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Article

Predicting Students' Academic Failure Using Machine Learning Algorithms: An Analytical Study Based on Large-Scale Educational Data

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Abstract: The fast adoption of new AI and learning analytics technologies, as well as the widespread usage of digital learning platforms, have allowed the education industry to undergo a fundamental transition. This has enabled the analysis of massive amounts of educational data to support academic decision-making and improve learning outcomes. The use of artificial intelligence and machine learning technologies to create predictive models that can anticipate students' academic challenges early on and enhance the efficacy of educational interventions by empowering educational institutions to proactively assist students who are at risk of academic failure or withdrawal has become more popular as a result of this development. Using extensive real-world educational data from the Open University Learning Analytics Dataset (OULAD), which comprises 32,593 student records, this study attempts to create a prediction model based on machine learning algorithms to forecast students' academic failure. To identify pupils at risk of academic failure in comparison to successful students, an experimental technique was used, which included data processing, behavioral and academic characteristic extraction, and the creation of a binary classification model. In order to distinguish between high-achieving children and those at risk of academic failure, the study used a binary categorization approach. It included a sequence of preprocessing steps and the extraction of academic and behavioral features. Statistical assessment measures were devised to compare five machine learning algorithms (Random Forest, Support Vector Machine, Decision Tree, Logistic Regression, and K-Nearest Neighbors). The results indicated that Random Forest performed better than the others, with an accuracy value of 89.43% and an AUC of 0.9633. This indicates that the model is highly discriminative between academically high-achieving students and those at risk of academic failure. Moreover, the Feature Importance analysis indicated that both continuous assessment performance scores and degree of digital interaction with the learning platform were the most important predictors for academic performance. Our findings further highlight the promise for machine learning technologies to play an important role in educational early warning systems and help develop more adaptive learning environments that serve students' needs.

Keywords: Machine learning, academic prediction, learning analytics, smart education, educational data mining, artificial intelligence in education.

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1. Introduction

Due to rapid digital transformation across higher education institutions, there has been considerable growth in learning management systems and e-learning platforms that produce large volumes of data associated with learners' behavior and day-to-day academic practices. This data can include how many times students interacted with educational content, records of measures from ongoing assessments, engagement-day counts, and retention patterns in digital learning environments [1]. Learning analytics has thus emerged as a new discipline trying to employ educational data to enhance the quality of the (educational) process and contribute to data-driven decisions in academia [2].

Within this framework, artificial intelligence has emerged as a fundamental pillar on which to build next-generation educational systems, thanks to the enormous advances in machine learning algorithms that can identify intricate patterns in state-of-the-art educational datasets and extract accurate predictive indicators about individual student academic achievement [3]. The main practical significance of these models is to change the current culture of assessment from post-diagnosis models that highlight problems, test performance, and retention rates toward predictive models that focus on early prevention and declining academic failure rates [4].

One of the greatest challenges that higher education institutions are facing in recent years is academic underachievement, since it has many adverse effects for institutions, such as a lower success rate of graduates from year to year, higher dropout rates among students, and an overall increased academic or administrative burden on the institution [5]. Although modern digital environments create large amounts of educational data, most existing institutions only use traditional assessment approaches, which lack the ability to provide early warnings for at-risk students. Such lag leads to underperformance cases being discovered only after their progression, thus dampening the effectiveness of remediation interventions [6].

Several studies have conducted research using various machine learning algorithms to predict academic performance in recent years, such as decision trees, random forests, support vector machines, logistic regression, and neural networks [7]. But the outcomes of these studies differ according to the data, preprocessing, and features. Third, weak generalizability, problems with data leakage, and biases in the data remain methodological challenges [8].

The major limitation of previous research approaches is that many of the studies relied on small datasets or local learning environments, which limited generalizability. More work is still needed in determining the performance of machine learning algorithms on realistic large-scale datasets that reasonably resemble genuine academic behavior.

Therefore, this study seeks to create a predictive model for academic failure analysis using real data from everyday learning contained in the Open University Learning Analytics Dataset (OULAD). This paper compares the performance of various widely used machine learning algorithms and investigates the characteristics that have a greater effect on whether students succeed or fail, in turn contributing towards intelligent, data-driven learning systems.

