Data-Driven Early Academic Intervention: Harnessing AI for Students Achievement

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***Abstract*—In the dynamic landscape of higher education, the timely identification and mitigation of factors contributing to academic failure among university students are paramount for fostering academic success and student well-being. This research follows a quantitative research method using machine learning algorithms and strategically designed features extracted from students' laboratory practices and questionnaires, to predict students' academic performance. The primary motivation driving this research is to develop a model capable of identifying students at potential academic risk at mid-course, thereby enabling timely intervention strategies. Changes in the evaluation of laboratory practices are introduced to enhance the model's predictive accuracy. Results demonstrate the model's effectiveness in predicting final exam outcomes, achieving over 90% accuracy at the end of the course. A mid-course identification experiment shows the feasibility of predicting student outcomes with an accuracy exceeding 85%. The findings suggest the potential for early intervention strategies to improve student success.**

***Keywords*—academic failure, artificial intelligence, machine learning, early detection, data-driven**

I. Introduction

In the dynamic landscape of higher education, identifying and addressing factors contributing to academic failure in university students is crucial for fostering academic success and overall student well-being [1–4]. The ability to detect early signs of academic risks holds the potential to implement timely interventions, ultimately enhancing retention rates and promoting a positive learning experience [5].

The transition from traditional education models to technology-enhanced learning environments has generated vast amounts of data, offering unprecedented opportunities for data-driven methodologies to play a fundamental role in academic assessment.

Previous works have already shown the relevance of different machine learning models to provide an identification of students with potential academic problems [6–9]. These approaches indicate the relevance of Artificial Intelligence (AI) and, more specifically, Machine Learning (ML) techniques to understand and predict students at risk of academic failure.

Although traditional approaches to identifying students at risk of academic challenges hold value, their practical impact is constrained by limitations in their early detection capabilities. Our research is distinctly oriented towards an innovative time-aware methodology for predicting students' performance.

In this work we propose a new model that is able to identify at mid-term, students in position of potential academic risk that may profit from intervention. For this purpose, we consider a number of factors contributing to the academic performance, including laboratory and questionnaire grades, completion rates, completion time and use machine learning models to predict if a student will pass the final exam.

The main contributions of this work are the following:

- Changes in the evaluation of laboratory practices to help improving the identification of students in risk of academic failure.
- Performance analysis for the identification of students in academic risk at the end of the course and, especially, at mid-course.
- Analysis of novel features proposed that intend to improve the signals collected from students' scores, such as, time spent answering a questionnaire or the fit to a normal distribution of laboratory assignment scores.

The remaining of this paper is organized as follows. Following we present the main related works from the state-of-the-art. Section III describes the data collected, the extracted features and the machine learning models considered on our research. Next, the experimental results are presented and, finally, the main conclusions are disclosed.

II. Related Works

On the literature we can identify different approaches to predict academic performance. Traditionally, the use of indicators such as past academic performance, standardized test scores, and demographic information have been used to gauge students' likelihood of success [10–16].

More recently, Educational Data Mining (EDM) has emerged as a prominent field for discovering patterns in educational data to develop and enhance methods and models, for example, for prediction, classification, machine learning, and clustering [17–23].

In this context, the study conducted in [24] involves the assessment of three classification algorithms (Naïve Bayes, Neural Network, and Decision Trees) to forecast students' performance in two undergraduate courses. In [25] different decision trees models are compared and showed that JRip obtained the best prediction results.

Some other works explore the use of Naïve Bayes to predict students' admission test scores [26] and final exam results [27], obtaining accuracy values between 71% and 85%. In [28] the authors compare several supervised learning algorithms and consider different students' attributes. Their results show that Artificial Neural Networks is the best

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prediction model, using students' assessments' marks and their interaction with learning material. Almarabeh provides a straightforward comparison of various classification algorithms utilizing a dataset of 225 students [29]. More recently, in [30], the authors analyze multiple research articles published between 2015 and 2021, concluding that machine learning can be advantageous in discerning diverse areas of academic performance.

While these approaches remain valuable, their limitations in providing early detections of students at risk limits their practical impact. In this sense our work is more focused on a time aware approach for the students' performance prediction.

