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INSTRUCTOR PERFORMANCE MODELING FOR PREDICTING STUDENT SATISFACTION USING MACHINE LEARNING - PRELIMINARY RESULTS

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ABSTRACT

The use of machine learning techniques in higher education can be beneficial in optimizing teaching and providing higher institutions with the solutions they need, like monitoring student satisfaction with the instructor's performance. In this study, ten machine learning classification methods are employed on a dataset to predict selected aspects of student satisfaction: Logistic Regression, Linear Discriminant Analysis, Kneighbors, Decision Tree, Naïve Bayesian, Support Vector Machine, Extra Trees, Gradient Boosting, Random Forest, and Multilayer Perceptron. The dataset consists of 5,820 instances obtained from the UCI machine learning repository, and it demonstrates how students rated their instructors in terms of course structure, and behavior. As a result, it was observed that the ten classifiers had better performance in terms of prediction accuracy after balancing the dataset. On the balanced dataset, the ten classifiers were 4% more accurate on average than when they were trained on the imbalanced dataset. In addition, the Extra Trees classifier achieved the highest performance rate based on all the evaluation metrics used in predicting all the targeted features, especially with the balanced dataset. This paper also included the finding of the most important attributes/variables affecting the predictability of the student-satisfaction aspects. As this finding demonstrated, the majority of the important variables were related to instructor characteristics. Moreover, in all cases of the predictions, one variable related to course characteristics (practice-based activities: laboratory work, fieldwork, and group discussions) frequently appeared as the most important attribute compared to other attributes. Thus, and in light of these findings, instructors should plan courses with fieldwork, applications, labs, and group discussion. Instructors should also use up-to-date materials, be well prepared, be friendly, encourage student participation, and give and talk about exam solutions.

Keywords: *EDM (Educational Data Mining), Student Satisfaction, Classification, Machine Learning*

1. INTRODUCTION

The continuous demand for higher education [1] presents a serious challenge in terms of improving educational quality. This challenge requires innovative solutions to support educational institutions in making the best decisions possible. One of these solutions is employing educational data mining (EDM) and machine learning approaches. Due to the collection of a huge amount of extremely detailed data in the cumulative work of these institutions, making the right decisions might be challenging at times. So, these challenges can be met by using EDM, which can analyze and investigate this detailed data to find out what it means. This helps stakeholders make better decisions in a wide range of higher-education applications. Among the most common of these applications include student modeling based on the analysis of their features related to behavior or performance information, such as predicting student success and retention, finding undesired student performances; or characterizing and categorizing students (see, e.g., [2]–[4]. Another important type of EDM applications is decision support systems. This type of applications seeks to improve the education process by supporting the stakeholders in making decisions. Providing feedback, signaling alarms, planning and optimizing resources' utilization, making recommendations, and optimizing learning content are all examples of this type (see e.g.,[6]–[19]. Another major use of educational data mining is identifying patterns of teaching practice among teachers in the classroom. As a consequence, the critical elements influencing student satisfaction and performance in the classroom will be identified.

Several articles have employed data mining approaches to improve instructor effectiveness (see e.g., [20]–[23]. As described in [24], ELearning environments and Massive Open Online Courses (MOOCs) are considered the main data sources, including a vast amount of highly relevant data for analysis and mining. In addition, teacher evaluation surveys can be viewed as one of the most essential educational management tools for collecting data used to ensure the quality of these institutions. It may be necessary to pay special attention to the extent to which students are satisfied with the teacher's instructional methods. Understanding the key factors that influence and predict student satisfaction may provide higher education administrators with the most effective strategies for improving the quality of their institutions' education. Thus, they should be aware of the main course-teaching related concerns affecting student satisfaction in order to make a rational decision. So, this study aims to develop an EDM model that can accurately predict student satisfaction with their instructor's instructional performance and course components. As a result, this research investigates the following questions in depth: 1) Which EDM techniques are optimal for addressing this issue? 2) Which factors can best predict student satisfaction with instructional performance and course constructs?

This study made three contributions to literature. Firstly, ten data mining classification techniques were applied to predict student satisfaction. As a result, the study model outperformed state-of-the-art results without removing any low-ranked features that could reduce prediction accuracy. Secondly, this study has demonstrated that these classification techniques can be accurate if the data is preprocessed in a particular way. Moreover, the study found and indicated the most important factors that mainly predict selected aspects of student satisfaction.

The rest of the paper is organized as follows: Section 2 is a literature review; Section 3 describes the dataset, while Section 4 explains the modeling methodology. Section 5 provides insights into the results of the applied classifiers, the discussion, and the finding of the most important features; Section 6 compares our work to the existing studies on the dataset, and Section 7 concludes the work of the paper.

2. PROBLEM STATEMNT

The continuous demand for higher education presents a serious challenge in terms of improving educational quality. This challenge requires innovative solutions to support educational institutions in making the best decisions possible. One of these solutions is employing educational data mining (EDM) and machine learning approaches. Due to the collection of a huge amount of extremely detailed data in the cumulative work of these institutions, making the right decisions might be challenging at times. So, these challenges can be met by using EDM, which can analyze and investigate this detailed data to find out what it means. This helps stakeholders make better decisions in a wide range of higher-education applications.

