1, 2016-2, 2017-1, and 2017-2), grouped in 165 different initial variables. A correlation analysis was carried out using the Kolmogorov Smirnoff (KS) test for each of the variables related to the dropout rates. Subsequently, a multivariate analysis method was used using a Random Forest Algorithm to determine the degree of contribution of various sets of variables in the prediction of dropout rate. Decision trees were generated for the most significant variables. The decision trees provided the ranges or values where the dropout rate is significantly lower or higher than the average (Figure 1). The students were classified in one of the branches (nodes), and in the row depending on the category in which the student is (1: drop out; 0: remain).

All the variables were ordered according to their predictive potential. This process requires the use of advanced Data Mining techniques because, for each variable, its conditional dependence on the presence of other variables with respect to dropout must be taken into consideration, and not only its non-conditional dependence. A Random Forest algorithm was used as a regression method on the data (not to be confused with Random Forest in its use as a classification algorithm, which is explained in the classifier selection stage). The process consisted of the following stages:

• Random groups are chosen from the variables present in the dataset, where each variable can be included in more than one tree, and the total of variables per group can vary.

• For each group, a random subset of rows is chosen from the original dataset (student enrollment).

• A decision tree is trained for each group, predicting dropout with the different training data.

• Each variable receives an importance value, which is measured considering the set of decision trees with and without it.

• The variables are ordered according to their importance, and a multivariate ranking is obtained.

3.2. Classifier Selection.

The procedure for the classifier selection started choosing the first variable in the multivariate ranking and training a model for each type of algorithm, predicting dropout based on that single variable. The precision result was measured according to the area under the (Receiver Operating Characteristic Curve) ROC, and the result of each partial model was saved. Then the procedure was repeated with the first two variables in the ranking, then the first three, and so on. The first 30 variables were used at most, to avoid overfitting and to reduce the number of variables that will enter the final result. The different classifiers tested in this stage are described below:

• AdaBoost Algorithm:

AdaBoost is an algorithm to build a “strong” classifier from the weighted sum of a large number of base classifiers, and by default, they are decision trees. AdaBoost classifiers generally have lower predictive quality, but they are easier to obtain. In each iteration, the algorithm learns from the misclassified data, updating the weights that accompany the weak classifiers, and thus improving the predictive quality at each stage [13,14].

• Bayesian GLM: In the same way as the Logistic Regression, this model focuses on predicting the occurrence of a binary (or dichotomous) phenomenon. However, the parameters of this model are random variables so that probability distributions can be assumed for them before the arrival of data, and the change in their distribution caused by the data considered in the analysis can be known [15].

• Decision Trees: A tree is made up of a set of nodes, branches, and leaves. Each node represents a variable, which can be divided into branches or leaves. The main decision rule is to separate the data into two groups, as different as possible and to do this, it looks for the variable that best performs this segmentation. All of this process continues until a constraint is met: it can be a fixed number of nodes or fixed depth of the tree. To predict using this method, a “new” student is taken, and how he moves inside the tree is observed, reaching a final decision, which in this case is whether to drop out or not [16].

• LogitBoost Algorithm: This algorithm uses the same principle as AdaBoost, but the base classifiers used in this process are classifiers created from logistic regressions [17].

• Random Forest Random Forest algorithm creates a large classifier formed from the development of many small decision trees created randomly. The final prediction is made through the weighted average of the classification of all trees. [18].

• Stochastic Gradient Boosting: This technique consists of iteratively creating a classifier that, using regressions obtained from sub-samples of the data, learns at each stage of the data that is misclassified, adapting to the observed reality [19].

The area under the ROC curve provides a measure of the performance of the model for the selected variables, equivalent to the probability that the model classifies a real dropout student with a higher probability than a false dropout student (false positive). The two algorithms with the largest area under the ROC curve (close to 80%) was the AdaBoost algorithm and Bayesian GML and provided the best balance between predictive level and model stability. From the initial 165 variables, the first 30 most significant were used to select the classifier. Finally, a set of 25 variables allowed the model to obtain a precise prediction. The probability of dropping out of each student was calculated using the 25 variables. This probability defines the level of priority that will be taken when carrying out activities to monitoring and preventing dropouts by those responsible for the follow-up process. The probability changes according to the alerts and interventions registered by the responsible for the follow-up process during the academic period (Section 3.3.2. and 3.3.3.). At the end of each semester, the impact of the interventions on the percentage of student retention is calculated.

Concluzii:

The implemented IS represents a powerful tool for predicting, monitoring, and managing the risk factors associated with the student dropout factors. Some advantages of the implemented IS include the centralization of the information allowing a comprehensive view of the students, the prioritization in the timely follow-up of students with

a higher risk of dropping out. Also, it allows individual and massive register of the interventions carried out to students. This includes scheduling of future interventions and defining a way to evaluate of the impact of follow-up strategies on student permanence.

Probleme ramase nerezolvate:

The limitations of the IS include the need to make more flexible the assignment of a higher number of monitoring managers to generate alerts and improving the cu stomization of reports. An update of the software is proposed that incorporates new functionalities in terms of bulk uploads, increasing data volumes when downloading reports, and improvements in the implementation of the strategy by those responsible, giving priority of intervention to students according to the level of risk using the following order 4, 3, 5, 2 and 1 for greater effectiveness. Among the opportunities for future research is the incorporation of new classification and weighting methods, which allow to improve the reliability of the information system predictions.