This research article constitutes a continuation and improvement of our previous work in [31], where we explored the use of different machine learning algorithms for the early identification of academic failure. In global term, good results were achieved to predict if a student will pass or not the final exam. However, in the classification problem students that did not attend to final exam were not taken into consideration and, moreover, only features considering the whole course were used, which limits the time available to notify students and overcome the situation.

III. Data and Methods

This research is based on the data collected from a course on Computer Networks taught at the University of A Coruña (Spain) at the degree in Computer Science Engineering. The course centers on key elements of networking, delving into the primary characteristics, functionalities, and structure of computer networks and the Internet. This is course is taught in the second semester (starting by the end of January and finishing in mid-May) and constitutes the first approach for most of the students to the operation and protocols involved in computer networks and can be challenging for them.

The syllabus of the course is the following:

- Unit 1: Introduction to computer networks.
- Unit 2: Application layer: World Wide Web, email and Domain Name System.
- Unit 3: Transport layer: User Datagram Protocol and Transport Control Protocol,
- Unit 4: Network layer: Internet Protocol.
- Unit 5: Link layer: Address Resolution Protocol, Ethernet and Wi-Fi.

The course also includes several laboratory practices that are not mandatory, but are evaluated for the final grade (as described below):

- Lab 1: Introduction to network programming: Echo service
- Lab 2: Simple Web server
- Lab 3: Introduction to network simulation
- Lab 4: Network simulation: subnetting and routing

Finally, the course includes five online questionnaires that cover the main aspects of each unit. These questionnaires are presented to the students at the end of each unit and have one week to answer. Similarly to the laboratory practices, the questionnaires are not mandatory, but contribute to the final grade of the course.

The assessment of the course involves a theoretical examination, with two opportunities provided for students (one at the conclusion of the semester and another approximately one month later), contributing to 70% of the final grade. Students are expected to obtain a minimum grade of 4 (out of 10) to factor into the final evaluation. Additionally, the final grade incorporates the laboratory performance, accounting for 25%, and the questionnaires scores, comprising 5%, with no specified minimum grade threshold. To successfully complete the course, students must attain a final score equal to or greater than 5.

With the objective of improving the identification of students at risk of academic failure, we introduced a change in the evaluation of the first two lab assignments for the course 2022–2023.

On the course 2021–2022, the first practice was evaluated through an online questionnaire with basic questions to confirm the correct understanding of the contents of the introduction. The second practice was evaluated testing the functionality of the Web server developed by the students.

On the course 2022–2023, we introduced an exam after laboratory practices 1 and 2, that covers the main aspects of both assignments. If the students achieve at least a score of 5 (out of 10) in this exam, then the functionality of the Web server is evaluated. Otherwise, a zero is assigned to this lab assignment and only the exam score is considered.

A. Data

The data collected include the grades from the students on courses 2021–2022 and 2022–2023. Table 1 shows a summary of the main characteristics of the data, where *Lab* refers to the laboratory practices, *Quest.* stands for questionnaires, *Final score* refers to the final grade obtained in the course and *NP* refers to students that did not present to the final exam.

Table 1. Data summary

Students		**Course 2021–2022**		**Course 2022–2023**	
		256		290	
Lab	Fail	122	48%	155	53%
	Pass	134	52%	135	47%
Quest.	Fail	79	31%	57	20%
	Pass	177	69%	233	80%
Exam	Fail	44	17%	44	15%
	Pass	169	66%	206	71%
	NP	43	17%	40	14%
Final score	Fail	42	16%	37	13%
	Pass	171	67%	213	73%
	NP	43	17%	40	14%

In global terms, for the course 2022–2023 there is a slight increase in the percentage of students that passed, compared with the previous year.

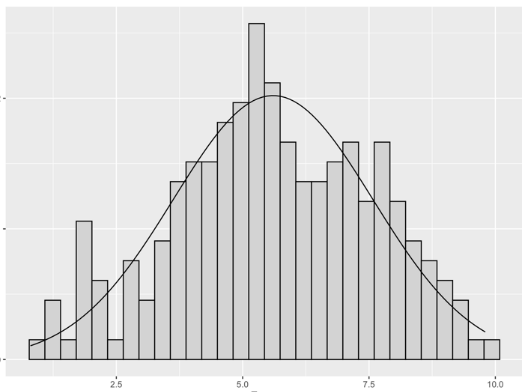

Fig. 1. Density plot for exam scores on course 2021–2022.