3. RELATED WORK

Educational data mining (EDM) is a research field that uses mining tools and techniques to analyze educational data [25]. This field is concerned with analyzing educational data in order to develop models for enhancing learning experiences and institutional effectiveness. The following is a review of the literature on instructor performance. This research [26] looked into the aspects that go into evaluating a teacher's performance. The researchers used the WEKA tool to build the teacher's performance models by employing data-mining techniques such as Association, Decision Tree, and Rule Induction. The data in this study was collected through a survey conducted on teachers in Palestine. The results showed that Rule induction of the aspect related to the professional-competence session has an accuracy of 76.23% when: the trainees' classroom experiences are used, the session begins with the trainees' knowledge (past experiences), the session is designed so that the teacher can teach descriptive higher levels, and discussion and exchange of views are encouraged. In additions, the findings showed that the model has an accuracy of 79.92% when using the K-NN classifier, and it has an accuracy of 77.46% when using the Nave Bayesian kernel classifier. In [27] a variety of machine learning approaches (SVM, MLP, Decision Tree, Random Forest, Decision Table, K-NN) were used to predict and infer the course and instructor-related factors that have a stronger impact on student satisfaction. As a result, the study focused on 5 dimensions of student satisfaction: course evaluation, class engagement, course expectations, course relevance and professional development. Furthermore, the results of the experiment indicated that course attributes had a stronger influence on student satisfaction than instructor attributes. When these approaches trained using the course and teacher-related factors, the accuracy of the results was

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between 80% and 85%, according to the study. This research [28] evaluated the instructor's performance using student questionnaires. The 32-features dataset was obtained from the UCI Machine Learning Repository. Using agglomerative clustering and k-means, the dataset is labeled. Five feature selection techniques "(Random Forest, PCA, Random Forests, UFS, and GA)" are used to extract essential features. After selecting the best-ranked features, the study applied 12 classification techniques ("K Nearest Neighbor, XGBoost, Multi-Layer Perceptron, AdaBoost, Random Forest, Logistic Regression, Decision Tree, Bagging, LightGBM, Support Vector Machine, Extra Tree, and Naive Bayes"). With the PCA feature selection method, the Support Vector Machine was the most accurate, with an accuracy of over 99%. Using several classification techniques such as Multilayer Perception, J48 Decision Tree, Sequential Minimal Optimization (SMO), and Naive Bayes, the researchers [20] have examined the aspects that are primarily influencing the success of learners in predicting the performance of instructors. The 32-features dataset was obtained from the UCI Machine Learning Repository. The attribute ranking method was used to identify the lowest-ranked attributes that reduced the prediction accuracy and eliminate them from the data set before training these techniques, and 9 features with high rank were selected. These techniques were employed with all features and with only the most strongly affected features. "J48" received an accuracy of "84.8%" for all features, while "SMO" obtained an accuracy of "85.8%" for selected features. The researcher in [29] conducted several experiments on real educational data to demonstrate how successful data mining is at converting educational data into knowledge. These experiments are designed to uncover instructor-behavior related factors that are influencing student satisfaction. A dataset of 608 instructor-evaluation records was used in the study. In this study, the researcher used the K-NN method to extract a new feature from these records. Then, as a class attribute, this feature was used to classify the student satisfaction by employing the C4.5 classification method. As a result, 592 of these records were accurately classified with an accuracy of 97.37%. This research [30] aimed to classify instructor evaluation reviews using deep learning. The study used machine learning algorithms, ensemble learning methods, and deep learning techniques to analyze 154,000 reviews. As a result, deep learning-based methods outperform the machine learning classifiers on classifying sentiment of instructor reviews.

In summary, several studies in the literature have employed data mining techniques to look and predict important factors in classroom teaching practice. Such studies [20], [22], [23], [28] used the same dataset that was used in our current study, but authors in previous studies rarely dealt with the data unbalancing issue in the features targeted in the analysis. This could make the techniques used for prediction less accurate. So, the current study used preprocessing on the dataset to make it balanced in the target features. In addition, this study used other classification techniques that were not used in the previous studies. As a result, this research is able to look at the power of these using techniques that has not been used in other works. In addition, an exploratory analysis of ten classification techniques for predicting various aspects is provided. These techniques are compared based on the accuracy of their predictions for every target aspect.

4. DATASET

The dataset used in this work was obtained from the UCI Machine Learning Repository [31] there are 5820 records in this data collection. There are 33 attributes in the dataset as explained in table 1: instruction code, class code, the number of times the course has been repeated, attendance, difficulty level, and 28 questions (Q1 to Q28). The Q1-Q28 questions are all 5-point Likert-type questions, so their responses range from 1 to 5, meaning "Poor," "Fair," "Good," "Very Good," and "Excellent" respectively. The seven attributes (Q1, Q2, Q3, Q4, Q5, Q6, and Q7) are concerned with course constructs. The attributes from Q13 to Q28 are about how the instructor teaches in the classroom, while the attributes from Q8 to Q12 are about the level of student satisfaction with (Q8) learning activities, (Q9) the student's interest in class participation, (Q10) the fulfillment of the initial expectations of course, (Q11) professional growth, and (Q12) the degree to which the course relates to and helps the student address real-world issues.

Table 1: Dataset Description [31].

Features	Description	Possible Values
instr	"Instructor's identifier"	1,2,3
class	"Course code (descriptor)"	1-13
repeat	"Number of times the student is taking this course"	0,1,2, 3,..

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attendance	"Code of the level of attendance; values from"	0-4
difficulty	"Level of difficulty of the course as perceived by the student"	1-5
Q1	"The semester course content, teaching method and evaluation system were provided at the start."	1-5
Q2	"The course aims and objectives were clearly stated at the beginning of the period."	1-5
Q3	"The course was worth the amount of credit assigned to it."	1-5
Q4	"The course was taught according to the syllabus announced on the first day of class"	1-5
Q5	"The class discussions, homework assignments, applications and studies were satisfactory"	1-5
Q6	"The textbook and other courses resources were sufficient and up to date."	1-5
Q7	"The course allowed field work, applications, laboratory, discussion and other studies."	1-5
Q8	"The quizzes, assignments, projects and exams contributed to helping the learning."	1-5
Q9	"I greatly enjoyed the class and was eager to actively participate during the lectures."	1-5
Q10	"My initial expectations about the course were met at the end of the period or year."	1-5
Q11	"The course was relevant and beneficial to my professional development."	1-5
Q12	"The course helped me look at life and the world with a new perspective."	1-5
Q13	"The instructor's knowledge was relevant and up to date"	1-5
Q14	"The instructor came prepared for classes"	1-5
Q15	"The instructor taught in accordance with the announced lesson plan"	1-5
Q16	"The instructor was committed to the course and was understandable"	1-5
Q17	"The instructor arrived on time for classes"	1-5
Q18	"The instructor has a smooth and easy to follow delivery/speech"	1-5
Q19	"The instructor made effective use of class hours"	1-5
Q20	"The instructor explained the course and was eager to be helpful to students"	1-5
Q21	"The instructor demonstrated a positive approach to students"	1-5
Q22	"The instructor was open and respectful of the views of students about the course"	1-5
Q23	"The instructor encouraged participation in the course"	1-5
Q24	"The instructor gave relevant homework assignments/projects, and helped/guided students"	1-5
Q25	"The instructor responded to questions about the course inside and outside of the course"	1-5
Q26	"The instructor's evaluation system (midterm and final questions, projects, assignments, etc.) effectively measured the course objectives"	1-5
Q27	"The instructor provided solutions to exams and discussed them with students"	1-5
Q28	"The instructor treated all students in a right and objective manner"	1-5
Total_SI	The total average of the student-satisfaction Index of question's aspects from Q8 to Q12	1-5