[7]

Scop:

The study aimed to characterize learners according to their learning patterns and to identify indicators that predict students’ success in an online environment.

Abordare:

Specifically, we focused on the role of a central factor affecting success in online courses: self-regulated learning and learner engagement. To this end, we used a mixed methods approach that combines semi-structured interviews and statistical analysis. We applied two logistic regression models and a decision tree algorithm and found two parameters that can predict completion of the course: the submission status of an optional assignment and the students’ cumulative video opening pattern (SCOP). Recommendations for institutions and lecturers regarding the benefits of implementing these models to identify self-regulated learning patterns in online courses and to design future effective interventions are discussed. Regarding students, we emphasize the importance of time management and how choices they make with respect to their learning process affect their potential for success.

Here we present a study on three online undergraduate general chemistry courses offered at the Open University of Israel (OUI). Existing research on predicting persistence in chemistry courses focused on background indicators, such as high-school achievement and SAT scores (Lewis & Lewis, 2007). However, the rise of online platforms (Amaral, Shank, Shibley Jr, & Shibley, 2013) opened an opportunity to focus on more proximate indicators that can predict student performance in each course and extend the analysis, beyond the students’ past achievements and background, by analyzing their actual online learning patterns.

As discussed above, completing online courses is known to be more difficult than traditional face-to-face courses. Our study has two main goals: (1) to characterize learners according to their learning patterns in the online learning environment and (2) to identify learning patterns that can predict students’ successful completion of online chemistry courses. Because online course data generally present information about learning behavior, this study includes measures that relate to the frequency of online lesson openings and assignment submissions, which are indicative of the extent of learners’ engagement and SRL. To meet this goal, we posed two research questions:

1.What learning behaviors do students apply in online general chemistry courses?

2. What indicators of online learning can predict course success, and at what stage?

We studied undergraduate general chemistry courses offered at the OUI, which does not have prerequisite admission requirements for undergraduate degrees. Nevertheless, the admitted students need to demonstrate high levels of knowledge and skills in order to successfully complete the courses. To maintain this kind of accessibility, the OUI offers a variety of learning tracks that allow students to choose between traditional face-to-face classroom, online learning, or a combination of the two (blended learning). Such flexibility provides more opportunities for potential students from the country’s geographic and socioeconomic periphery, as well as other students that can benefit from flexible academic schedule (https://www.openu.ac.il). Here we followed students who took the chemistry courses in an online format.

The research design included both qualitative and quantitative tools (mixed methods). Integrating quantitative and qualitative research methods is known to increase the precision and trustworthiness of the results (Leech & Onwuegbuzie, 2007). The study was conducted in two stages: The first stage was descriptive and the second was predictive. The purpose of the first stage was to identify learning behaviors that students apply in the online general chemistry courses. This stage was based on interviews with participants enrolled in each of the these courses, and a descriptive analysis of the courses’ log files. Before deciding which variables to use in the quantitative analysis, we conducted a preprocessing phase of data collection, categorization, and filtering (see Section 4.2). Then, we found that the reliable features that can be used are the activity time stamp, video play, demographic data, and the assignment submission status. In addition, we considered the course pedagogy, which enabled students to choose which assignment to submit (see Table 1), and the flexibility of the online course, which allowed students to play the video at their own time and pace. Following this stage, the predictive stage began, during which we quantitatively evaluated the collective power of the major variables that were identified in the first stage as predictors of course success.

4.1.Qualitative analysis In order to reveal students’ learning habits, we conducted 13 semistructured interviews with participants enrolled in each of the three courses included in this research. Semi-structured interviews aim to enable flexibility. The interviewer prepares a list of topics and questions and follows that list during the interview. In order to ensure that the questions elicit open responses, the interviewer enables the responses to be developed in ways that were not anticipated when the interview was planned (Brown & Danaher, 2019). Out of the 13 interviews, 10 were conducted with students who successfully completed one of the three courses analyzed in this study, whereas the other three were with students who did not complete the course they took. Twelve interviews were conducted by phone, and one in a face-to-face meeting. In each semester we posted an advertisement in in one course website (alternating between the three courses throughout the year) and invited volunteers to be interviewed at the end of the course, after the final exam. The semi-structured interview protocol included twenty two questions organized around subthemes (see the Supplementary Materials file). All three authors validated the interview’s questions. Each interview lasted 20–60 min and was audio recorded and transcribed.

4.2.Quantitative analysis The quantitative analysis covered data from Moodle log files, course grades, and students’ demographic profiles. The Moodle log files contained the course activity reports, which showed the number of views for each course website resource. The grades (including the assignment submission data) and demographic data included a complete set of student characteristics (from a particular semester), such as the district of residence according to the socio-economic background, gender, educational background, achievements, and the assignment submission status. Each Moodle log file contained data about a course in a particular semester and included a free text column that described an action performed by a Moodle user, identified by a Moodle ID string. In order to follow research ethics principles and to safeguard students’ privacy and in accordance with the EU’s General Data Protection Regulation (GDPR) and Israel’s Protection of Privacy Law, prior to transferring any data to the researcher, identifying fields such as the given name and surname were removed. In addition, national ID numbers and Moodle identifiers were encrypted. The research received IRB (Institutional Review Board) approval by the OUI Ethics Committee.