Related work

The prediction of academic performance using artificial intelligence techniques (AI) has attracted tremendous development lately, which can be attributed to many factors, including the recent increase in digital educational data and the rise of e-learning surrounding pupil engagement models usable for logging every detail of student behavior patterns [9]. Consequently, there has been a growing interest in developing accurate prediction models with machine learning and educational data mining techniques that help educational institutions improve early predictions of academic difficulties and enhance academic intervention strategies [10].

A method by **Chiu et al. (2026** for predicting at-risk students with AI using only student interaction data from an LMS used ranking-based features to make it domain-agnostic and more complete. In the third week of the semester, the model was accurate over 90% of the time, fed by

records covering more than 1.7 million interactions. However, this was limited to LMS data, and the model was not tested in other educational institutions or to assess actual learning activities [11].

Conversely, **Abougalala** discussed the application of automated machine learning (AutoML) techniques to predict students' academic performance. Their results showed that automating model selection and hyperparameter tuning can yield results that are very competitive. These approaches involve developments that typically sacrifice interpretability, which is often more important for the educational problem [12].

Using big data, **Ahmed** studied how multiple classification models could be constructed to predict students' final performance in a recent paper. The results demonstrated that the random forest and vector support machine algorithms yielded maximum accuracies, endorsing the increasing trend of classification models with population-based, real-world data [13].

Johora employed a stacking ensemble model for predicting undergraduate student success that incorporates explainable AI methods (SHAP and LIME) to help indicate how the model makes its decisions. The study was conducted using data from 872 students from different universities in Bangladesh, where preprocessing techniques and SMOTE methods were used to balance the data. Additionally, the proposed model surpassed other ML models with 86.38% accuracy. However, the use of national survey data may somewhat limit generalizability to other educational settings [14].

Aithal prepared a predictive study concerning the impact of ubiquitous educational technology on higher education and scientific inquiry for the future. This study analyzed contemporary trends and technological progress in an effort to create a framework involving cloud computing, artificial intelligence, Internet of Things (IoT), and analytics to advance learning, research, and academic decision-making. The results showed that these technologies will improve the effectiveness of educational institutions and raise the quality of teaching. However, it provided as yet no empirical validation or applied evaluation of the proposed framework but rather a theoretical exploration and futuristic predictions [15].

Specifically, **Yağcı** presented an empirical analysis to compare multiple machine learning algorithms for predicting educational performance with multivariable education data. Individual modeling showed the superiority of ensemble learning algorithms over traditional linear models due to their ability to capture nonlinear relationships, especially for Random Forest, among which a consistent and high predictive accuracy was achieved between academic and behavioral variables, compared to earlier conventional approaches [16].

While there is substantial progress in this space, a number of persistent research limitations are present in earlier studies. These include dependence on small or region-specific datasets, utilization of features that might cause data leakage (which overstates model performance), and, in many studies, comparison of different models is not fair or systematic [17].

The main contributions of this research are to fill some of these gaps by using a large-scale, open, and real-world educational dataset; designing an experimental framework that reduces possible data leakage; and doing a systematic comparison between several state-of-the-art machine learning algorithms commonly used in academic prediction.

2. Materials and Methods

Please In this paper, an applied experiment with the aim of developing a predictive model for students' academic underachievement is performed using machine learning algorithms based on real-world and large-scale educational data. The methodology promotes analytic transparency, reproducibility, and conformity to best practices when developing predictive models for educational interventions.

2.1 Dataset

In this study, the Open University Learning Analytics Dataset (OULAD), a well-established

open-access educational dataset in the field of learning analytics and educational data mining, was employed. On the other hand, it relates to real-world data from OL.D park about Open University students in a digital learning environment, which combines records of academic, behavioral, and demographic information from diverse educational activities.

The dataset consists of a total of 32,593 student records spread across multiple courses and time slots. It consists of networks of data files that represent:

- Student demographics
- Academic assessment results
- Records of interaction with the virtual learning environment
- Academic registration data
- Digital learning activity data.