The study introduced a new attribute called Total_SI. This attribute's value is calculated as the average of satisfaction scores for aspects of the questions ranging from Q8 to Q12. As target features for the prediction, the attributes Q8, Q9, Q10, Q11, Q12, and Total_SI will be considered during the study.

5. METHODS AND MODELING APPROACH

Examples of data mining procedures that explain data exploration and knowledge extraction include data preprocessing, data analysis, and knowledge representation. The induction of classification models [32] rules of association [33] and clustering of related data [34] are among the most common data mining activities. Cleaning, sampling, and conversion into a mining-ready format should be used to prepare the data for these.

In the current study, we experiment with different machine learning algorithms for the classification of different labels in the dataset at hand.

This research used classification techniques since it aims to predict specific labeled-features. As shown in Figure 1, this section explains the research methodology, including the methods used to make predictions and analyses. Table 1 shows the dataset used in this study, which was obtained from the UCI Machine Learning Repository. There is no missing data in the dataset, and it has been cleaned. The study

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checked the balancing of the targeted features in the dataset. Figure 2 shows the distribution of these features. The study found that these features are not balanced. So, the study considered this issue and balanced the dataset through its experiments. Working with imbalanced datasets offers a challenge that the most machine learning algorithms will overlook, and so they will perform badly on the minority classes, despite the fact that these are frequently the most important. To address the imbalance in the dataset, the study used the Synthetic Minority Oversampling Technique (SMOTE) [35].

In the study approach, ten classification algorithms were applied to predict the aspects of targeted features. These algorithms were employed with the dataset before the balancing procedure and also with the dataset after the balancing. As a result, the performance of these classifiers has been evaluated and compared. Then, the best models of algorithms were presented and chosen to identify the most important features, which affected student satisfaction.

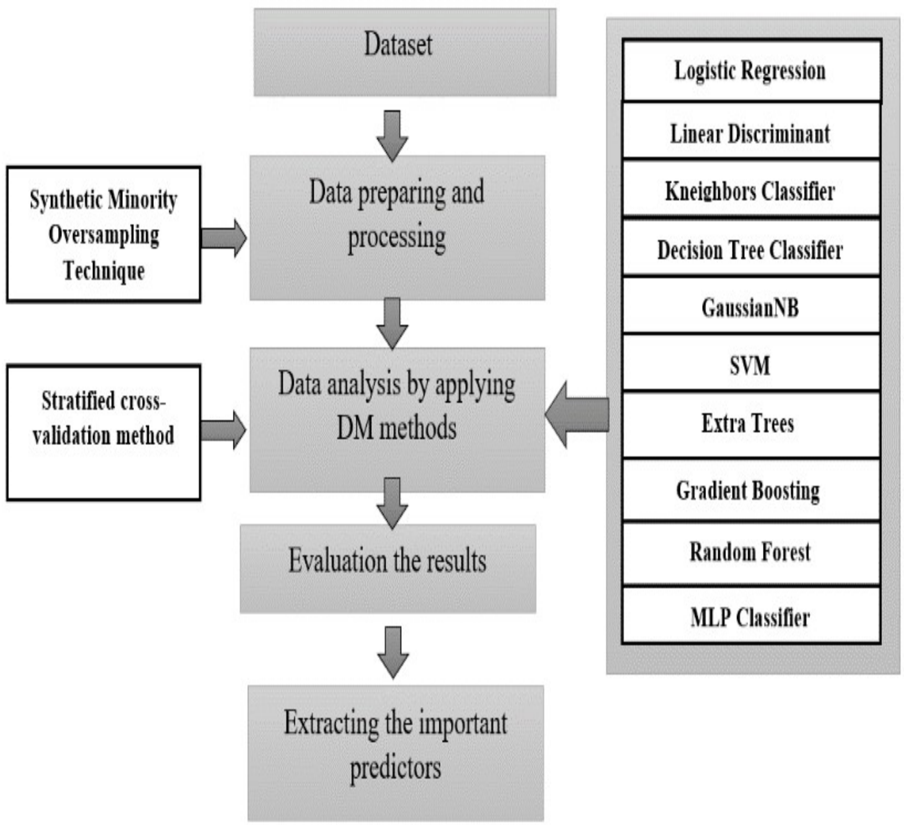

Figure 1: The proposed Methodology

The following classification algorithms were used in modeling: Logistic Regression [36] (C = 0.2, max_iter = 140, solver = 'newton-cg', penalty = 'l2'), Linear Discriminant Analysis (Izenman, 2013), Kneighbors Classifier [34] (n_neighbors = 5), Decision Tree Classifier [34] (probability=True), GaussianNB ()[34], SVC (probability=True)[38], Extra Trees Classifier, Gradient Boosting Classifier [39], Random Forest Classifier [40], and Multilayer Perceptron Classifier (max_iter = 400) (Gardner & Dorling, 1998). All these were applied with a tenfold-stratified cross-validation method. This is based and implemented on the stratified sampling principle and used to ensure that the percentage of the feature of interest in training and test sets is the same as in the original dataset. Therefore, performing this with the target feature validates the prediction performance of the classifiers.