4.2.1. Quantitative collective variables The database described above listed numerous instantaneous activities of individual students in specific courses. In order to analyze these data in a meaningful way, we defined two collective variables, listed below, which describe students’ learning patterns. Further details regarding the rationale for developing these variables are presented in the Results section. a) Student Cumulative Opening Pattern (SCOP): The SCOP represents cumulative video sessions that each student opened until a given week, disregarding a repeated opening by the same student (discrete interval variable). For example, if student A opened one video in the first week, another one in the second week, and none in the third week, then by the third week his SCOP would equal 2. We used the SCOP to estimate learners’ progress in the course throughout the semester. b) The submission status of the first optional assignment: This is a binary variable that distinguishes between students who submitted the first optional assignment and those who did not. A Shapiro-Wilk test of normality distribution was statistically significant, indicating a univariate normality deviation (Villasenor Alva & Estrada, 2009). Therefore, we used chi-square and Mann-Whitney U tests to examine the association between the measured parameters and students’ success rate (MacFarland & Yates, 2016; Onchiri, 2013). 4.2.2. Logistic regression In order to address the research questions and predict whether a student is going to succeed in a course, there is a need for a statistical methodology that could explain a dichotomous outcome (successful/ unsuccessful) based on a collection of categorial, ordinal, and interval independent variables. The logistic regression approach (Osborne, 2015) provides such an analysis by moving from predicting an event occurrence to predicting its probability to occur. This type of analysis was used successfully in a number of educational studies (Artino Jr & Stephens, 2009; Yair, Rotem, & Shustak, 2020). In our research, we followed the user-controlled method of entry approach described by Osborne (2015), in which the researcher decides which variables to include, and they are all entered simultaneously. According to Osborne (2015), this is theory driven, meaning that the analysis is based on prior theory or research and is therefore more defensible. The method involves defining a new dependent variable, Logit: Logit = Ln(p/(1 p)) , (1)

where p is the probability for an event occurrence, here – success in the course (Osborne, 2015). The Logit function is estimated by a regression model, which is a linear function of a set of independent variables {Xk} with coefficients {bk}: Logit(Y)= b0 + b1X1 + ... + bkXk (2) Here Y is the dependent variable, b0 is the intercept, and {bk} measures the slopes, or the effects with respect to {Xk}. Logistic regression is a commonly used prediction algorithm with strong predictive performance and good comprehensibility. Despite these strengths, logistic regression results can be biased due to interaction effects between variables or multicollinearity. To address this weakness, we also used a decision tree algorithm (De Caigny, Coussement, & De Bock, 2018).

4.2.3. Decision tree algorithm

A decision tree (DT) is a data mining technology that carries out various classification and regression tasks and is generally considered effective and simple (Lin & Fan, 2019). Starting from a parent node, DTs involve a recursive process of splitting nodes into smaller and purer subsets by iterative determination of optimal splitting criteria that divide the data over two child nodes. This process terminates when no further splits are desirable or possible (De Caigny et al., 2018). Here we used the chi-square Automatic Interaction Detection (CHAID) (Kass, 1980) method as an attribute selection measure, based on the statistical chi-square test for independence. Following Hershkovitz and Nachmias (2011), we applied a significance level of 0.05 for splitting nodes and merging categories, and 10-fold cross-validation. CHAID is considered to have a high defection prediction accuracy (Lin & Fan, 2019). It is mainly used to calculate the degree of dependence between several variables – the larger the value calculated by chisquare, the higher the degree of dependence and the probability value of the variable. Moreover, a probability value is used to determine whether to continue the splitting process in the CHAID algorithm to estimate all the possible predictive variables. The significance levels of the differences between the various categories of dependent variables are tested for each variable. Then, the insignificant categories are merged into a homogeneous group, and the remaining categories are analyzed repeatedly until the differences are no longer significant.

Let us start with a description of the interviews, which represents the first qualitative analysis stage. We used the interviews to characterize students’ learning behavior in the online chemistry courses according to the SRL framework. They also helped us identify the main variables for the regression model. Out of the 13 interviewees, 10 successfully completed one of the three courses analyzed in this study, whereas the other three did not complete the course they took. Fig. 1 presents a summary of the interview analysis in the form of a heatmap of the 33 mapped categories that represent students’ SRL characteristics (see Methodology, Section 4). These categories are divided according to the six main SRL dimensions of Barnard et al. (2009): (1) goal setting, (2) environment structuring, (3) task strategies, (4) time management, (5) help-seeking, and (6) self-evaluation. The heatmap’s scale shows the frequency that each category appeared in our interviews. To prevent bias, we counted each category once for each interview, even when it emerged multiple times, such that high frequency refers to categories that emerged in different interviews. This analysis allowed us to examine SRL in the context of online education in chemistry, since students often described their difficulty with chemistry content.

