BRAIN. Broad Research in Artificial Intelligence and Neuroscience
ISSN: 2068-0473 | e-ISSN: 2067-3957
Covered in: Web of Science (WOS); PubMed.gov; IndexCopernicus; The Linguist List; Google Academic; Ulrichs; getCITED; Genamics JournalSeek; J-Gate; SHERPA/RoMEO; Dayang Journal System; Public Knowledge Project; BIUM; NewJour; ArticleReach Direct; Link+; CSB; CiteSeerX; Socolar; KVK; WorldCat; CrossRef; Ideas RePeC; Econpapers; Socionet.

2024, Volume 15, Issue 2, pages: 23-45 | https://doi.org/10.18662/brain/15.2/562
Submitted: May 3th, 2024| *Accepted for publication:* May 11th, 2024

Classifying Engineering Students Performance in Online Education with Machine Learning: Affective, Cognitive, and Behavioral Aspects

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Abstract: *In the rapidly evolving online learning environment, accurate prediction of student performance plays an important role in improving the quality of education and overall student outcomes. This study investigated the effectiveness of machine learning algorithms in classifying student performance in online courses based on affective, cognitive, and behavioural factors to develop more effective teaching strategies and interventions to support student success. A dataset of 485 engineering students who took Astronomy Physics at a private university in the fall and spring semesters of 2022-2023 was used to train and evaluate six machine learning algorithms: Support vector machines (SVM), K-nearest neighbours (KNN), Naive Bayes (NB) classifier, logistic regression, decision tree, and random forest. The random forest algorithm achieved the highest classification accuracy (87%), correctly classifying 87% of students into one of three performance categories: high, medium, or low. Moreover, the study determined that anxiety and expectations are the most influential factors in increasing student performance in online courses, while the least effective feature is social isolation. The findings suggest that Machine learning can efficiently categorize student performance in online courses, even with a limited set of features, enabling educators to enhance teaching strategies and interventions for better student support.*

Keywords: *classification; machine learning; online education; student performance*

How to cite: Aşiksoy, G., & İslek, D. (2024). Classifying engineering students performance in online education with machine learning: affective, cognitive, and behavioral aspects. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 15*(2), 23-45. https://doi.org/10.18662/brain/15.2/562

Introduction

The COVID-19 pandemic created a massive crisis worldwide that affected the education systems. During this period, online education has become vital to ensure that students continue their education without interruption (Ling, 2021).

Online education has revolutionized access to information by eliminating constraints related to time and location. It offers students the flexibility to advance at their own pace, presenting significant advantages such as cost-effectiveness. Notably, these benefits have persisted beyond the pandemic, as evidenced by the continued widespread utilization of online learning platforms (Al-Obaydi et al., 2022). However, due to the social isolation of online learning environments, educators may need help to track students' learning status. Lack of interaction between students may cause a loss of motivation and technology addiction (Qiu et al., 2022). The reduced opportunities for face-to-face interaction in online courses can hinder students' ability to grasp concepts and engage in in-depth discussions fully, ultimately impacting their understanding of the subject matter (Ferri et al., 2020; Vlachopoulos & Makri, 2019). Additionally, the lack of adequate assessment and feedback in online environments can make it difficult for students to track their progress accurately (Tanis, 2020). These issues are increasing concerns about students' performance and participation in online education (Alhothali et al., 2022). However, previous research has shown several significant ways to improve student performance in online courses. One way is to use various interactive learning tools to engage students and increase their participation (Tran et al., 2022). Similarly, providing timely and constructive feedback can significantly contribute to student development. In this context, regular feedback on exam results, assignment evaluations, and student performance can help students understand their strengths and weaknesses (Yousuf et al., 2020). The use of tools such as group projects, forums, or online discussion platforms can also be used to create a sense of collaboration and community among students, thereby increasing student motivation and participation (Wang et al., 2019). Combining these elements makes it possible to improve student performance in online courses.

Recent studies have emphasized the significance of early prediction of student performance, improving online learning experiences, and responding to students' needs on time (Alhothali et al., 2022; Arce et al., 2015). Accurate projections of the students' performances, determining the needs of the students, and providing adequate support and guidance could improve the quality of online education by optimizing educational strategies

(Qiu et al., 2022). Understanding students' behaviours, affective moods, and cognitive aspects is difficult in online learning settings due to their complexity. It is crucial to comprehend how these factors relate to students' performance (Su et al., 2018).