It is interesting to note how the percentage of students that passed the lab assignments decreased for the course 2022–2023. We hypothesize that this may be motivated by the change in laboratory evaluation criteria, which is somewhat more demanding for the students.

Fig. 1 and Fig. 2 show a density plot for the exam grades for year 2021–2022 and 2022–2023, respectively, with the corresponding fit to a Normal distribution.

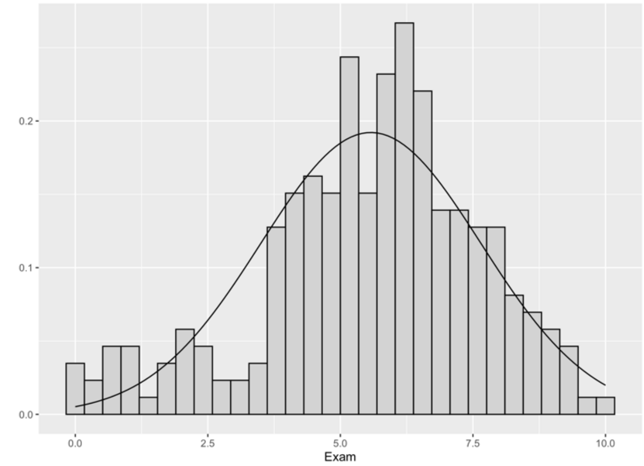

Fig. 2. Density plot for exam scores on course 2022–2023.

B. Features

Based on the data collected we have extracted a series of features that intend to capture as much information as possible from the different evaluations done by the students throughout the course.

In particular, we divide the features into two main groups: lab practices and questionnaires. The motivation behind this selection of features is described on Fig. 3, which presents a heat map for the final exam grades (for both courses), with respect to the lab practices scores (X axis) and questionnaire scores (Y axis). From the figure we can observe the higher presence of red colors (i.e. higher scores in the final exam) on the upper right corner of the graph, corresponding to higher scores on labs and questionnaires.

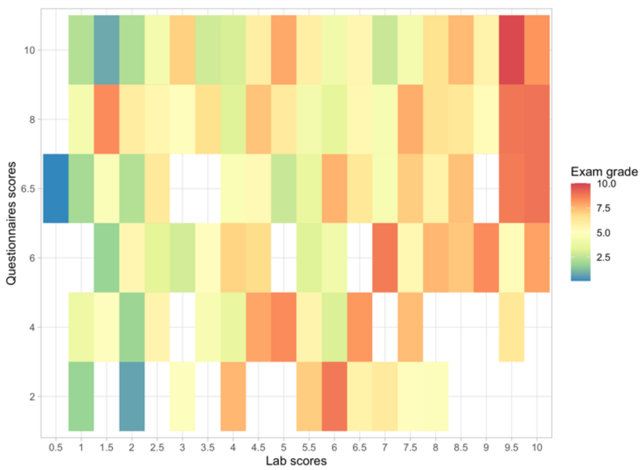

Fig. 3. Heat map for exam grades with respect to lab practices scores (X axis) and questionnaire scores (Y axis).

For the lab practices we have collected the individual score for each practice, the final score (weighted) for all the practices, individual binary markers to indicate if a practice was passed, average, median and standard deviation for all laboratory scores, number of practices passed and tried. Also, to help produce an early prediction the first two assignments scores are aggregated as sum, average and standard deviation (see Section IV.C). Note that all scores have been normalized between 0 and 1.

Additionally, for each lab practice score, the probability that the score fits a Normal distribution is computed with the intention of identifying outliers.

Similarly, questionnaires information is represented with their individual and final scores, individual markers to indicate if a questionnaire passed, and aggregation values with mean, median and standard deviation, along with the number of questionnaires passed and tried.