6.2.1. Assignments submission

At the OUI, students receive the assignments and their submission schedule in advance before the semester begins. The teaching staff of all three courses made the first assignment mandatory, to take advantage of the students’ motivation at the beginning of the course and to create a commitment for learning. Hence, it is not surprising that most of the students submitted it, and therefore, it could not be used as a predictorof course success. Likewise, the other 2–3 mandatory assignments in each course had a relatively high submission rate. In addition, each course included 2–3 optional assignments, of which the students had to submit at least one. Naturally, those who submitted more optional assignments had a higher probability to succeed in the course (Fig. 2), thus making the submission rate of optional assignments a good parameter that distinguishes between those students who successfully completed the course and those who did not. Of these, the first optional assignment (which was the second assignment in all three courses, with a submission deadline at the 5th week) had a much lower submission rate, compared with the first mandatory assignment, which made it an informative variable for predicting success at an early stage of the course. Table 5 shows the percentage of students that submitted the first two assignments. 6.2.2. Video sessions’ opening pattern The courses in this study consisted of 12 online sessions, which students can view either live (synchronous) or recorded (asynchronous). Since many students did not participate in the live sessions and opened the recorded sessions asynchronously, we did not distinguish between synchronous and asynchronous video opening. Note that, as with most online generated data, we know whether a student clicked and opened a video, but we have no way of knowing whether the student actually viewed the entire session. Therefore, we referred to this as an opening pattern and not as a viewing pattern. Fig. 3 shows unified data from all the courses; it counts the number of students who opened each session throughout the semester. The colors indicate two groups of students: (1) those who succeeded in the courses and (2) those who did not complete them. Here we counted each student once per session. As can be seen, the first group shows a steady pattern of sessions that opened – the number of students is constant throughout the semester, and almost all of them opened each video session at least once. On the other hand, the second group of students did not follow a steady pattern, and the number of students who opened each session significantly decreased throughout the semester. Fig. 4 presents a different view of these data; the percentages of students from each group that opened the sessions’ first, second, third, and fourth quartiles are counted. As is evident, almost all the students in the first group, who successfully completed the courses, played the entire set of tutoring sessions. Most of the students who did not complete the course opened only some of the sessions. Based on these results alone, we could not determine whether students who did not complete the course decided to use other course learning materials. Nevertheless, all learning materials were available to all the students, to begin with. Figs. 3 and 4 provide information about the opening patterns that accumulated throughout an entire semester. Both figures help distinguish between students who successfully completed the course and those that did not. A close look at Fig. 3 shows that the number of students who opened the first few video sessions was approximately similar between the two groups. Our original goal was to detect the course completion status during the semester. Therefore, we needed a more accurate parameter that could distinguish between the two groups at the early stages. From the interviews, we learned that there were students who successfully completed the course and watched the online sessions from week to week. The SCOP variable (see Section 4.2.1), which counts the total number of different video sessions that each student opened up to a specific week, was used to analyze different learning patterns. We designed the SCOP variable to disregard multiple plays of the same video. In this way, it represents students’ progress with the course material throughout the semester. For example, if learners’ SCOP equals 9, we know that they played nine of the course’s videos. If we had counted multiple video plays, we would not know whether the number 9 in dicates that the student progressed in the course material or stopped to repeat specific lessons. Fig. 5 presents the weekly average SCOP for each group (who successfully completed and did not complete the course). As is evident, this parameter is quite informative for distinguishing between the two groups, even at earlier stages of the course. Note that the course lasted for 14 weeks. Data for weeks 15–20 represent the exam period. It is included here to show that students continued to open the video sessions at high rates toward the exam date. The group of successful students used the video resources much more than the other group did. In order to assess the statistical association between the SCOP and the course success, we conducted a Mann-Whitney U test of the SCOP distributions among students who completed the course and those who did not. We found that starting at the second week and throughout the rest of the semester, the first group displayed statistically significantly higher scores in the Mann-Whitney U test than the second group (p < 0.05), teaching that this variable is a good candidate for predicting success rates. 6.2.3. Logistic regression models Based on the results presented above, we defined two main independent variables for the logistic regression model: the first optional assignment submission status and the SCOP. Prior to the logistic regression analysis, we conducted a correlation analysis for the set of independent variables in order to test for multicollinearity. Two categories of independent variables were used as control variables in the analysis. The first are demographic variables that included gender and the district of residence. The age variable was not used, since we found multicollinearity between this variable and both the advanced diploma and the district of residence. The second category is educational background, which included prior and current studies: the existence of a prior advanced diploma, an indication whether the current course is the first course at the OUI, the semester index, and the course name. These variables are suitable as controls, since although they may influence students’ success in the course, they do not change during the semester and do not depend on students’ learning choices during the course. No significant associations were found between any of the control variables, as well as the variables of assignment submission status and the SCOP. However, we did find multicollinearity between the assignments’ submission status and the SCOP (namely, these variables are correlated). Therefore, we ran two different models of logistic regressions for each of them. Then, we carried out a logistic regression analysis using SPSS version 24 (IBM Corp., 2016) and R version 4.1.2. For each model we chose which variables will be included in the model and they were all entered simultaneously. 6.2.3.1. Logistic regression analysis of the course achievements. Logistic regression models were built based on the data collected from all three courses. Each model was based on the data of students enrolled in the years 2016–2019 (n = 797). Data from the first semester of 2020 (n = 157) were used to validate these models. The course name was used as a control parameter. Model A used the submission status of the first optional assignment, which was the second assignment in all courses. Among the 797 students, 478 (60%) submitted the first optional assignment. A chi-Square test found a statistically significant association between the first optional assignment submission status and the overall course success (χ(1) = 129.49, p < 0.000). The effective size of this finding, Cramer’s V, was moderate (Kotrlik, Williams, & Khata, 2011) and significant (φ = 0.403, p < 0.000.). As shown in Table 6, most of the students who successfully completed the course submitted the first optional assignment, whereas most of the students who did not complete the course did not submit it. These results justified building the model based on the first optional assignment submission rate. The results of model A are presented in Table 7. The Wald statistic, defined as the square of a regression coefficient divided by the standard error of that coefficient (Osborne, 2015), was applied to determine the statistical significance of each independent variable. The logistic regression model for the entire sample (n = 797) was found to be statistically significant χ2(6) = 129.079, p < 0.001. Following our expectations described above, the submission rate of the first optional assignment (p < 0.01) was found to be a significant parameter for predicting the final course success status, along with the advanced diploma (p < 0.05). The course name was found to be insignificant, justifying the analysis of the three courses as a single database. The model correctly classifies 70% of the cases (see the model evaluation). Furthermore, using the Hosmer-Lemeshow Goodness-of-Fit tests (Hosmer & Lemesbow, 1980; Paul, Pennell and Lemeshow, 2013), we found that our regressions are assessed to be well fitted. These results suggest that when students submit their first optional assignment, we can determine the probability that a specific student will complete the course. Model B’s results, which are based on the SCOP variable as a pre dictor, are presented in the two rightmost columns of Table 7. It was found to be statistically significant, χ2(6) = 63.54, p < 0.001, suggesting that one can identify the probability to succeed in the courses based on the following parameters that were found to be significant: The SCOP at the 8th week (p < 0.01) and having an advanced diploma (p < 0.05). Again, the course name was found to be insignificant in this model. The model correctly classifies 66% of the cases (see the model evaluation), and similar to the model A above, the Hosmer-Lemeshow Goodness-ofFit tests (Hosmer & Lemesbow, 1980) found it to be well fitted. Both our models indicate that the early prediction models, based on students’ data collected before the course’s mid-point, enable identifying students who will probably succeed as well as those who probably will not succeed and might need extra attention. 6.2.3.2. Evaluation of the models. In each model, we defined a student with a probability of 0.5 or higher to succeed as someone who will probably successfully complete the course, and a student with a probability of below 0.5 as someone who will probably not complete the course. The overall correct predictions of model A are higher than those of model B. This means that model A is more accurate than model B and that the submission of assignments is a strongerpredictor than the video sessions’ opening patterns. We further evaluated the models by plotting the area under the curve (AUC) to estimate their accuracy based on the Receiver Operating Characteristic (ROC) curve (See Tables 10 and 11 for details). The ROC curve is plotted with sensitivity in the Y-axis and specificity values in the X-axis. The sensitivity measures the probability that a given statistic correctly predicts the actual condition with respect to a pre-defined threshold. tails). To check the robustness of the logistic regression results, we ran a forward entry stepwise logistic regression. In this process, one starts with a blank slate, and all variables are assessed for their potential predictive power (Li & Liu, 2019; Osborne, 2015; see Table 8). In a forward entry, one starts with a blank slate, and all variables are assessed for their potential predictive power. The variable with the single greatest relationship is entered into the equation, and then all remaining variables are assessed according to whether they add significant predictive power to the equation above that variable in the equation. The next strongest predictor is added, and the process continues until no variable