Developing and improving innovative and data-driven methodologies, such as machine learning, allows for reliable prediction of students' performances. These methodologies are widely acknowledged as valuable tools for accurately predicting and evaluating students' success levels (Alyahyan & Düştegör, 2020).

Demographic data such as socioeconomic level and gender, as well as their interactions with digital materials obtained through the Learning Management System, have been frequently used in previous studies to predict student success (Gadhavi & Patel, 2017; Kim et al., 2018; Lemay & Doleck, 2020; Qiu et al., 2022; Wang et al., 2022). However, research by Ortiz-Vilchis & Aldo Ramirez-Arellano (2023) successfully predicted student achievement without using these conventional factors, marking a significant departure from common approaches in the literature.

Related Studies

Related studies on behavioral, affective, and cognitive factors in online education

This section reviews previous studies that have explored the significance of behavioural, affective, and cognitive factors in online education.

Acosta-Gonzaga & Ramirez-Arellano (2023) underscored the importance of considering both affective and cognitive factors in comprehending student learning experiences and outcomes. They posit that these factors serve as critical determinants of student success, with positive emotions playing a more prominent role in blended learning environments than in traditional face-to-face settings.

The research conducted by Almaiah et al. (2020) examined the key challenges and factors influencing the adoption of e-learning systems in developing countries, such as Jordan and Saudi Arabia, during the COVID-19 pandemic. The findings revealed that achieving success in the e-learning environment necessitates the development of teacher self-efficacy in effectively utilizing the e-learning system, alongside the quality of the e-learning system and cultural factors.

Almaiah & Alyoussef (2019) investigated the primary factors influencing student engagement with e-learning systems. The study determined that course design, content support, course evaluation, and instructor characteristics were all crucial determinants of student engagement with e-learning systems. However, the impact of social influence on actual usage was not statistically significant. Additionally, the study found that all four factors were positively correlated with student perceptions of the usefulness of e-learning systems.

Almaiah et al., (2022) explored student perceptions of the Madrasati platform, a web-based learning platform, and the factors influencing student adoption. The study's findings demonstrated a strong association between system quality, service quality, content quality, technological infrastructure, university management support, and student utilization of the Madrasati platform.

Graham et al., (2023) sought to examine how effectively a university in Colombia supports the emotional, behavioural, and cognitive dimensions of engagement in online and blended learning courses. The study revealed that institutional support for affective engagement was strongly connected to all three aspects of student engagement. However, institutional support for behavioural and cognitive engagement produced a different impact

Related studies on the use of machine learning algorithms to predict student performance

Numerous studies have employed machine learning algorithms to assess and enhance student performance. For instance, via Moodle, a study Purwoningsih et al. (2020) investigated the educational information access patterns and academic progress of 1710 students at Turbeka University in Indonesia. Their research evaluated five different machine learning approaches, concluding that support vector machines (SVMs) exhibited superior accuracy performance. They emphasized the potential for validating these findings across diverse courses and improving educational content quality to increase student performance.

Bognár & Fauszt (2020) explored categorizing academic achievements among 57 students enrolled in a course utilizing Moodle's online learning platform at Dunaujvaros University in Hungary. The study employed Moodle activities, including exams, lecture notes, textbook access, and data on accessing external resources like videos, mini tabs, and PDFs. Logistic Regression (LR) was employed for student achievement classification, utilizing a five-fold cross-validation methodology for training, testing, and validating the dataset. The LR method achieved an accuracy rate of 84% for accessing Moodle events and 91% for accessing non-Moodle events.

Ruiz-Rodríguez et al. (2020) investigated the success prediction and classification of the same course offered in two semesters. They employed random forest and neural network approaches for binary and quadruple classifications. Data from one semester was used for training, and data from the other for testing. In the study, while 91% accuracy was achieved with random forest binary classification, 92% accuracy was achieved with neural networks.

Cruz-Jesus et al., (2020) used machine learning algorithms to predict student performance based on 16 types of demographic data, including academic internet access, computer ownership, and course enrollment. The study found that the Random Forest algorithm was the most accurate predictor of student academic performance, achieving an impressive 87% accuracy rate, followed by ANN, SVM, and LR.