This dataset was selected due to its large size, operational feasibility, and diverse data types, making it suitable for building generalizable predictive models.

2.2 Data Preprocessing

Combining those various files into one coherent, analyzable format was necessary to create the predictive model. In order to do that, learning files were integrated by means of shared identifiers linking the curriculum and academic slot with student, course, and time.

Below are the steps in this preprocessing phase:

1. Assessment data integration with Learning test data.
2. Collecting student engagement data in the digital learning platform.
3. Linking the academic registration records with the student's master profile.
4. Handling Missing Values Using Appropriate Compensation Strategies:

   Median Imputation for Numerical Variables.

   Most Frequent Imputation for Categorical Variables.
5. Encoding Categorical Variables Using One-Hot Encoding.
6. Normalizing Numerical Variables Using Standard Scaling.

They improve the quality of data and diminish noise and bias introduced by missing values or different numerical scales.

2.3 Feature Engineering

A number of academic and behavioral factors linked to academic performance were identified based on the available raw data. The characteristics used included the following:

❖ Academic Characteristics:

- Average Assessment Score
- Total Assessment Score
- Assessment Count
- Studied Credits
- Number of Previous Attempts

❖ Behavioral Characteristics:

- Total Clicks
- Activity Count

❖ Demographic Characteristics:

- Gender
- Age Group
- Previous Educational Level

- Geographic Region
- Social Deprivation Index
- Disability Status

Certain characteristics that could lead to data leakage, such as data directly related to the final score, were excluded to ensure the integrity of the pilot assessment.

2. 4 Predictive Model Development

After data processing and extraction of relevant characteristics, a binary classification framework was developed to predict students' academic failure. The target variable was defined based on students' final academic results, classifying them into two main categories:

- Positive Category (Successful Students): Students who achieved Pass or Distinction results.
- Negative Category (At-Risk Students): Students whose results resulted in Fail or Withdrawn.

This classification resulted in a relatively balanced distribution between the two categories, with 17,208 students at risk of academic failure compared to 15,385 students in the successful category.

In order to preserve the relative distribution of classes, the data were divided using a Stratified Train-Test Split technique, with:

- 80% of the data allocated to training
- 20% of the data allocated to testing.

To evaluate the comparative performance of machine learning algorithms, five classification algorithms widely used in educational applications were trained:

Random Forest

Support Vector Machine (SVM)

Decision Tree

Logistic Regression

K-Nearest Neighbors (KNN).

These models were selected due to the diversity of their mathematical and analytical properties, allowing for a systematic comparison between linear and nonlinear models, tree-based models, and models based on similarity measurement.

The general framework of the suggested predictive system is shown in Figure 1, which begins with the collection of educational data, moves through the preprocessing and feature extraction stages, and concludes with the training of the predictive models and decision-making to support academic intervention.

