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Explainable Machine Learning Framework for Early Academic Risk and Student Performance Prediction

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Abstract: The early detection of academically at-risk students can aid the timely educational intervention; however, the robustness of the used predictive models can highly depend on the prior academic grades that become available after completing a considerable part of the course. In this paper, an explainable machine learning approach is proposed for predicting the student performance and early academic risks and analysing the impact of prior-grade data on the predictive performance of the models. The experiments are performed individually on the Mathematics and Portuguese subsets of the UCI Student Performance dataset with 395 and 649 student records, respectively. The final performance is mapped to three academic risk levels, and four machine learning algorithms - Logistic Regression, Support Vector Machine, Random Forest, and XGBoost – are compared based on two types of information sets: the full set including the first and second period grades (G1 and G2) and the early set excluding G1 and G2. The models are evaluated using accuracy, macro-F1, multiclass ROC-AUC, and high-risk recall metrics. The XGBoost model showed the best results in the full-information setting, reaching the macro-F1 of 0.870 and 0.825 for Mathematics and Portuguese, respectively. Further investigation using SHAP interpretation uncovered existing failures and absences among the non-grade features that were important in prediction. This paper shows the significance of distinguishing between good grade-based prediction and actual early detection of academic risks.

Keywords: Student Performance Prediction, Academic Risk, Explainable Machine Learning, Early Prediction, XGBoost, SHAP, Educational Data Mining.

I. INTRODUCTION

The abundance of educational data has presented immense prospects for education data analysis, academic monitoring, and individualized student guidance. EDM and machine learning (ML) methods are often applied to discover associations with good learning outcomes, make predictions about future student performance, and deliver timely help to students likely to fail. The recent research has shown that classification, ensemble learning, feature selection, and explainable artificial intelligence (XAI) methods can be successfully applied to student-performance prediction [1]–[4]. Moreover, it has been reported that UCI and OULAD are some of the most commonly used benchmarks in the field, whereas tree-based and neural methods serve as popular methods for prediction [5].

Earlier prediction is especially significant as accurate predictions made after most of the academic assessments are done leave very little room for preventive actions to be taken. The predictive model which predicts academic risk at an earlier stage might help educators focus their attention on providing academic counseling, resources, etc. for those students who need extra attention. The current research trends in this field have moved away from traditional performance classification to earlier warning and intervention systems [6], [7]. For instance, Alkan et al. studied machine learning prediction in relation to early intervention and formative assessment, whereas the more recent studies focused on ML frameworks for early prediction of at-risk students.

However, despite the above advances, there is one methodology question related to the timing of the availability of the predictive characteristics. As it was shown in the widely popularized UCI Student Performance dataset, the final grade (G3) is accompanied by grades for the first and second periods (G1 and G2). These characteristics could provide significant predictive information about the final academic performance of students. Recent research performed with the use of the same UCI dataset shows very good performance in feature selection, ensembles, and hybrid machine learning approaches [8]. Moreover, explainability-oriented studies of the UCI data showed that G1 and G2 are among the most significant predictive factors of the final results [9]. ScienceDirect Thus, the reliance on such past grades makes the

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prediction task different since a model could perform well on the prediction task by using relatively recent academic information.

Interpretability provides a second point of consideration. Predictions in education may inform intervention and support efforts, such that it becomes vital to know which features help form the results of the classifier. In recent years, some research has considered the use of SHAP, LIME, and other XAI techniques to interpret academic performance models [9]-[11]. MDPI Thus, the problem at hand is not merely to provide explainability to yet another predictive model, but to explore how the predictions change if previous academic scores are unavailable.

Driven by this problem, this paper proposes an explainable ML approach for predicting academic-risk and student performance early, considering the Mathematics and Portuguese sets of the UCI Student Performance dataset. In contrast to testing a unique prediction scenario, two different information situations will be examined in this work. One involves the full information setting which considers G1 and G2, while another involves the early information situation where neither previous period grades nor future period grades are available. Under these two situations, LR, SVM, RF, and XGBoost are compared in a consistent way. Accuracy, Macro F1 score, multiclass AUC, and high-risk recall are the metrics used to assess their performance.