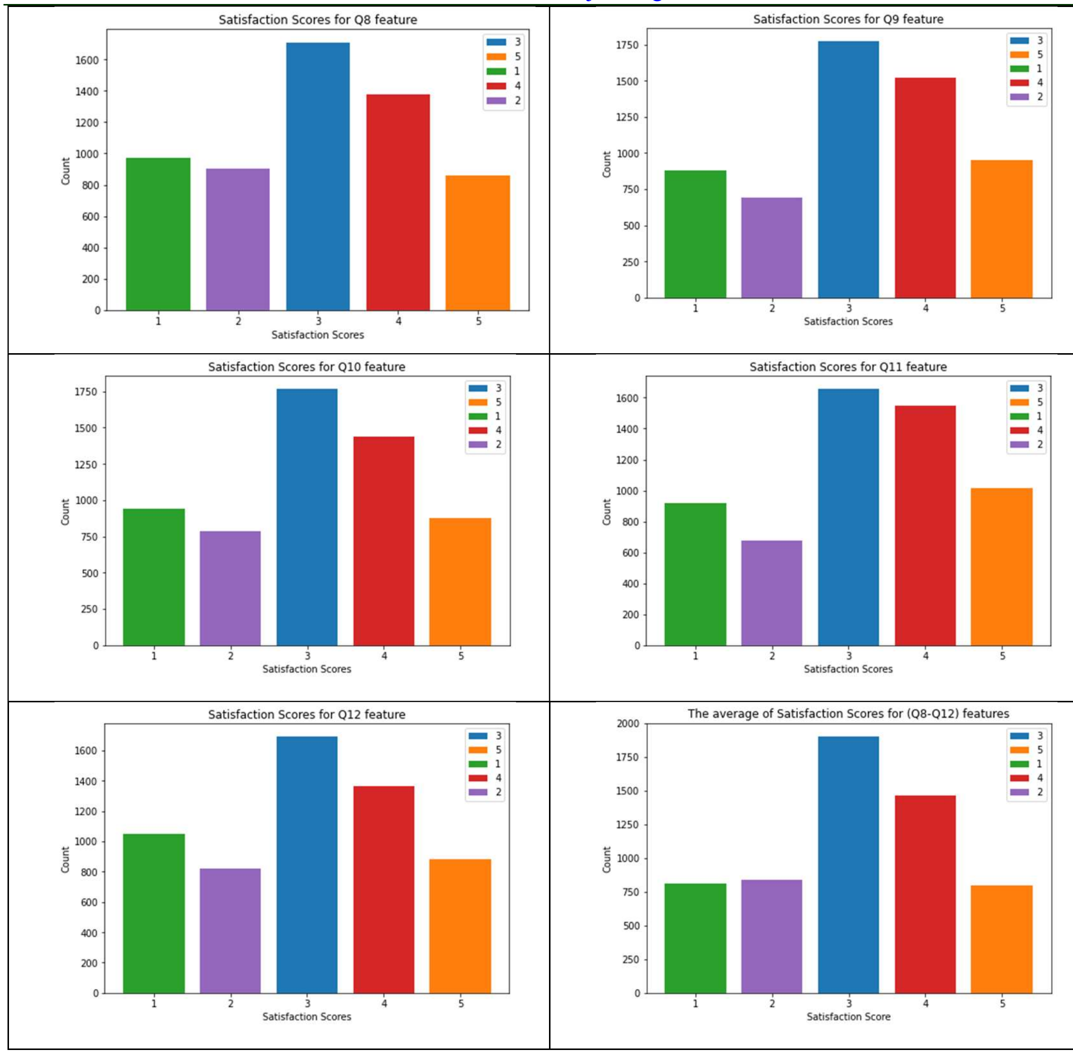

Figure 2: Distributing of the targeted features (Q9, Q10, Q11, Q12, and Total_SI)

6. RESULTS AND DISCUSSIONS

The study has conducted all its experiments using different Python libraries on the Google colab. Examples of these libraries are pandas, numpy, sklearn, etc. Most the employed classifier algorithms are from the sklearn library, which includes a lot of machine learning methods. A few of these algorithms' parameter default values have been changed manually. However, the study preferred to keep these algorithms at their default settings in order to keep their computational features. The classifiers have been evaluated using metrics which measure the prediction performance of these classifiers. The experiments calculated these metrics of precision, recall, F1-Score, and accuracy and AUC (Accuracy Under Curve) during classifier testing. The formulas [42] that were used in these calculations are in Equations 1, 2, 3, and 4.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

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

$$Accuracy = \frac{TP+T}{TP+FP+FN+TN} \quad (3)$$

$$F1-Score = \frac{2*Precision*Recall}{Precision+Rec} \quad (4)$$

Precision is the proportion of correct predictions among the positively predicted cases, whereas recall is the proportion of correct predictions among the actual positive cases [43]. These measurements are also associated with the F1-score, which is the harmonic mean of precision and recall. Accuracy is the proportion of all correct prediction among all predicted cases. The higher Accuracy, Precision, F1-score, and Recall values indicate more accurate predictions. AUC metric

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quantifies the classification's ability to distinguish between classes [44].

In the flowing subsections, the results of the ten classifiers in predicting the target features (Q8, Q9, Q10, Q11, Q12 and Total_SI) are presented using predictors features related to instructor characteristics (Q13-Q28) and course attributes (repeat, attendance, difficulty, Q1-Q7)

5.1 Predicting the Target Features before Balancing the Dataset.

In this section, the results of the ten classifiers on the dataset before balancing are presented in predicting each target feature. In addition, the classifiers are compared in terms of the prediction-performance metrics mentioned above.