In another study, Babić (2017) developed a classification model based on data based on their behaviour in Learning Management System (LMS) courses to identify students with low academic motivation early. Three machine learning classifiers (neural networks, decision trees, and support vector machines) were used in the study. Although all classifiers were successful, the neural network model was the most successful in detecting the student's academic motivation based on their behaviour in the LMS course.

Building upon the emphasis on emotional and cognitive learning a study (Zhen et al., 2023) conducted a comprehensive analysis of live classes within a significant online learning platform in China. Employing natural language processing (NLP) techniques, they extracted features related to interactive genres and emotional expressions from classroom dialogues. The development of neural network models incorporating these features enabled the prediction of student performance variability. Additionally, interpretable artificial intelligence (AI) techniques were employed to identify critical predictors within the models. Notably, their findings revealed a consistent pattern across STEM and non-STEM courses: high-performing students consistently exhibited more positive emotions and cognitions and engaged in off-topic dialogues at all stages of the courses compared to their low-performing counterparts.

Previous research has demonstrated that affective, cognitive, and behavioral factors play a significant role in online learning environments. These factors can have a major impact on students' learning experiences and outcomes. Therefore, in this study, in addition to these factors, different factors were also investigated to predict student performance in online courses.

Methodology

Data collection tools

The data used in this study is based on a sample of engineering faculty students who took the Astronomy Physics course in the fall and spring semesters of the 2022-2023 academic year. The researcher taught Astronomy Physics courses according to the online learning model. At the beginning of the semester, the attitudes toward learning scale, internet addiction scale, future anxiety scale and perceived self-regulation scale were shared with 534 students via Google Form, an online platform. Thus, the students were able to access the surveys and save their responses easily. 485 of the students completed the surveys. The student's course grades were downloaded from the university's grade entry system. This study was approved by the Ethics Committee of Near East University under protocol number YDU/EB/2022/251. Information on the scales in which the data were collected is presented below:

Attitudes toward learning scale.

The scale developed by Kara (2020) was used to determine students' attitudes towards learning. This scale contains 40 items and consists of four sub-dimensions about learning: "Anxiety", "Openness", "Nature of Learning", and "Expectations". The scale type is 5-point Likert and presented as terms: 1=totally disagree, 2 = disagree, 3=undecided, 4=agree, 5=totally agree. The Cronbach alpha internal consistency reliability coefficients for the sub-dimensions of the scale are as follows: Anxiety 0.81, Openness 0.78, Nature of Learning 0.77, Expectation 0.72.

Internet addiction scale.

The scale developed by Young (2009) was used to determine students' Internet addiction. The scale was adapted into Turkish by Keser et al. (2013). It measures 4 dimensions such as "Difficulty to Control", "Avoidance", "Social Isolation" and "Deprivation". The scale is in five-point Likert type and its expressions are (1=Never, 2=Rarely, 3=Sometimes 4=Often, 5=Always). The Cronbach alpha internal consistency coefficient of the scale is 0.91 for the first sub-scale, 0.87 for the second sub-scale, 0.89 for the third sub-scale, 0.90 for the fourth sub-scale, and 0.90 for the whole scale.

Future anxiety scale

The scale developed by Geylani & Yildiz (2022) was used to determine the future anxiety of university students. This scale consists of two factors: 'Fear of the Future' and "Hopelessness for the Future". The scale is in five-point Likert type and presented as 1=Never, 2=Rarely, 3=Sometimes 4=Often, 5=Always) out of 19 items. The Cronbach alpha value for the "Fear of the Future" sub-factor of the Future Anxiety scale was 0.95 and 0.88 for the "Hopelessness for the Future" sub-factor.

Perceived self-regulation

The scale developed by Arslan & Gelisli (2015) was used to measure students' self-regulation skills. This scale includes 16 items gathered under two factors "Openness" and "Seeking". The scale is a five-point Likert-type statement (1=Never, 2=Rarely, 3= Sometimes, 4=Often, 5=Always). The Cronbach alpha internal consistency reliability coefficients of the Perceived Self-Regulation Scale were 0.84 for the "Openless" sub-factor and 0.82 for the "seeking" sub-factor.