6.2.4. Decision tree algorithm and model compression

As explained above, the multicollinearity between the optional assignments’ submission status and the SCOP forced us to run separate logistic regression models for each variable. To test these variables together in a single model that predicts students’ success in the course, we utilized a DT algorithm, as detailed in the Methods section. Results are presented in Table 12. The dependent variable was the course completion status. We ran a separate DT analysis for each week of the course and updated the values of the SCOP and the assignments’ submission rate accordingly. The suggested independent variables were the SCOP of each week, the optional assignment submission status (starting from week 5), gender, the district of residence, and the most advanced diploma. The independent variables were selected for each week according to the CHAID algorithm (Lin & Fan, 2019). Fig. 6 exemplifies the DT procedure at week 8. The algorithm’s accuracy was found to be 76%using tenfold cross-validation. The model starts with a ‘parent’ node (node 0) containing all 797 students, which displays the number and percentages of students who completed or did not complete the course. From this point, the tree splits in the order of importance. The first optional assignment was the most significant factor regarding course completion. Thus, the ‘parent’ node splits into two ‘child’ nodes, one containing students who submitted the assignment (Node 1, left branch) and the other containing those students who did not submit it (Node 2, right branch). Next, each node splits by the SCOP value at week 8 into three ‘grandchild’ nodes.