The main contributions of this study include three key aspects: (1) A systematic analysis to measure the impact of excluding previous period grades on academic risk prediction; (2) An across-subject analysis of students from both Mathematics and Portuguese courses within a similar experimental setup; and (3) An explainable analysis of the other parameters that contribute to early academic risk predictions without grades. The purpose of the study is to differentiate between the full information performance of an algorithm and grade-free early prediction.

II. RELATED WORK

Recent literature on the prediction of academic performance has shifted from simple grade prediction to early warning systems, feature aware learning, ensemble modeling, and explainable artificial intelligence (XAI). According to a 2026 systematic review of 72 articles, UCI and OULAD datasets have become quite popular, while tree-based models and neural networks have taken the lion's share in the predictive space. Moreover, the use of XAI for the interpretation of predictions has become increasingly popular, although less common than traditional predictive modeling [5].
One research avenue is to identify relevant student features while minimizing unnecessary information. Hemdanou et al. [2] contrasted feature selection and feature extraction techniques among both ML algorithms and deep learning and stressed that student performance is affected by multiple variables, including individual, family, and social variables. ScienceDirect Rathod et al. [12] explored the use of feature selection techniques using evaluation data and demonstrated that feature reduction can enhance prediction accuracy relative to the use of the full set of features. The results from their work indicate precision rates of 93.14% and 86.24% based on features selected by J48- and Random-Forest-based techniques, respectively, compared to 79.9% without feature selection. ScienceDirect This literature demonstrates the importance of feature engineering and selection for educational predictive analysis, but feature selection does not take into account whether the selected predictors are available in time for intervention.

Predicting the academic performance of students has therefore recently received more attention in recent studies. Alkan et al. [6] constructed an ML-based approach for predicting the results of the students with a clear aim to help in implementing early interventions. Nature Sonnleitner et al. [13] further established that very complicated prediction pipelines may not be better under dynamic conditions in education. In their evaluation of early student performance prediction with concept drift, they revealed that simple models with well-chosen features can predict with similar accuracy while minimizing predictive bias. ScienceDirect Similarly, a systematic review carried out in 2025 on early student-performance prediction revealed that the timing of the prediction, the features of the data sets, and the type of information available early on are still important methodological factors.

Recent studies have also proven that high prediction performance may rely on academic assessment factors to a significant degree. In a study of early prediction of performance in programming courses in 2026, background information, academic assessment, interaction in digital learning, and engagement were taken into account. The model XGBoost demonstrated over 91% accuracy in the development term and over 84% in the test term, but the grade at midterm was among the most important predictors [15]. MDPI This is an important difference between attaining high prediction performance based on collected academic data and identifying risks before collecting any academic data.
Consequently, interpretability has turned out to be another important area of research. The recent student-performance studies based on XAI have utilized approaches such as SHAP and LIME to explain the impact of individual variables on the output of models. Explainable Framework for Academic Performance has suggested that SHAP can provide global

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and local explanations for ML-based predictions [3]. ScienceDirect Furthermore, one more study conducted in 2025 has combined Decision Tree, Random Forest, Gradient Boosting, and XGBoost models along with various approaches of explanations, namely SHAP and LIME. XGBoost demonstrated the accuracy of classification of 83%, and the explanations helped to find the factors associated with academic performance prediction [4]. ScienceDirect Additionally, the approach of explainability has been introduced in regression frameworks.

Nevertheless, there are particular gaps identified in the reviewed literature with regard to risk assessment in the early stage. It has been individually shown in previous researches that advanced classifiers, feature selection, early warning models, and XAI have positive effects on predictive performance. The thing is that a high level of prediction performance can be very sensitive to academic factors obtained after the learner has made many efforts at a certain course. Thus, comparison only in terms of accuracy does not show how much predictive performance is retained when past period academic scores are absent.

As a result, this study examines the prediction of risk in students' academic performance in two controlled information environments: the full information environment where G1 and G2 remain, and the early information environment where both are stripped away. Differing from a typical study of model ranking, the goal is to measure the effect of the stripping of these variables and then explain which non-grade features become significant. The same experiment is conducted separately on Mathematics and Portuguese students.