Academic performance

This study used the course grades of the students to evaluate their academic performances. The course grades of the students were downloaded as an Excel file from the university's course grade entry system. The overall course grades are calculated using 30% of the midterm grades and 70% of the final exam grades.

Machine learning algorithms

The following machine-learning techniques were used in the study:

Support vector machines (SVMs). SVMs work by creating linear or non-linear boundaries that separate a dataset from each other. These boundaries can be used to separate classes in classification problems or to predict the value of the dependent variable in regression problems (Géron, 2022). The hyperparameters that affect the performance of SVMs are as follows:

- The C parameter sets a trade-off between the SVM's classification accuracy and generalization performance. Higher C values provide more accurate classification, but can lead to a less generalized model.
- The gamma parameter adjusts the shape of the SVM's nonlinear boundaries. Lower gamma values produce smoother boundaries, while higher gamma values produce sharper boundaries.
- The Kernel is the function that the SVM uses to generate non-linear boundaries. The most commonly used kernels are the Gaussian kernel and the polynomial kernel (Alpaydin, 2004). Their ability to transform

data into a more suitable representation using kernel functions makes them applicable to both normal and non-normal data distributions.

Naïve bayes (NB) classifier. This supervised learning algorithm uses Bayes' theorem to classify data. It works by estimating the probability distributions for each class and then comparing the probabilities of those distributions to determine which class a new data point belongs to. The hyperparameters that affect the performance of the Naive Bayes algorithm are as follows:

- Alpha: Alpha is a hyperparameter that controls the prior probabilities used by the Naive Bayes algorithm. Prior probabilities are the probabilities of each class before any data has been seen. Higher alpha values give higher probabilities to unseen data. This can help the algorithm to generalize better to new data, but it can also lead to overfitting if the data set is small or noisy.
- Priors: Priors are the values that represent the prior probabilities for each class. Priors can be manually set or estimated from the data set. Manually setting priors can be useful if you have prior knowledge about the data set. Estimating priors from the data set is usually more accurate, but it can be computationally expensive for large data sets (Feng et al., 2004).
- Decision tree. Decision trees are a supervised learning method that uses a series of conditions to classify or regress data. Decision trees have a hierarchical structure that ranges from simple to complex. The hyperparameters that affect the performance of decision trees are as follows:
- Max_depth is a hyperparameter that controls the maximum depth of the decision tree. The depth of a decision tree is the number of splits that it makes. Higher max_depth values create more complex models, but they also carry a higher risk of overfitting. Overfitting occurs when a model learns the training data too well and is unable to generalize to new data.
- Min_samples_split is a hyperparameter that controls the minimum number of samples required to split a branch. Higher min_samples_split values create simpler models, but they may not be as accurate. This is because simpler models are less likely to overfit the training data, but they may also be less likely to capture the true relationship between the features and the target variable.
- Min_samples_leaf is a hyperparameter that controls the minimum number of samples required for a leaf. Higher min_samples_leaf values reduce the risk of overfitting, but they may also reduce accuracy. This is because leaves with more samples are more likely to be representative of the true relationship between the features and the target variable (Long & Wu, 2012).

K-nearest neighbor (KNN). KNN is a flexible and straightforward supervised machine learning algorithm that can be used for both classification and regression tasks. Its functioning involves computing the distance between the training and testing examples. The classification of testing examples is determined based on their proximity to the nearest training examples. To calculate distances, various distance metrics are utilized. In this study, the Euclidean distance was employed. Euclidean distance, which is one of the fundamental distance measurements, quantifies the linear distance between two points. The formula given in equation 1 is used to calculate the distance between two points in an n-dimensional (Durgesh & Lekha, 2010).

$$\boldsymbol{dist_{euklidean}(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}} \quad (1)$$

Logistic regression (LR). It is a regression method in which the dependent variable is categorical. In other words, the classes of the dependent variables are estimated instead of the continuous output values. LR, f, is expressed by the linear function where the independent variable, x, could take any value between -∞ and +∞ (Equation 2) (Trexler & Travis, 1993).

$$f(s) = \frac{e^s}{1+e^s} = \frac{1}{1+e^{-s}} \quad (2)$$

Random forest algorithms. Random Forest is an ensemble method used for classification and regression tasks, employing a collection of decision trees. Each tree in the forest independently classifies the input sample, and the final class of the instance is determined through majority voting by the entire forest. By integrating the findings of numerous decision trees and making a single judgment on behalf of the forest, the random forest algorithm produces relatively trustworthy predictions. Random Forest algorithm may be applied in both categorical and continuous data sets. It can also be utilized for both big and small data sets.