Moreover, some more detailed information is extracted from the online tool used to answer the questionnaires (i.e. Moodle): time employed by each student to answer each questionnaire and exact number of correct answers.

C. Machine Learning Models

The following standard off-the-shelf machine learning models are considered for our experimental evaluation:

- Naïve Bayes (NB): probabilistic classification algorithm based on Bayes' theorem.
- Repeated Incremental Pruning to Produce Error Reduction (JRip): rule-based machine learning classifier. It operates by iteratively constructing rules and pruning them to improve classification accuracy.
- k-Nearest Neighbors (kNN): supervised machine learning algorithm based on the classification of data point using the majority class of its k nearest neighbors in the feature space.
- Adaptive Boosting (AdaBoost): ensemble learning algorithm, which combine the predictions of multiple weak learners to create a strong learner.
- Support Vector Machine (SVM): supervised machine learning algorithm that works by finding the optimal hyperplane that separates different classes in the feature space while maximizing the margin between them.
- Logistic Regression (LR): linear model used for binary classification problems that applies the logistic function to a linear combination of input features to produce probabilities of belonging to a particular class.
- Random Forest (RF): ensemble learning method that builds a multitude of decision trees during training and merges them to get a more accurate and stable prediction.

D. Evaluation

We establish a data mining classification task employing a supervised learning methodology. For this purpose, we carry out an evaluation through a 10-fold cross-validation scheme to validate the model's performance and resilience.

The data collected is inherently imbalanced, with a higher number of students that passed than students that failed or did not present. To mitigate this class imbalance, we employ Synthetic Minority Oversampling Technique to oversample the minority classes.

As evaluation metrics we include precision, recall and F1-measure. Precision measures the accuracy of the positive predictions made by a model. It is calculated as the ratio of true positive predictions to the total number of positive predictions made by the model. The formula is:

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

where *TP* stands for True Positives and *FP* stands for False Positives. A high precision indicates that the model is making few false positive predictions.

Recall measures the ability of a model to capture all the relevant instances of a class. It is calculated as the ratio of true positive predictions to the total number of actual positive instances. The formula is:

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

where *FN* stands for False Negatives. A high recall indicates that the model is good at identifying most of the positive instances, even if it means having more false positives.

Finally, the F1-measure is the harmonic mean of precision and recall. It provides a balance between precision and recall, considering both false positives and false negatives. The formula is:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

F1-Score ranges from 0 to 1, where a higher score indicates a better balance between precision and recall.

IV. Result and Discussion

A. Models' Performance

In the first set of experiments, we compare the performance of the several ML models to correctly predict if a student will pass or fail the final exam, or not present, for both years. The results are summarized on Table 2, where P stands for precision, R stands for recall and F1 stands for F1-measure.

Table 2. Performance results including all features for main ML models

Model	Course 2021–2022			Course 2022–2023		
	P	R	F1	P	R	F1
NB	0.717	0.724	0.708	0.858	0.840	0.840
JRip	0.760	0.761	0.760	0.891	0.892	0.891
kNN	0.596	0.554	0.524	0.749	0.669	0.649
Ada	0.741	0.732	0.713	0.827	0.829	0.827
SVM	0.746	0.751	0.738	0.897	0.887	0.887
LR	0.755	0.757	0.757	0.862	0.862	0.862
RF	0.841	0.838	0.838	**0.902**	**0.901**	**0.901**

From the table we can observe how the results are consistently better for the course 2022–2023 than for the previous course, independently of the ML model used. We consider that this is motivated by the change introduced in the lab assignments evaluation that has proven able to increase the ability of the model to correctly predict the final academic result.

Focusing on the different ML models performance, clearly Random Forest achieves the best results, independently of the course, confirming results from previous works [31]. In particular, more than 90% of the students are correctly classified for the course 2022–2023.

The next best performing models are JRip and SVM, while kNN algorithm achieves the worst results for both courses.

B. Ablation Study

In the next series of experiments, we perform feature pruning to produce a refined subset of features aiming at improving the model performance, reducing computational complexity and enhancing interpretability. For these experiments we consider only the Random Forest model since it achieved the best performance in the previous section.