5.1.1 Predicting the Q8 feature.

Table 2 shows the performance of the classifiers in the prediction of the Q8 aspect. In terms of the accuracy value that evaluates the efficacy of the models, the Gradient Boosting classifier performed the best, followed by the SVM and the Extra Trees classifiers, and the Naïve Bayzin performed the worst. Precision, which measures predictive power, confirmed SVM and Gradient Boosting as the best classifiers; however, Random Forest also had high predictive power. In contrast, recall values, which reflect the sensitivity and true positive rate of the models, vary across classifiers. According to recall, the Gradient Boosting is the most powerful classifier, followed by the Extra Trees and SVM. In addition, according to the F1-score, which measures both recall and precision and is helpful in comparison to the accuracy measure, the Gradient Boosting is once again the superior algorithm, while the SVM is the second-best algorithm. According to AUC (Area Under the Curve), which evaluates the classifier's ability to distinguish between classes, the 4-top AUC values are all at least 96.39%. AUC indicates that the LR classifier had the highest performance, followed by Random Forest, SVM and Gradient Boosting, and CART had the lowest. In terms of precision, specificity, recall, and F1-score, NB also did the worst. Thus, the Gradient Boosting, SVM, Extra Trees, and Random Forest classifiers are the top comparable to the other classifiers. According to these performance metrics, Gradient Boosting can be regarded as the most effective classifier among all others.

Table 2. Evaluation of Q8-prediction results of each classifier.

Target Feature	Classifiers	Performance Metrics (%)				
		Accuracy	Precision	Recall	F1-score	AUC
Q8	Linear Regression(LR)	82.027	83.019	81.462	82.078	96.609
	Linear Discriminant Analysis(LDA)	81.993	82.84	81.347	81.951	96.364
	Knearest Neighbor(KNN_5)	80.825	82.297	80.133	81.008	95.605
	Decision Tree(CART)	78.505	78.842	78.358	78.529	93.825
	Naïve Based(NB)	75.911	74.948	75.748	75.213	94.555
	Support Vector Machine(SVM)	83.608	84.263	83.57	83.859	96.489
	Extra Trees	83.419	84.033	83.574	83.742	96.367
	Gradient Boosting	83.849	84.162	84.034	84.041	96.394
	Random Forest	83.196	83.921	83.417	83.609	96.506
	Multiple Layer Perceptron (MLP)	81.873	82.093	81.893	81.915	96.353

5.1.2 Predicting the Q9 feature.

The results are explained in table 3, regarding the predicting of the target feature Q9. According to the accuracy measure, the Gradient Boosting is the best, followed by Random Forest and Extra Trees, while the CART is the worst. Regarding the precision value, the SVM and the Random Forest are the best, followed by the Gradient Boosting and Extra Trees. Once again, the Gradient Boosting and the Random Forest are the two best in terms of recall and F1-score. According to the AUC, the Random Forest is the best while the CART is the worst.

Table 3. Evaluation of Q9-prediction results of each classifier.

Target Feature	Classifiers	Performance Metrics (%)				
		Accuracy	Precision	Recall	F1-score	AUC
Q9	Linear Regression(LR)	77.423	79.112	74.369	75.634	91.456
	Linear Discriminant Analysis(LDA)	76.117	75.538	71.88	72.608	92.084
	Knearest Neighbor(KNN_5)	79.244	79.706	77.654	78.432	91.474
	Decision Tree(CART)	75.43	75.258	74.478	74.745	89.933
	Naïve Based(NB)	76.22	75.286	76.214	75.479	91.276
	Support Vector Machine(SVM)	79.88	82.619	77.566	79.223	91.984
	Extra Trees	79.828	80.521	78.49	79.305	91.867
	Gradient Boosting	80.584	80.752	79.811	80.176	92.038
	Random Forest	80.326	81.376	78.988	79.952	92.185
	Multiple Layer Perceptron (MLP)	77.904	77.979	76.673	77.105	91.928

5.1.3 Predicting the Q10 feature.

Regarding the prediction of the target characteristic Q10 in terms of course's initial expectations being met, the results are presented in table 4. According to the accuracy metric, Random Forest, Gradient Boosting, Extra Trees, and SVM performed the best, with an accuracy of at least 83%. According to precision, recall, and F-score, the Random Forest and Gradient Boosting were the two tops, and they also performed well in terms of the AUC metric. In addition, the CART was the worst among the different classifiers in all metrics.

Table 4: Evaluation of Q10-prediction Results of Each Classifier.

Target Feature	Classifiers	Performance Metrics (%)				
		Accuracy	Precision	Recall	F1-score	AUC
Q10	Linear Regression(LR)	82.371	82.91	81.158	81.898	96.228
	Linear Discriminant Analysis(LDA)	82.543	83.301	81.506	82.264	96.118
	Knearest Neighbor(KNN_5)	81.546	82.836	80.654	81.54	95.529
	Decision Tree(CART)	79.003	78.795	78.622	78.643	94.538
	Naïve Based(NB)	79.433	79.588	79.96	79.479	95.291
	Support Vector Machine(SVM)	83.041	83.587	82.304	82.833	96.16
	Extra Trees	83.643	84.13	83.07	83.518	96.003
	Gradient Boosting	83.78	83.8	83.454	83.567	96.098
	Random Forest	83.986	84.469	83.44	83.864	95.998
	Multiple Layer Perceptron (MLP)	82.371	82.7	81.93	82.191	95.92

5.1.4 Predicting the Q11 feature.

Table 5 shows the results of the target feature Q11 prediction about how the course will help with professional growth. According to the accuracy metric, the Random Forest and Gradient Boosting outperformed the others, with an accuracy of at least 80%. According to precision, the SVM and the Gradient Boosting were the best. In terms of recall, and F1-score, the GPR was the best, and it also performed well in terms of the AUC metric. On the other hand, the CART was the worst among the different classifiers in all metrics.

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Table 5. Evaluation of Q11-prediction results of each classifier.