In this method, the Gini index is used as the splitting criterion, as it is in classification and regression trees. A decrease in the Gini index is desirable, as it indicates an increase in purity, and a result of zero indicates maximum purity. The Gini index for a given node t is calculated as follows:

$$GINI(t) = \sum_j [p(j\backslash t)]^2 \quad (3)$$

The equation's $p(j\backslash t)$ represents the relative probability of class j at node t. The Gini index is a measure of class heterogeneity in a decision tree node. It is calculated as the weighted average of the probabilities of each class in the node, where the weights are the probabilities of the classes in the parent node. The Gini index increases as the class distribution becomes more uneven, and decreases as it becomes more even. A branch is successful when it reduces the Gini index of the child node relative to the parent node. The tree-branching process continues until all of the leaf nodes contain a single class (Archer & Kimes, 2008; Bastem, 2021).

Data pre-processing

The data set in this study is in an Excel format, and the SPSS 24.0 program was used for statistical analysis. The data set was imported directly from the Excel environment for analysis. The data set was also processed in CSV (Comma comma-separated values) format for machine learning applications. The scale items contained a total of 18 reverse expressions. These inverse expressions were transformed to make them consistent with the other items.

Missing/incorrect data in the data set were checked. If there is more than one data belonging to a student, that student was not evaluated. After all the information identifying the students (name, surname, student number) in the Academic Performance data set was cleared, the deficiencies in the data lines were corrected. Students who did not take the midterm and final exams received a grade of zero for the course. Course grades are on a scale of 0 to 100, and grades have been converted to a five-point system.

Outliers were inspected during the data preprocessing stage. Mahalanobis distances were used to construct Z-scores to identify outliers and to establish a threshold value in the range (-3,+3). Outlier values were those that fell outside of this range and weren't included in the sample used for the study. The techniques concluded that the 485 individuals' data may be used for statistical analysis.

Statistical analysis

The data collected from the scales in the study were analyzed using SPSS 24.0. Cronbach's alpha, a statistical method that measures the internal consistency of a scale, was used to assess the reliability of the scales in this study. This value indicates the strength of the relationship between the items in the scale. As Nunnally (1978) recommended, scales with a Cronbach's alpha value of 0.70 and above are considered reliable. Figure 1 displays Cronbach's alpha values calculated for each sub-factor of the scales within the scope of the study. According to the results, the computed values for all sub-factors were more than 0.70. These results demonstrate that the scales are dependable and have sufficient internal consistency.

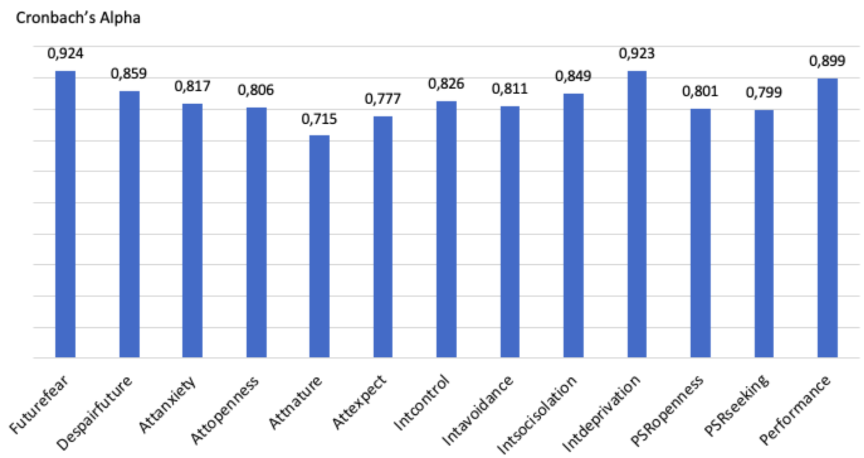

Fig. 1. Internal consistency reliability results of scales and course grades

The study examined the relationship between the scales using a correlation analysis. The Pearson correlation test was employed to assess the correlation relationship, where the correlation coefficient known as the Pearson correlation coefficient was calculated. This coefficient quantifies the linear association between two variables and ranges from -1 to 1. The sign of a correlation coefficient indicates whether the relationship between two variables is positive or negative. Conversely, a value of 0 suggests the absence of any significant relationship between the two variables (Sedgwick, 2012). The Pearson correlation test in this study was assessed at a 95% confidence interval and significance levels of 1% to 5%.