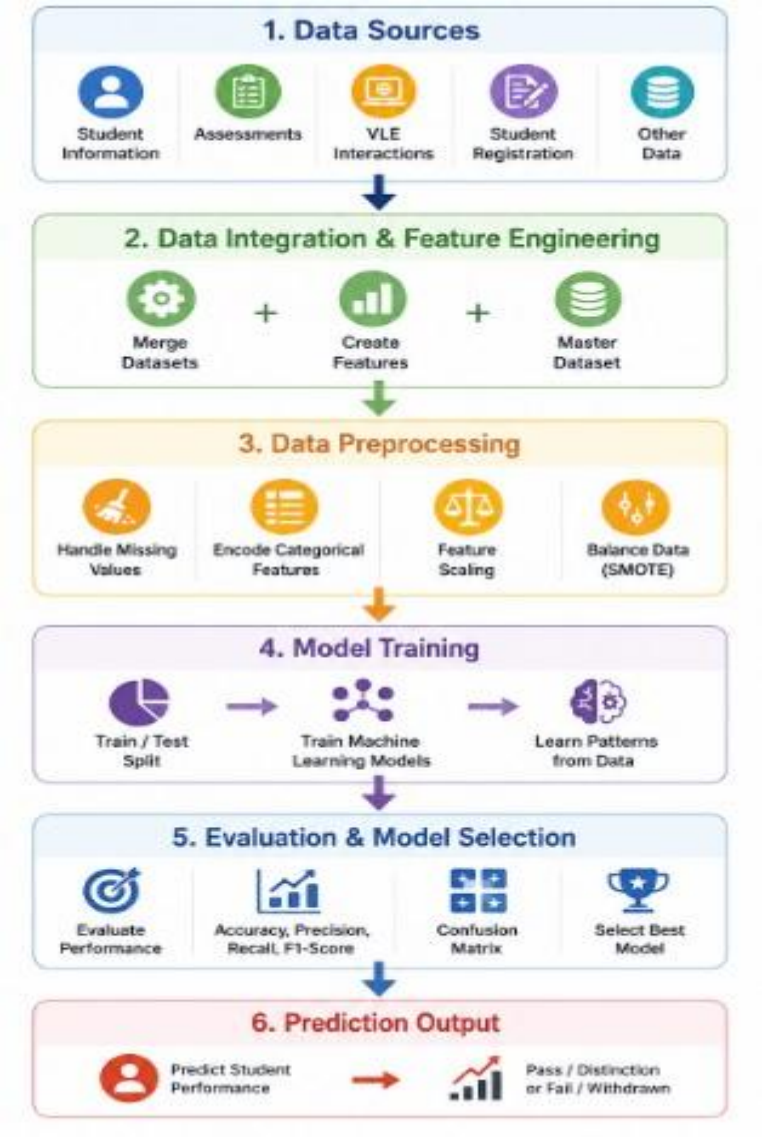


Figure 1. Proposed Predictive Learning Framework

2.5 Evaluation Metrics

Instead of depending just on the accuracy metric, the prediction models' performance was assessed utilizing a collection of common statistical metrics used in binary classification tasks to give a thorough and fair evaluation of performance.

1. Accuracy

   Describes the number of correct predictions out of all the total predictions:

   Accuracy = TP + TN / TP + TN + FP + FN

2. Precision

   It is the ratio of correct positive predictions to the total number of positive predictions:

   Precision = TP / TP + FP

3. Recall

   The proportion of actual positives that are correctly detected by the model as true positives:

   Recall = TP / TP + FN

4. F1

   It denotes the weighted average between Precision and Recall:

F1 = 2 × Precision × Recall / Precision + Recall

5. Area Under the Curve (AUC)

We used the Area Under the Curve (ROC) to evaluate the model performance in distinguishing between different categories of observations at multiple classification thresholds.

- TP = Correct Positive Predictions
- TN = Correct Negative Predictions
- FP = Incorrect Positive Predictions

FN = Incorrect Negative Predictions.

3. Results

3.1 Comparison of Model Performance

Results show that Random Forest is unquestionably better than the other models used in this study after the five models were trained and assessed using a different test set.

Table 1: Performance comparison of machine learning models

Algorithm	Accuracy	Precision	Recall	F1-score
Random Forest	89.43%	86.45%	92.04%	89.15%
SVM	89.28%	85.90%	92.46%	89.06%
Logistic Regression	86.29%	89.85%	79.98%	84.63%
Decision Tree	85.86%	85.81%	83.91%	84.85%
KNN	83.33%	84.41%	79.33%	81.79%

The findings show that the Random Forest method outperformed SVM with an accuracy of 89.43%, as demonstrated by an 89.28% success rate.

The reason behind the remarkable performance lies in Random Forest's adaptability to nonlinear relationships and its capability of handling multi-type data effectively, combined with its relative resistance to overfitting compared to single-tree-based models.

This is illustrated in Figure 2, providing a visual comparison of the prediction accuracies the models achieved, with Random Forest most accurately predicting the data.