Target Feature	Classifiers	Performance Metrics (%)				
		Accuracy	Precision	Recall	F1-score	AUC
Q11	Linear Regression(LR)	76.838	78.289	73.662	74.724	91.493
	Linear Discriminant Analysis(LDA)	75.189	74.407	70.361	70.878	91.193
	Knearest Neighbor(KNN_5)	78.557	79.253	77.227	77.923	90.938
	Decision Tree(CART)	75.687	74.971	74.798	74.808	89.517
	Naïve Based(NB)	76.718	76.002	76.485	75.991	90.71
	Support Vector Machine(SVM)	79.759	81.131	77.902	79.005	91.802
	Extra Trees	79.759	80.29	78.437	79.167	91.808
	Gradient Boosting	80.704	80.826	79.699	**80.131**	91.803
	Random Forest	80.223	80.77	79.014	79.713	91.816
	Multiple Layer Perceptron (MLP)	78.694	78.443	77.581	77.843	91.007

5.1.5 Predicting the Q12 feature.

Table 6 presents the findings regarding the prediction of the target characteristic Q12 in terms of the degree to which the course relates to and assists the student in addressing real-world challenges. With an accuracy of 80.5%, the Gradient Boosting classifier was superior in the majority of metrics. The feature importance diagram of the Gradient Boosting classifier for this target feature is shown in Figure 4. The following are the three most important features in the Gradient Boosting classifier: Q7, Q17, and Q6.

Table 6. Evaluation of Q12-prediction results of each classifier.

Target Feature	Classifiers	Performance Metrics (%)				
		Accuracy	Precision	Recall	F1-score	AUC
Q12	Linear Regression(LR)	74.158	72.576	70.276	69.437	93.665
	Linear Discriminant Analysis(LDA)	73.969	71.703	70.102	69.739	93.703
	Knearest Neighbor(KNN_5)	77.904	78.883	76.601	77.442	93.035
	Decision Tree(CART)	74.485	73.895	73.875	73.824	91.08
	Naïve Based(NB)	75.069	73.988	74.53	74.061	92.94
	Support Vector Machine(SVM)	79.141	79.676	77.662	78.357	93.712
	Extra Trees	79.141	79.244	78.204	78.616	93.84
	Gradient Boosting	80.052	79.90	79.169	79.428	93.885
	Random Forest	79.107	79.319	78.219	78.632	93.421
	Multiple Layer Perceptron (MLP)	78.058	77.743	77.338	77.377	92.474

5.1.6 Predicting the total SI feature.

The results of the prediction of the target aspect total SI, which describes the total average of student satisfaction related to the aspects Q9, Q10, Q11, and Q12, are presented in Table 7. With an accuracy of 84.12%, the Gradient Boosting classifier was once again superior in the majority of metrics.

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Table 7: Evaluation of Total_SI-prediction results of each classifier.

Target Feature	Classifiers	Performance Metrics (%)				
		Accuracy	Precision	Recall	F1-score	AUC
Total_SI	Linear Regression(LR)	83.265	84.159	82.742	83.286	97.868
	Linear Discriminant Analysis(LDA)	83.196	83.792	83.027	83.327	97.794
	Knearest Neighbor(KNN_5)	82.749	83.468	82.334	82.804	97.402
	Decision Tree(CART)	78.471	78.657	79.012	78.726	96.956
	Naïve Based(NB)	80.378	80.855	81.379	80.955	96.632
	Support Vector Machine(SVM)	83.608	84.608	83.13	83.731	97.835
	Extra Trees	83.505	84.555	83.175	83.752	97.741
	Gradient Boosting	84.124	84.421	84.129	84.199	97.90
	Random Forest	83.849	84.815	83.701	84.164	97.874
	Multiple Layer Perceptron (MLP)	81.89	82.439	82.057	82.105	97.805

5.2 Predicting the Target Features after Balancing the Dataset

The study has performed the experiments of predicting all the target satisfaction features on the dataset after over sampling the minority classes. The study used the accuracy metric to evaluate the results of the classifiers on the balanced dataset, As a result, table 8 shows the accuracy-metric comparison of the 10 classifiers in predicting these target features using the instructor predictors(Q13-Q28) and course predictors (repeat, attendance, difficulty, Q1-Q7). As thus, the Extra Trees classifier (Extra Trees) had the highest accuracy rate in predicting all of these features, especially with the balanced dataset. In addition, the Extra Trees classifier had the highest AUC as explained in table 9, making it superior to other classifiers considered in this study.

Table 8: Accuracy Evaluation of All Classifiers after Balancing.

Classifiers	Target Features					
	Q8	Q9	Q10	Q11	Q12	Total_SI
	Accuracy (%)					
LR	83.904	79.01	83.557	78.952	78.019	85.656
LDA	83.822	78.368	83.851	78.145	77.995	85.561
KNN_5	86.37	84.817	87.25	83.349	82.913	88.646
CART	83.799	82.477	84.878	80.59	80.472	86.432
NB	77.931	76.804	80.61	77.096	76.474	82.466
SVM	85.681	82.026	85.319	81.229	81.108	86.821
Extra Trees	88.72	87.867	89.645	86.578	86.545	90.881
Gradient Boosting	86.242	83.422	86.652	82.361	82.087	88.08
Random Forest	88.253	87.147	89.351	86.06	85.884	90.472
MLP	84.944	81.632	85.071	80.988	80.094	86.768

As thus and regarding to the first research question, the top accurate classifier in predicting all the target aspects ((Q8, Q9, Q10, Q11, Q12, Total SI) was Extra Trees Classifier (Extra Trees). Therefore, it was selected to identify the most important variables for these target features.

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Table 9: AUC Evaluation of All Classifiers after Balancing.