The correlation matrix is a tool for assessing the correlations between independent variables, one factor influencing the success of machine learning models. The highest correlation value is 1.0, which stands for a perfect positive relationship between the two variables. Therefore, the correlation matrix plays a vital role in the evaluation process of the model. The correlation matrix resulting from the Python program conducted in the scope of this study is illustrated in Figure 2.

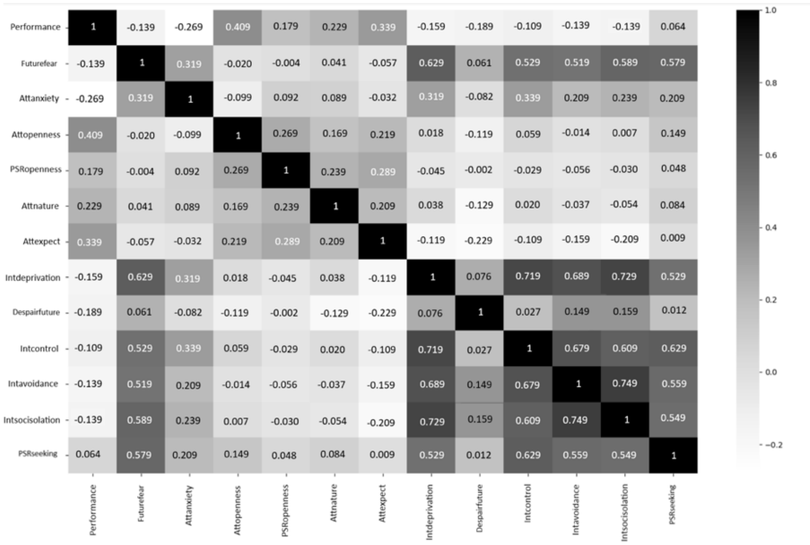

Fig. 2. Interfactor correlation matrix values

Attribute extraction

In this study, the features used for machine learning consist of sub-scales of internet addiction, future anxiety, perceived self-regulation and attitude towards learning scales. The dataset comprises 12 distinct features, wherein responses to the scale inquiries are expressed in numerical values. These values are recorded as floating-point data types in the dataset. The descriptive statistics outcomes for the attributes are illustrated in Table 1.

Table 1. Descriptive statics of attributes.

Features	**N**	**Mean**	**std**	**Min**	**25%**	**50%**	**75%**	**Max**
Futurefear	485	3.338	0.919	1.05	1.80	2.40	3.20	4.85
Attanxiety	485	3.422	0.890	1.05	2.40	3.50	4.20	4.93
Attopenness	485	4.341	0.659	1.25	2.45	3.50	4.10	4.75
PSRopenness	485	3.733	0.653	1.00	3.20	4.30	4.70	4.80
Attnature	485	3.775	0.703	1.15	2.90	3.70	4.30	4.85
Attexpect	485	2.145	0.627	1.20	2.90	3.70	4.30	4.80
Intdeprivation	485	2.176	0.838	1.20	1.54	2.10	2.60	4.60
Despairfuture	485	2.564	0.963	1.05	1.50	2.20	2.80	4.85
Intcontrol	485	2.018	0.689	1.00	1.70	2.50	2.90	4.82
Intavoidance	485	1.811	0.696	1.24	1.38	2.05	2.42	4.76
Intsocisolation	485	2.717	0.877	1.20	1.38	1.70	2.30	4.60
PSRseeking	485	3.459	0.601	1.20	1.90	2.75	3.40	5.00
Performance	485	2.454	0.803	1.00	2.66	3.50	4.00	4.80

Attribute classification performance metrics

Evaluation of the developed model's performance is crucial for machine learning applications. This evaluation includes the performance measures of the techniques used. Classification problems are focused on correctly classifying data with categorical values. The error rates that occur as a result of the machine learning model's classification of categorical data, which is the target variable, are considered the most essential criterion for performance evaluation. This criterion is called the accuracy rate, which refers to the percentage of correctly classified fields in the entire dataset (Marsland et al., 2015).