Regarding the video recordings, we found that only a few interviewees attended the live sessions, and that the rest watched the recordings at their convenience. In addition, students reported that they communicated with each other through a social media platform (students’ WhatsApp group), which is external to the course. This platform allowed students to consult with each other and to answer questions. This finding supports previous studies (Rap & Blonder, 2016; Rap & Blonder, 2017) that found that students use social media platforms to interact with each other and discuss the course materials. Finally, we learned that the submissions of the assignments, both mandatory and optional, were also used as a learning strategy and for self-evaluation. These learning choices guided us in choosing the learning variables that could be used to construct a model to predict students’ success in the courses, namely, video sessions’ opening and the submission of optional assignments. This helped us develop predictive models and address the second research question (Q2): “What indicators of online learning can predict course success, and at what stage? Based on Model A, we found that already at week 5, in accordance with the deadline for submitting the first optional assignment in the studied courses, we could identify students who had a high probability to successfully complete the course. This finding shows that an optional assignment, which we view as an indication of student choice, is an important predictor of course completion. This expands on previous studies that found that the more assignments students completed on time and the earlier they did so, the better they performed on the quizzes and the final exams (Baker et al., 2020). Model B showed that by week 8, around the midpoint of the semester, students who eventually successfully completed the course had different accumulated video opening patterns than those who did not succeed in the course. The SCOP variable, which is the main predictor in this model, is an indicator of students’ time management, since it reflects their advancement in the course from week to week. Naturally, each model’s specific week in the course can differ between courses and institutions. Nevertheless, our models show that students’ choices (whether to submit an optional assignment or open the video sessions) are key predictors of students’ likelihood to successfully complete the course. Comparing the two logistic regression models, we found that except for the last two weeks, Model A was a stronger predictor of course success than was Model B. This can be understood considering that submitting an assignment better represents active learning than opening a video (Gabbay, Cohen, & Festinger, 2020; Glick, Cohen, & Gabbay, 2020). By active learning, we mean that participants are dynamically or experientially involved in the learning process, which is known to be a more important feature of successful online learning (Davis, Chen, Hauff, & Houben, 2018). Future research should examine whether embedding active learning features within the video sessions can increase the predictive power of video opening variables such as the SCOP used here. Improved prediction for students who didn’t complete the course was achieved with the DTCHAID model.

Concluzii:

Nevertheless, we recommend that new dashboards for a specific course be created along with an evaluation process for the relevant courses, and that it will involve both researchers and course staff. This evaluation would provide guidance regarding choosing the most relevant SRL and learner engagement indicators. Academic institutions could also consider embedding an automatic weekly statistical analysis in a dashboard that will present the lecturers with the probability of students’ success in the course. Finally, the findings from this research are especially relevant in the context of the covid-19 pandemic and will continue to be important in the post-covid-19 world. Online learning has been growing considerably in recent years and became extremely important with the rapid transition to online learning in both schools and universities following the coronavirus outbreak. This dramatic change continues to attract the attention of educators, researchers, policymakers, and the media to various learning theories that can promote more effective online learning, as well as addresses the major open questions in the field regarding students’ persistence, the learning process, course design, and student-instructor interactions.

Probleme ramase nerezolvate:

Another limitation of this study stems from ethical considerations that restricted us from connecting the online activities of individual students to their interview data. Thus, we could not successfully relate to an online learning pattern in the course on a personal basis, and it remained in the framework of statistical analysis. Finally, an important limitation is related to interpretation of a repeated video opening. We knew from the interviews that many students re-watched the course’s videos, but we could not accurately assess their re-watch patterns. This was because our data on multiple video opening included both students who re-watched lessons and those that simply re-opened them due to technical issues. Therefore, we decided not to analyze this pattern using the analysis.

[8]

Scop:

In this paper, we propose a novel stacking ensemble based on a hybrid of Random Forest (RF), Extreme Gradient Boosting (XGBoost), Gradient Boosting (GB), and Feed-forward Neural Networks (FNN) to predict student’s dropout in university classes.

Abordare:

To address the issues presented in the literature,this study proposes a novel stacking ensemble based on a hybrid of Random Forest (RF), Extreme Gradient Boosting (XGBoost), Gradient Boosting (GB), and Feed-forward Neural Networks (FNN) to predict student’s dropout in university classes.

Decision trees and rule-based classifiers, on the other hand, are white-box models that are moreunderstandable and easily interpretable because they expose the reasoning process underlying the predictions. Clustering algorithms or association rule mining are other options. Correlation analysis of course grades and attributes defining credits obtained by students and their average grades can also be useful (Lang et al., 2017).

The raw dataset used to conduct experiments in this study was collected directly from Constantine the Philosopher University in Nitra records from 2016 to 2020 (Kabathova & Drlik, 2021). The initial data contains 261 samples and 12 features of students registered in the preparatory lesson on database systems. The features in the raw datasets include information about [access], [tests], [tests\_grade], [exam], [project], [project\_grade], [assignments], [result\_points], [result\_grade], [graduate], [year] and [acad\_year]. The output variable has two values either 1 for non-dropout or 0 for studentswho dropped out of the university course. Among all students, 210 (80.46%) passed the course successfully and have not dropped out the school and 51 (19.54) failed to pass. In order to find the screened features for model building, the dataset cleaning process was performed to deal with, irrelevant, noisy, and inconsistent data (M ́arquez-Vera et al., 2016 ). The null and unre alistic values were dropped. Additionally, for categorical features, one-hot encoding was performed to transform integers to binary vectors. Besides, the feature selection process was conducted to decide the input variables for model building. As shown in Fig. 1, a correlation heat map was designed to analyze the correlations between input features and output variables. There exist a medium correlation between important features and grade points. Features such as tests, access, and project have a strong correlation with grade points. As a result, strongly correlated features are considered in the model building due to their highest impact on student outcomes. In the last stage of data preprocessing, the dataset was normalized using a standard scaler to eliminate the mean and scale it to unit variance (Obonya & Kapusta, 2018).