Classifiers	Target Features					
	Q8	Q9	Q10	Q11	Q12	Total_SI
	AUC (Accuracy Under Curve) (%)					
LR	96.824	92.351	96.347	92.103	93.95	98.365
LDA	97.091	92.817	96.487	92.351	94.182	98.312
KNN_5	97.018	94.483	97.232	93.113	95.317	98.592
CART	96.566	93.841	96.764	92.233	94.21	98.506
NB	95.102	92.451	95.5	91.895	93.471	97.366
SVM	97.024	92.881	96.482	92.745	94.746	98.456
Extra Trees	98.255	95.84	97.885	95.342	96.498	99.137
Gradient Boosting	97.058	93.251	96.589	93.25	94.844	98.668
Random Forest	98.012	95.409	97.765	95.071	96.246	99.052
MLP	96.942	93.459	96.411	92.998	94.716	98.351

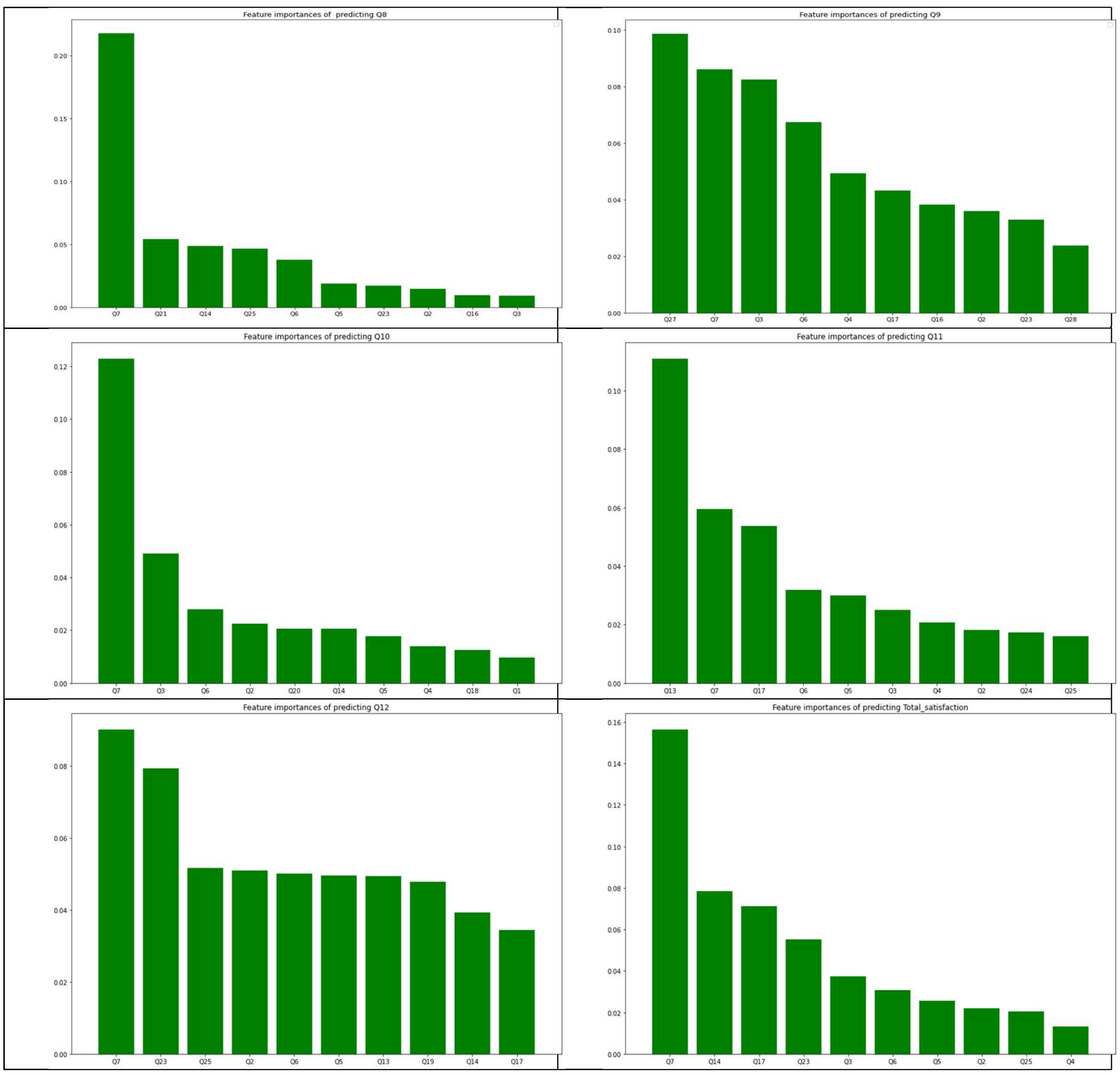

Figure 4: The Mean Decrease in Accuracy (MDA) for the Extra Trees classifier.

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In terms of the second research question, figure 4 shows the top 10-most important attributes of the Extra Trees classifier in predicting the target aspects by using predictors related to course (repeat, attendance, difficulty, Q1-Q7) and instructors (Q13-Q28). This figure shows the distribution of the most important attributes according to Mean Decrease Accuracy (MDA) metric. MDA measures how much a classifier accuracy is decreased when feature values are shifted randomly. If the MDA is zero, it means that the feature wasn't used in the prediction. If the MDA is high, it means that the classifier relied heavily on that feature [45]. In predicting Q8, the top three attributes are Q7, Q21, and Q14. In predicting Q9, the top 3 attributes are Q27, Q7, and Q3. In predicting Q10, the top three attributes are Q7, Q3, and Q6. In predicting Q11, the top three attributes are Q13, Q7, and Q17. In predicting Q12, the top three attributes are Q7, Q23, and Q25. In predicting Total SI, the top three attributes are Q7, Q14, and Q17. As it can be noticed that the features related to the "course features" Q3, Q6, and Q7 were identified as important predictors. In addition, the features related to the "instructor features" Q13, Q14, Q17, Q21, Q23, Q25 and Q27 were also identified as important predictors. As is evident from these results, the largest proportion relates to instructor characteristics. Moreover, in all cases of the predictions, the Q7 frequently appeared as the most important attribute compared to other attributes. This result indicates that the most important attribute type that mainly predicts student satisfaction was related to course attributes. In light of these findings, instructors should think about course constructs including fieldwork, applications, labs, and group discussions while planning to teach classroom courses. Additionally, instructors should be encouraged to use up-to-date teaching materials. Instructors should be well-prepared, friendly, encourage students to take part in class, and give and talk about exam answers.