It may be a wrong approach to evaluate the performance of the model in a classification problem based only on its accuracy. The matrix used for performance measurement is called the complexity matrix, which varies depending on the number of categories of the target variable to be classified. When N categories are in the classification problem, a matrix containing NxN blocks is formed (Gorunescu, 2011).

In this study, the classification problem is treated as binary classification. The complexity matrix of the binary classification problem is shown in Figure 3. Correctly predicted classes are called "True", while incorrectly predicted classes are defined as "False".

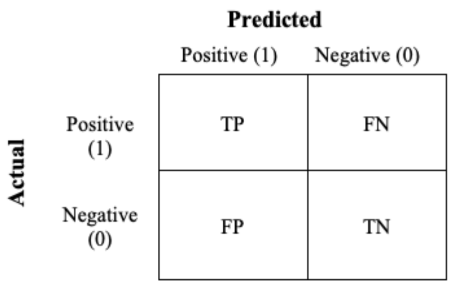

Fig. 3. Example of binary classification complexity matrix

Other metrics used to assess the model's performance are derived from the terms in the complexity matrix. These metrics include precision, recall, and F1 score, which allow a more detailed analysis of the model's performance (Mursalin et al., 2017).

Precision refers to the ratio of how many positive values are actually obtained in the positively predicted class. Recall shows how many positive values were obtained in the class that should be predicted positively. The F1 score represents the harmonic mean of precision and recall measurements.

These metrics could be used to evaluate the success of the developed model. However, a high accuracy rate does not always indicate a successful classification. If the other metrics are examined, the errors in the data set could be determined. For example, in inequable data sets, even though the accuracy rate of the model is high, the performance metrics could be low. This could help detect inequable data set errors.

This study used SVM, KNN, NBS, LR, decision tree and random forest algorithms for classification. The dataset was divided into two parts, with 70% used for training and 30% reserved for testing. Table 2 contains the classification performance results applied to the dataset. Classification performances performed on the model were compared using accuracy, precision, recall, and F1 scores. The students who fail the course are represented as 0, while those who pass the course are represented as 1.

Table 2. Classification performance results

Algorithms	**Accuracy**	**Precision**		**Recall**		**F1**	
		0	1	0	1	0	1
RF	0.87	0.83	0.87	0.87	0.83	0.85	0.85
DT	0.86	0.84	0.88	0.88	0.84	0.86	0.86
SVM	0.83	0.79	0.87	0.88	0.76	0.83	0.82
KNN	0.82	0.72	0.93	0.93	0.67	0.82	0.79
LR	0.79	0.79	0.79	0.79	0.78	0.79	0.79
NBS	0.78	0.80	0.78	0.78	0.80	0.80	0.79

According to the results (Table 2), the random forest algorithm had the highest accuracy rate of %87 and showed the highest performance. The decision tree was a close second with % 86 accuracy rate, while SVM was %83, KNN was %82, and logistic regression was %79. The Naïve Bayes algorithm, on the other hand, showed the lowest performance with an accuracy rate of %78.

The most significant features of the random forest algorithm that gives the most successful result are presented in Figure 4.