4.Methodology

In this study, a novel stacking ensemble made up of a hybrid of RF, XGBoost, GB, and FNN is proposed to predict student’s dropout in university classes. A hybrid of four models is proposed to make a powerful meta-learner (Xing et al., 2016). Stacking generalization is defined as an ensemble modeling technique to merge several classification models via a meta-classifier (Wolpert, 1992). The process of combining multiple classification models applies non-linear weightings for low-level predictors to minimize the generalization error rate and enhance the prediction accuracy (Wolpert, 1992). The proposed approach consists of two layers. In the first layer, temporal predictions of the RF, XGBoost, and GB are generated using a complete training dataset to extract the merits of each base classifier. In the second layer, the predictions generated in the first layerare fed to the FNNmodel to compute the final prediction of student dropout using cross-validation (Jiang et al., 2020). As shown in Fig. 2, the proposed approach has four important stages namely, feature engineering and selection with rationale, dataset splitting, final prediction, and evaluation. In the proposed stacking ensemble, the raw data with messy and irregular features will be processed through multiple classification models, and valid features will be extracted. Stacking’s learning ability stems primarily from the representation of features, which is consistent with the structure of neural networks (NN). The first layer in Stacking is analogous to the first N-1 layer in a NN, while the second layer in stacking is analogous to the last output layer in a NN. Stacking’s first layer can be thought of as a highly complex nonlinear feature converter. In stacking, different classifiers represent heterogeneity for different features. To effectively extract features from raw data, the first layer’s base classifiers must meet two requirements such as high accuracy and high diversity. RF, XGBoost, and GB are chosenas the first layer’s base models in this study. All base classifiers accomplish learning tasks by combining multiple learners, but their modeling concepts are completely different. These three base models were chosen and combined in the first layer of the proposed model because of their similarities and differences, and they all performed well in crossvalidation as well as returning the best accuracy.

Because features are extracted using complex non-linear transformations in the second layer of our model, complex classifiers in the output layer are unnecessary. FNN is a good candidate because of its simple structure and additional benefits.

1.1. Artificial neural network (ANN)

ANN is a commonly used model for prediction systems and it maps several inputs data into a set of suitableoutputs (Thanh et al., 2019). The ANN is widely used by many researchers due to its ability of parallel computation, ease of implementation, and swift operation. This model contains a set of many algorithms in which the intelligence of human beings is integrated into the computing machines that can solve extremely complex problems with excellent accuracy performance (Sun et al., 2016). ANN structure consists of three layers, namely, the input layer which functions as raw data receiver, the hidden layer for which the nodes of one layer and next layer are connected entirely, and the output layer which functions as a result displayer (Shahin et al., 2008). The process of learning originates from the error backpropagation utilizing the gradient descent research approach while the predicted output is represented by the symbolic function ̂y denoted by Eq. (1) (He et al., 2009)

4.1.2. Gradient boosting (GB) model

GB or gradient boosting tree is an ensemble ML method utilized to solve both classification and regression problems (Ikeagwuani, 2021). The GB was first introduced by (Friedman, 2001) as multiple additive trees that can be usedto improve the decision tree approach by utilizing stochastic gradient boosting. The main objective of GB is to decrease a loss function by stirring on the opposite side of the gradient (Friedman, 2001). This means that the GB builds the new base learners to principally correlate with the negative gradient of the loss function in the prediction process. A loss functionis an indicatorof how gooda model is in the prediction process given a number of different parameters. Generally, when the loss functionis small, the performance of the model becomes accurate and efficient (Friedman, 2001). The input training samples are represented as {(x1, y1), (x2, y2), ..., (xn, yn)} while the output is the probability of predicting one among the target classes (crash injury severity levels). The detailed description of this algorithm is summarized in Algorithm 1. In the GB model, the gradient descent diminishes complex loss functions that cannot be reduced directly. The loss function to decrease is denoted as L. Initialize the model with a unique forecast value F0(x) with the average of training target values. For initial iteration m = 1, calculate the gradient of L in relationship to prediction value F1(x) and then fit a base learner to the gradient constituents. Compute the magnitude multipliers and update the function to get the predictionvalue. The process continues recursively until the final result sign(Fm(x)) from the collection of all regression trees produced throughout the iteration is computed. The GB employs cross-validation and Out-of-bag (OOB) approaches to find out the optimal number of boosting iterations. OOB permits on-the-fly calculation with no need for persistent model fitting (Friedman, 2001).