6. DISCUSSION

In this paper, ten classification algorithms are applied to a dataset, namely Turkiye Student Evaluation, which is obtained from the UCI machine learning repository. In the literature as summarized in table 10, various researchers applied data mining techniques to this dataset to evaluate the instructor's performance. In [27], a variety of machine learning approaches (SVM, MLP, Decision Tree, Random Forest, Decision Table, K-NN) were used to predict and infer the course and instructor-related factors that have a stronger impact on student satisfaction. The study focused on five dimensions of student satisfaction, as in our study: course evaluation, class engagement, course expectations, course relevance, and professional development. They have not explored the unbalancing issue in the dataset and how they can improve the accuracy of the used algorithms. This research [28] evaluated the instructor's performance using 12 classification techniques. Using agglomerative clustering and k-means, the dataset is labeled. As a result, the Support Vector Machine was the most accurate with PCA feature selection. They also have not manipulated the unbalancing of the dataset and have not identified the important features that influence student satisfaction. The researchers [20] applied four classification techniques, and an attribute ranking method was used to identify the lowest-ranked attributes that reduced the prediction accuracy and eliminate them from the data set before training the classification techniques. "J48" received an accuracy of "84.8%" for all features, and Sequential Minimal Optimization (SMO) received an accuracy of "85.8%" for selected features. The researcher [46]-[50] applied eight classification algorithms targeting the "repeat" feature. As a result, ZeroR outperformed the other algorithms. He has not used any balancing method on the dataset and has not figured out what the most important features are.

The following are the key findings from our study:

i) In this study, 10 classifiers are applied to a dataset to predict student-satisfaction features. Our model outperformed state-of-the-art results without removing low-ranked features that reduced prediction accuracy.
ii) We have addressed the issue of the imbalance in the dataset that may have a negative effect on the classifiers through ignoring minority features that could be crucial to the prediction process.
iii) Feature/variable importance is also computed using the most accurate classifier. The results show that when planning classroom courses, instructors should consider fieldwork, applications, labs, and group discussion. In addition, instructors should also use current materials. And also, instructors should be well-prepared, friendly, encourage student participation, and give and discuss exam answers.
iv) The chosen prediction model can uncover the gap between instructional performance in classrooms and student satisfaction where

instructors have to change their methods of teaching so the students can be more satisfied.

Table 10: Comparison of our work with existing studies on the dataset

Paper	Best model and Performance Parameters (%)	Classification techniques	Target Features	Feature importance metric
F. Afrin et al.,2020 [27]	Best model: SVM Accuracy:84.16	6 classification techniques: ("SVM, MLP, Decision Tree, Random Forest, Decision Table, K-NN")	5 target features: Q8, Q9, Q10, Q11, and Q12	Mutual Information (MI)
Ravinder Ahuja, et al., 2020 [28]	Best model: PCA with SVM Accuracy:99.6, Precision:99.66, Recall: 99.67, F-Score:99.67	12 classification techniques: ("K Nearest Neighbor, XGBoost, Multi-Layer Perceptron, AdaBoost, Random Forest, Logistic Regression, Decision Tree, Bagging, LightGBM, Support Vector Machine, Extra Tree, and Naive Bayes").	1 target feature: label-class feature introduced by clustering methods	-
Suh S., 20216, [46]	Best model: ZeroR Accuracy: 84.34	8 classification techniques: ("Naïve Bayes, k-nearest neighbor, Logistic regression, J4.8, JRip, Random Forest, Multi-Layer Perceptron, and ZeroR")	1 target feature: "repeat"	-
Ahmed A. M.,et al., 2016 [20]	Best model: SMO Accuracy:85.8	4 classification techniques: ("J48 Decision Tree, Multilayer Perception, Naïve Bayes, and Sequential Minimal Optimization")	1 target feature: label-class described the instructor performance	-
Our work	Best model: SMOTE with Extra Trees Accuracy: 90.88 AUC: 99.13	10 classification techniques: ("Logistic Regression, Linear Discriminant Analysis, Kneighbors, Decision Tree, Extra Trees, Gradient Boosting , Random Forest, and Multilayer Perceptron")	6 target features: Q8, Q9, Q10, Q11, Q12 and Total_SI (introduced by averaging Q7, Q8, Q9, Q11, Q12)	Mean Decrease Accuracy (MDA)

7. CONCLUSION

Data mining techniques are used in higher education to help make better decisions about how to improve the learning process and deal with other important issues. In this study, ten different classifiers are used to analyze a dataset in order to make predictions for selected features of student satisfaction regarding the learning activities, the student's interest in class participation, and the fulfillment of the initial expectations of course, professional growth, and the degree to which the course relates to and helps the student address real-world issues. It is observed that the ten classifiers have better performance in terms of prediction accuracy after balancing the dataset. On the balanced dataset, the ten classifiers were 4% more accurate on average than when they were used on the imbalanced dataset. This study also includes the finding of the most important features used to predict student satisfaction. It is observed that "course features" Q3, Q6, and Q7 were identified as important predictors. In addition, "instructor features" Q13, Q14, Q17, Q21, Q23, Q25, and Q27 were also important predictors. The majority of these results relate to instructor behaviors. In all predictions, the Q7 often topped other features. In light of these findings, instructors should plan courses with fieldwork, applications, labs, and group discussion. Instructors should also use up-to-date materials, be well prepared, be friendly, encourage student participation, and give and talk about exam solutions.

8. LIMITATION AND FUTURE WORK

For future work: we can try different techniques for feature selection and analysis. We can experiment with hyper parameters for the different machine learning algorithms. Furthermore, we can use Ensemble techniques that use a group of machine learning algorithms and combine them according to some methodology (like Voting) to get better accuracy results.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: AA, SA, NY; data collection: AA, NY, SA; analysis and interpretation of results: AA. Author; draft manuscript preparation: AA, SA, NY. All authors reviewed the results and approved the final version of the manuscript.

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