Table 3 summarizes the results. The scores for each class are presented to facilitate the comparison of the different alternatives, along with the global and final score (denotated as Final).

Table 3. Performance results for the ablation study pruning different subsets of features. Notation is equivalent to Table 2

Features	Class	Course 2021–2022			Course 2022–2023		
		P	R	F1	P	R	F1
All features	Fail	0.777	0.800	0.788	0.858	0.910	0.883
	Pass	0.915	0.819	0.864	0.913	0.836	0.873
	NP	0.831	0.894	0.861	0.935	0.958	0.946
	Final	0.841	0.838	0.838	0.902	0.901	0.901
Pruning Normal probability features	Fail	0.793	0.812	0.802	0.867	0.920	0.892
	Pass	0.904	0.825	0.862	0.913	0.836	0.873
	NP	0.829	0.882	0.855	0.931	0.953	0.942
	Final	0.842	0.840	0.840	0.903	0.903	0.902
Pruning questionnaire features	Fail	0.779	0.747	0.763	0.925	0.873	0.898
	Pass	0.872	0.836	0.854	0.911	0.869	0.889
	NP	0.821	0.888	0.853	0.889	0.981	0.933
	Final	0.824	0.824	0.823	0.908	0.907	0.907
Pruning laboratory features	Fail	0.770	0.571	0.655	0.887	0.849	0.867
	Pass	0.782	0.860	0.819	0.829	0.864	0.846
	NP	0.731	0.847	0.785	0.929	0.929	0.929
	Final	0.761	0.759	0.753	0.882	0.881	0.881
Pruning individual questionnaire features	Fail	0.786	0.800	0.793	0.865	0.910	0.887
	Pass	0.894	0.836	0.864	0.915	0.864	0.889
	NP	0.843	0.882	0.862	0.948	0.953	0.951
	Final	0.841	0.840	0.840	**0.910**	**0.909**	**0.909**

Firstly, it is interesting to note how for the course 2022–2023, using all features, the performance improvement is mainly obtained due to the improvement on the classification of failing students and not presented students. While the precision for students that passed is slightly better for the course 2021–2022, the worse results in the identification of failing or not presenting students, significantly decreases the final score. We theorize that the changes introduced in the laboratory practices evaluation are behind this improvement for the course 2022–2023.

The first subset pruned corresponds to the features measuring the normality fit of the laboratory assignment scores. The slight increase in performance achieved, for both courses, indicates the lack of a relevant effect of these features in the overall classification. Although these features were intended to capture the outliers, the limited fitting to the distribution of the scores may have reduced the expected impact.

Regarding the questionnaire features, the effect is different depending on the course. For the course 2021–2022, removing all questionnaire related features produces a significant reduction of F1-Score. On the other side, on the next course, the effect is the contrary, and there is a slight improvement of the F1 metric (from 0.901 to 0.907). Again, we consider that this is motivated by the change in the lab practices evaluation, which produces more meaningful signals and, therefore, the impact of removing questionnaire features is neglected.

Pruning laboratory features produces a decrease in the performance for both courses. This is somehow expected, since these features have a higher impact in the models' prediction capabilities, as proven in previous works [31].

Finally, we have tested the pruning of sub-subsets from the questionnaires features, achieving even better results when discarding individual questionnaire features (i.e. response time and number of right answers). These features were supposed to introduce relevant information, but the results prove the contrary. We consider that this may be motivated because the time constrains allow the students to stop and continue much later the questionnaires, which reduces the representation of the effort from the time required to answer the form.

C. Mid-Course Identification

This final set of experiments intends to explore the performance when trying to identify students in risk of academic failure at mid-course. The aim is to detect potential academically vulnerable students with enough time to provide with advice, help or tools to overcome the situation.

For this purpose, we limit the features available to those corresponding to the first two lab assignments and the first two questionnaires (usually finished by Easter).

We employed Random Forest in all our experiments and evaluated using 10-fold cross validation and the same metrics as in the previous experiments. Table 4 summarizes the results for these experiments.