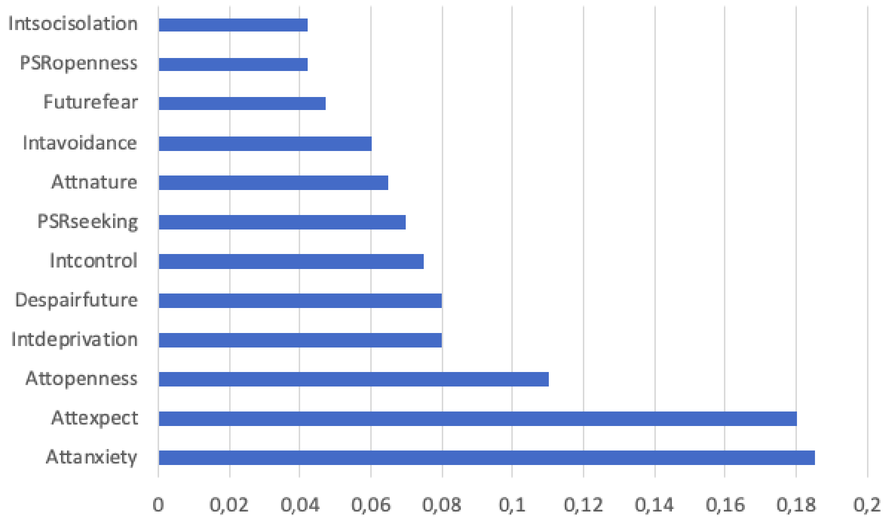

Fig. 4. Random forest algorithm attribute importance order

According to Figure 4, "anxiety" and "expectations", the sub-factors of the scale of attitude towards learning, were determined as the two most important attributes. On the other hand, the factors of "social isolation" and "openness" of the perceived self-regulation scale were determined as the least important features

Discussion and conclusion

This study was investigated the efficacy of machine learning algorithms in predicting student success in online education by focusing on affective, behavioural, and cognitive factors. The six machine learning algorithms were used which are Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Naive Bayes Classifier (NBS), Logistic Regression, Decision Tree, and Random Forest.

The results showed that the RF algorithm outperformed other algorithms by achieving the highest classification accuracy (87%). This finding of our research is in line with Orji & Vassileva (2022)'s study in which they stated that the RF algorithm achieved the best results in predicting academic performance based on students' affective characteristics. The finding is also similar to a study by Yağcı (2022) which showed that RF, NN, and SVM algorithms were most accurate in predicting students' final exam results from their midterm results, while KNN was the least accurate. A further finding of this study showed that the Nave Bayes Classifier has the lowest accuracy of 78%.

The study also revealed that the two most important factors that improve student performance are the attitude scale's sub-dimensions for learning, "anxiety" and "expectations". These findings align with previous research showing that anxiety and high expectations strongly correlate with student success (Acosta-Gonzaga & Ramirez-Arellano, 2021; Boca, 2021; Yaghi, 2022). Anxiety is essential in determining students' academic performance (Schutz & Pekrun, 2007). Students with high anxiety levels can have trouble focusing, learning new things, and doing well on tests (Awadalla et al., 2020). In this case, teachers can use various strategies to reduce the anxiety level of students. For example, providing students with information about common types of anxiety and emphasizing that learning and test anxiety are normal emotional reactions can help students understand and cope with these feelings (Cassady, 2022; Romano et al., 2020).

According to another vital research finding, a critical factor affecting students' academic success is their expectations. Expectations include students' beliefs about their abilities, learning capacity, and the likelihood of success (Nabizadeh et al., 2019). If students have overly high expectations, it can negatively impact their academic performance. In order to prevent this situation, it is of great importance that teachers and parents support these students. The support provided to students can help them raise their expectations to a realistic level, manage their anxiety effectively, and help them understand that failure is just a natural learning process (Yeung & Leadbeater, 2010).

Another finding is that the "social isolation" feature has the least effect in estimating student performance in online education. This finding shows that although social interaction is essential for learning, student success is not the only determinant.

This study's findings have several significant implications for educators. First, it underscores the crucial role of emotional, behavioural, and cognitive factors in designing and implementing practical online courses. Second, educators can effectively enhance student performance by prioritizing anxiety reduction and fostering positive expectations among learners. Third, teachers can leverage various strategies and tools to promote social interaction among students within online courses. In addition to these implications, the study's findings can be used to develop more effective teaching strategies and interventions in online education processes. For example, teachers can use the results of machine learning models to identify students at risk of failure and provide them with additional support. Additionally, the study's findings can be used to create personalized learning plans tailored to the needs of students.

Limitations and future studies

There are some limitations to this research. First, the study's dataset is based on a small sample and focuses on a single educational institution. Future studies may incorporate larger samples. Second, the number of factors evaluated in the study is restricted; other elements that may influence student performance, such as socioeconomic status, student motivation, learning styles, and instructional material quality, can provide a more comprehensive study. Another limitation is that the study utilized six machine-learning methods. In future studies, using a range of machine learning models other than the ones mentioned above could increase prediction performance substantially.

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