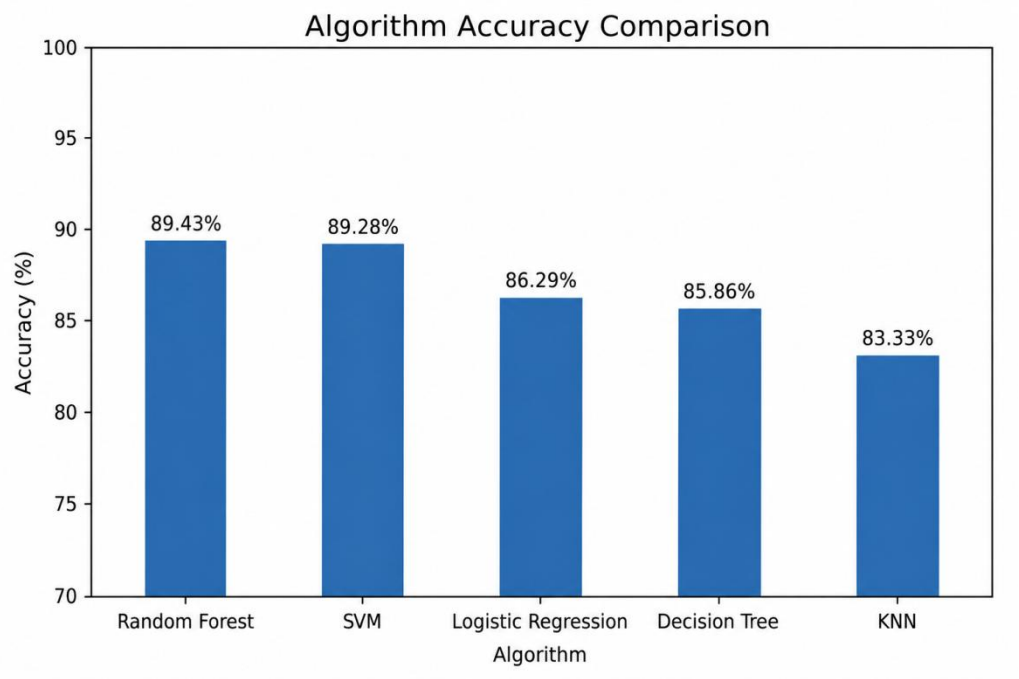


Figure 2: Comparison of model accuracy

3.2 Performance Analysis of the Best Model

The Random Forest model fit the best overall, so it was chosen for further investigation.

The model achieved:

- Accuracy = 89.43%
- Recall = 92.04%
- Precision = 86.45%
- F1-score = 89.15%

The high value of Recall shows that the model is very good at identifying students who are likely to fail in their subjects, which must be considered when you use your predictive model for educational early warning applications.

The correct and wrong prediction distribution for the best model is presented in Figure 3, where we can easily see that this model was able to differentiate between successful students or and students at risk of failure.

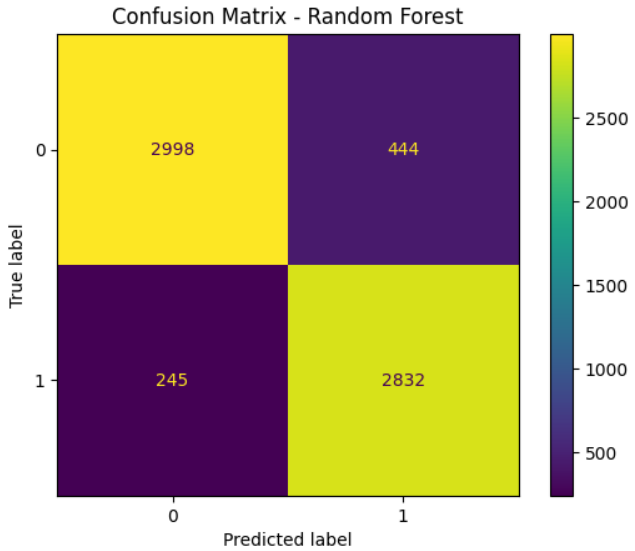


Figure 3: Confusion Matrix for Random Forest classifier

3.3 ROC Analysis

ROC curve was carried out to calculate the diagnostic performance of the model.

The value was:

AUC = 0.9633

This number is quite high, so it also tells us that the model has performed exceptionally well at separating classes.

As shown in Figure 4, the ROC curve of the proposed model demonstrates that this system can achieve relatively satisfactory classification performance.