Table 4. Performance results for the results for mid-course identification and the corresponding ablation study pruning different subsets of features. Notation is equivalent to Table 2

Features	**Class**	**Course 2021–2022**			**Course 2022–2023**		
		P	R	F1	P	R	F1
All features	Fail	0.809	0.647	0.719	0.768	0.858	0.811
	Pass	0.806	0.825	0.815	0.873	0.775	0.821
	NP	0.780	0.918	0.843	0.886	0.882	0.884
	Final	0.798	0.796	0.792	0.842	0.838	0.839
Pruning Normal probability features	Fail	0.785	0.624	0.695	0.771	0.873	0.819
	Pass	0.805	0.819	0.819	0.892	0.775	0.829
	NP	0.762	0.906	0.906	0.887	0.887	0.887
	Final	0.764	0.783	0.778	0.850	0.845	0.845
Pruning questionnaire features	Fail	0.835	0.565	0.674	0.836	0.745	0.788
	Pass	0.763	0.883	0.818	0.886	0.836	0.860
	NP	0.768	0.894	0.826	0.785	0.915	0.845
	Final	0.788	0.781	0.773	0.836	0.832	0.831
Pruning laboratory features	Fail	0.566	0.429	0.488	0.745	0.675	0.708
	Pass	0.777	0.813	0.794	0.704	0.746	0.724
	NP	0.591	0.706	0.643	0.854	0.882	0.868
	Final	0.645	0.650	0.642	0.767	0.768	0.767
Pruning individual questionnaire features	Fail	0.820	0.588	0.685	0.809	0.858	0.833
	Pass	0.769	0.877	0.820	0.908	0.836	0.870
	NP	0.794	0.906	0.846	0.866	0.882	0.874
	Final	0.794	0.791	0.784	**0.861**	**0.859**	**0.859**

In the first row, the results using all features proposed are shown, for both courses. As in the previous case, the performance for the course 2022–2023 is higher for all classes, in particular, for the identification of students failing or not presented. As expected, there is a decrease in the performance achieving a F1-Score of 0.839 for the course 2022-23 and 0.792 for the course 2021–2022. However, this reduction is modest on both scenarios: 6.9% and 4.6%, respectively.

The following rows present the results for the ablation study, similarly to the previous case.

Regarding the removal of the probability fitting features, it produces a positive effect on the scores for the course 2022–2023 and negative on the other case.

Removing lab practices or questionnaires feature produces a negative impact for both years, especially for the latter. Again, as in our previous experiment, laboratory features are expected to have a higher importance for the classifier.

Finally, the removal of the individual features for the first two questionnaires produces the best results for the course 2022–2023. Following the tendency from previous experiments, these features produced a high level of noise on the classifier, misleading the results. Interestingly, this does not apply for the course 2021–2022, where the performance slightly decreases when removing these features.

Overall, these experiments show that it is feasible to correctly predict in more than 85% of the cases if a student will pass or not the final exam, with the evaluation information available at mid-course.

This result is encouraging and throughout the present course we expect to conduct some A/B testing to analyze the actual impact of an early identification and a posterior intervention to help the students.

V. Conclusion

In this study, we have demonstrated the effectiveness of machine learning algorithms coupled with some strategically designed features extracted from the grades obtained in laboratory practices and questionnaires. Our approach enabled the correct prediction of whether a student will pass, fail, or not attend the final exam in over 90% of cases.

Additionally, we have proved that a careful change in the laboratory evaluation can have a positive impact in the accuracy of the model. Finally, our proposed model achieved an accuracy of 85% in predicting, at mid-course, whether a student will pass, fail, or not attend the final exam.

In the near future, we expect to apply these results during the course to identify students on a risky position, offer additional support and supervision, and validate their potential academic improvement.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

F.C. conceived and designed the study, contributed to the background research and contextualization, drafted the original manuscript. M.L. collected the data and performed the statistical analysis, contributed to the experimental design and validation experiments. Also contributed to the revision and critical editing. D.F. conducted an extensive literature review, providing the theoretical foundation for the study. Also contributed to the revision and critical editing. V.C. contributed to the methodology development, background research and contextualization and provided revisions and critical editing. Also assisted in the graphical representation and data visualization. All authors had approved the final version.

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