4.1.3. Random forest

Random forest (RF) is a ML algorithm that was first invented by Tin Kam Ho (Yuan & Hu, 2016). It is used to train weak learners so that identical problems get solved and combine them to obtain accurate results (Liaw & Wiener, 2002). RF was extendedby (Breiman, 2001) as an accurate classifier made by a group of tree predictors in such a way that there exists the dependence of each tree on independent values of a sampled random vector. Fig. 4 explains the general idea of the RF procedure. It is made up of four important parts: Firstly the training data sample is selected from a given dataset with the help of bootstrapZ times (Breiman, 2001). From this process, each sample set has an equalchance of being selected to represent the training set in every round the sample is selected. In the second phase, the decision trees are formed through the process represented as tree-based learner generation. In this phase, the node splitting process is responsible to select randomly the features to represent the set of tree-basedpredictors. The third phase consists of a forecasting process where the set of selected features is used to present the outcome of each tree predictor. Finally, the outcomes from each tree-based learner are merged where any predictor has equal proportion to the final result.

4.1.4. Extreme Gradient Boosting (XGBoost)

The XGBoost model is one of the most commonly used algorithms introduced by (Chen & Guestrin, 2016) to solve prediction problems. The objective function of XGBoost relies on regularization to the cost function terms such as tree depth and leaf nodes ’ weights (Zhu et al., 2021). This means that this model has the capacity of enhancing the performance of building trees when the iteration process reduces. Regularization to the cost function which makes XGBoost a regularized boosting technique is mathematically denoted by (Chen & Guestrin, 2016):

5.1. Model training and hyper-parameters tuning

aximum depth of the tree (Chen et al., 2015). In the second layer of our method, the input features were trained using FNN. The input layer of FNN consists of five neurons, each representing one input variable, while the output layer consists of one neuron which represents the output variable (Eldan & Shamir, 2016). To determine the number of hidden layers and the number of neurons in each layer, a replication searching process was followed to find out an optimized method with accurate prediction performance (Pontes et al., 2016). After performing several iterations, the optimal topology which produced efficient prediction results was found to be two hidden layers comprising of five neuronswith tangent sigmoid activation function and two neurons with Softmax activation (Pontes et al., 2016). The leading training function which resulted in the best prediction accuracy in the FNN is the Levenberg–Marquardt (Yu & Wilamowski, 2018). This was selected after comparing with other training algorithms such as Bayesian regularization backpropagation, scaled conjugate gradient, variable learning rate backpropagation, resilient backpropagation, and BFGS quasi-Newton (Yu & Wilamowski, 2018). After optimizing the parameters for the models in the first layer and the remaining in the second layer, a novel stacking ensemble model proposed was tested using the same testing set, and finally, the prediction performance was assessed based on the contingency table.

The discussion of the various performance metrics confirms that the selected binary classification models can be used to predict students’ dropout or Non-dropout at the individual course level, even when the dataset is scarce and has a limited number of input features. However, before the classifiers can be used to predict student dropouts, a broader set of performance metrics must be investigated. This statement is consistent with the findings of other research papers published in the domains of AI and ML.

Concluzii:

On the dataset collected from 2016 to 2020 at Constantine the Philosopher University in Nitra, the proposed method has demonstrated greater performance when compared with the base models using testing accuracy and the area under the curve (AUC) evaluation metrics under the same conditions. Based on the findings of this study, students at the risk of dropping out the school can be identified based on influential factors and different agents of education can refer to this infor mation for early intervention in the uncontrolled behavior that can lead to the risk of dropping out and take proactive precautionary measures before the issue arise.

The study presented here helps to solve the problem of student dropouts at the course level. The results demonstrated that, despite a small dataset, appropriately selected indicators that do not require access to system logs can be beneficial if different performance metrics are evaluated. The predictive models were fed with data gathered about students’ online learning environment activities and partial achievements. Simultaneously, a proposed methodology is reliable for predicting course completion when there is enough time for educators to intervene timely. The results obtained for our method can help in reducing the dropout rate based on identified students that are likely to be affected and the influential factors. Moreover, once the students who are at the risk of being affected are identified, the agents of education can gather their forces to take efficient measures of eradicating the issue. Furthermore, the different learner’s motivation strategies can be emphasized to improve the performance and help learners finish their programs successfully. For future research, other computation approaches such as deep learning and other hybrid models can be used to predict student dropout and compare the results with the findings of this study. Other influential factors not presented in this study must also be considered and a further feature analysis study is recommended to help the agents of education in handling successfully the issues of student dropout.

Probleme ramase nerezolvate:

Another limitation of this study is that different runs of the courses provided different data to be analyzed. As a result, it was difficult to determine which attributes are important enough to predict the stu dent’s performance in general. The next limitation is the selection of the classifiers used in this case study. Literature reviews of the current state of the researchand trends in LA and EDMprovide numerous examples of more or less advanced ML techniques that can be used to predict early student dropout at the course level. However, none of them have produced noticeably better results thus far. Because the main goal of this study was not to find the best one, the final choice of the classifier used in this case study allows mentioning that good prediction could also be achieved using stacking ensemble, but the performance metrics must be evaluated. The case study’s final flaw is a type of appropriate intervention that is not discussed in depth. The case study has already demonstrated that the student’s dropout at the university level can be predicted based on the activities chosen. The reason for this unflattering state, on the other hand, remains unknown and necessitates further investigation. It would be interesting to investigate whether other types of activities have a similar impact on student engagement and which types of activities can be exchanged during the intervention phase.

[9]

Scop:

Abordare:

Concluzii:

Probleme ramase nerezolvate:

[10]

Scop:

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[11]

Scop:

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Concluzii:

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