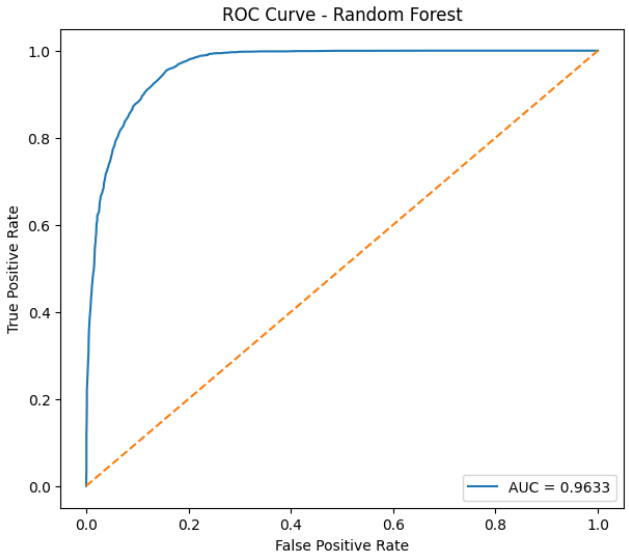


Figure 4: ROC curve for Random Forest model

3.4 Feature Importance Analysis

So predictive models are not just judged by their statistical performance measures. The scientific value of a given model is enhanced by the explainability of its most effective features in affecting predictive decision-making. To this end, Random Forest was chosen for Feature Importance Analysis as it had better overall results.

The findings indicated that academic and behavioral characteristics made up the strongest predictors of academic failure, while there was a comparatively smaller effect due to demographic variables.

Table 2: Top predictive features ranked by importance

characteristic	Important
Total Assessment Score	0.251
Assessment Count	0.166
Activity Count	0.159
Total Clicks	0.148
Average Assessment Score	0.118
Studied Credits	0.021
Previous Attempts	0.007
Highest Education Level	0.007
Gender	0.006

Age Band	0.005

The findings show that the total mark is the strongest predictor of academic performance, a reasonable finding because stable performance on assessments mirrors the academic level of a student.

Additionally, our findings revealed that digital activity indicators, the number of activities performed inside the learning platform (Activity Count) and the total number of digital interactions engaged in a course (Total Clicks), are very important features for improving the predictive performance of the model. This finding lends credence to the belief that active engagement in the digital learning environment is tied to better odds of academic success.

Because of this, the impact of demographic characteristics (e.g., gender, age group, and previous educational background) was not as great as that of behavioral and academic variables. This implies that the learner's behavior in the learning environment might be a more stable indicator than any personal fixed characteristics.

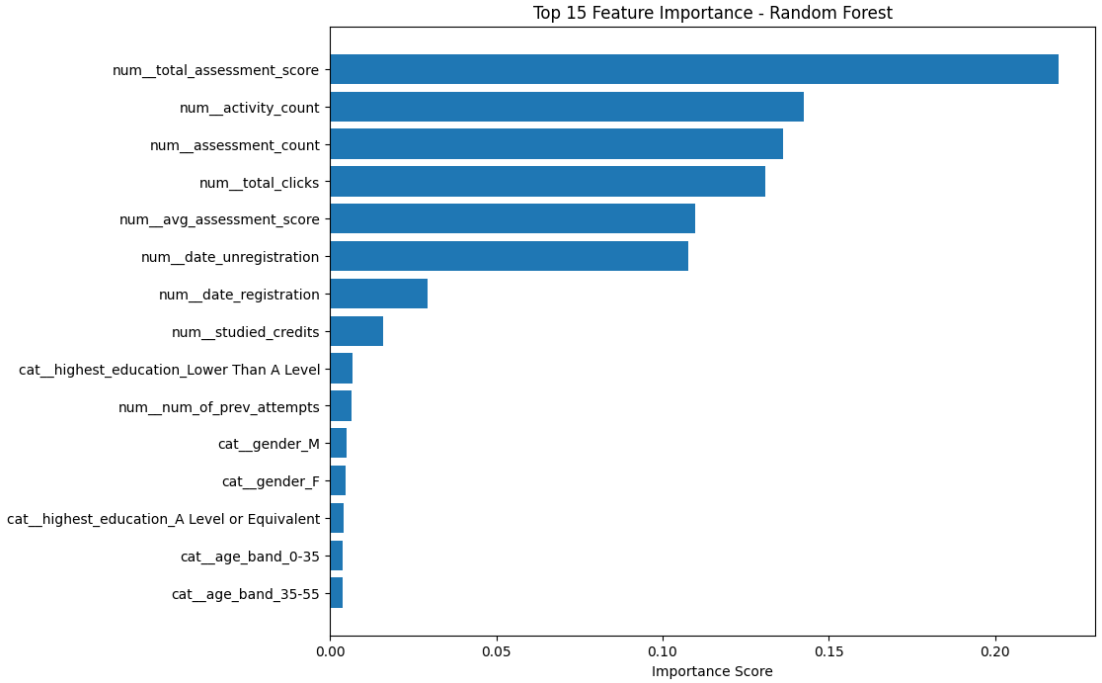


Figure 5: Feature importance ranking for Random Forest

In Fig. 5, the most important features are presented, revealing that academic and behavioral factors play a far larger role in risk prediction than demographic ones.

4. Discussion

Leveraging large-scale real-world educational data, experimental results show that outstanding performance in predicting academic default can be achieved by machine learning algorithms. In comparison among various models, the Random Forest algorithm provided the best model performance at large, while a relatively lower margin was noted for the Support Vector Machine algorithm.

This is due to the nature of the educational data, which consists mainly of a mixture of numerical and categorical features along with intricate non-linear dependencies between academic and behavioral factors. Due to their nature of variance reduction and increased generalization over single models, this type of environment is well suited for ensemble learning algorithms, for instance, Random Forest.

Results are also based on the fact that above-average predictors of performance in a subject are digital interactions. High activity analysis of students in online learning environments correlates positively with academic performance, with recent directions in learning analytics that approach behavioral data as a goldmine of predictors.

The fact that the SVM model got almost as close to Random Forest performance demonstrates that after preprocessing, there is quite a large separation between different classes in feature space. One benefit of Random Forest, though, is that it can better explain feature importance, which is a key feature in educational applications that provide decision support.

Although it brings an acceptable level of accuracy, Logistic Regression performed worse than the nonlinear models, which is expected given that most real-world education data are non-linear.

Taken together, these results imply that building machine learning-based educational early warning systems may represent an effective tool for potential use by educational institutions across naturally occurring large-scale digital learning and teaching contexts.

Research limitations

However, the study has limitations that need to be acknowledged with caution when conclusions are made from the findings.

First, the research is based on data from a particular institution within an open educational environment, limiting the ability to generalize the findings across different institutions with varying educational structures and learning styles.

Second, the model is built on a limited set of academic and behavioral features that may not be available in the very beginning stages of the semester, meaning that it currently predicts well only during the progress of an academic career, but not from the start of any given system.

Third, although systematic strategies have decreased the risk of data leakage previously, the design of educational predictive models is still sensitive to feature choice, meaning methodological caution should remain.

Fourth, the study examined a more traditional machine learning model and not also deep models or, notably, temporal models able to analyze the temporal sequence of learning behavior.

5. Conclusion

This work proposed a mature machine learning predictive framework to predict at-risk learners using large-scale real-world educational open data- the Open University Learning Analytics Dataset (OULAD). The outcomes indicated that the Random Forest Model achieved the highest accuracy (89.43%) and AUC (0.9633) among all models evaluated, showing good discriminatory power between student success in college and students at risk for academic failure. Characteristics significance analysis also indicated that continuous assessment performance and digital interaction with the learning environment were the most powerful determinants of academic performance, whereas demographic variables were less influential. Overall, these results highlight the potential role that machine learning techniques can play in interacting with educational early warning systems that enable academic institutions to identify students at risk of academic difficulty in a timely manner and take more effective actions. This work can be extended in the future by utilizing deep learning models, conducting a time-sequence analysis, and generating other explainable models that would provide more explicit academic insights.

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