III. PROPOSED METHODOLOGY

This methodology will help us assess the academic-risk prediction of students on the basis of two different information states: full-information prediction in which prior-period grades are known, and early-information prediction in which prior-period grades are intentionally excluded. In such a manner, it will be possible not only to see which model is better in terms of predictive performance, but also how much prediction depends on prior-period grades. The whole process will include dataset preparation, risk-level definition, preprocessing, modeling, prior-grade ablative analysis, evaluation, and explanation.

A. Dataset Description and Target Definition

Experiments have been done on the Student Performance dataset which can be found at UCI Machine Learning Repository [16]. These datasets contain information on demographic, family, social, behavior, school, and learning characteristics. There are two specific subjects' datasets studied individually; these are Mathematics, comprising 395 student records, and Portuguese, consisting of 649 records. Each dataset consists of 33 variables which include the first period grade (G1), second period grade (G2), and final grade (G3). As per the description provided by UCI, G3 is the final output, and it shows strong correlation with G1 and G2.

Apart from taking the final performance as a continuous value, G3 is defined into three risk categories as per the following definition:

$$Risk(G3) = \begin{cases} High, & G3 < 10 \\ Moderate, & 10 \le G3 \le 13 \\ Low, & G3 \ge 14 \end{cases}$$

This gave us 130 High Risk, 165 Moderate Risk, and 100 Low Risk students in Mathematics, and 100 High Risk, 355 Moderate Risk, and 194 Low Risk students in Portuguese.

TABLE I. DATASET AND RISK-CLASS CHARACTERISTICS

Characteristic	Mathematics	Portuguese
Student records	395	649
Total variables	33	33
Missing values	0	0
High risk (G3 < 10)	130	100
Moderate risk (G3 = 10–13)	165	355
Low risk (G3 ≥ 14)	100	194
Prediction target	Academic risk	Academic risk

B. Data Preprocessing

The categorical features have been transformed into a machine-readable format using encoding, whereas the numerical features remained in their numeric form. Scaling has been applied for those models which are affected by variance in

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feature magnitude, i.e., Logistic Regression and SVM. The feature G3 has been excluded from the set of predictors after creating the three risk groups.
Preprocessing steps have been carried out within the training process to prevent any leakage of information from training to test dataset.

C. Full and Early Information Predictions

The key methodology in this research involves creating two prediction scenarios.
Scenario 1 - Full Information: All eligible predictors were used, including G1 and G2. Scenario 1 can be considered traditional student performance prediction, where academic records are known.
Scenario 2 - Early Information: The predictors G1 and G2 were not used in the predictor space. Hence, the models used the predictors independent of the prior period grades, including demographic, family, behavioral and school-related information.
The difference in the two prediction settings serves as an ablation experiment on the prior grade. If there is significant deterioration in performance after excluding G1 and G2, then the difference measures the dependence of the model on academic performance.

D. Machine-Learning Models

Four supervised classifier algorithms were chosen for the succinct evaluation of linear, kernel, bagging, and boosting techniques:
Logistic Regression (LR) is a linear classifier algorithm offering an easy-to-understand baseline for multiclass risk prediction in education.
Support Vector Machine (SVM) algorithm learns nonlinear decision boundaries based on kernel approach and serves as a comparison with traditional statistical classifier technique.
Random Forest (RF) algorithm is an ensemble bagging classifier that can identify nonlinear interdependences between different educational attributes.
XGBoost classifier utilizes gradient-boosted decision trees in a sequence and tries to minimize classification error to find complex interdependences between student features.
The identical modeling procedure was performed independently for Mathematics and Portuguese data to avoid the confusion due to merging the two datasets.

E. Model Evaluation

Given that the target variable consisted of three classes with different frequencies, performance evaluation was not limited to only accuracy but rather included Accuracy, Macro-Precision, Macro-Recall, Macro-F1, Multiclass ROC-AUC, and High-Risk Recall.
For C risk classes, Macro-F1 is calculated as,

$$Macro\text{-}F1 = \frac{1}{C}\sum_{c=1}^{C}\frac{2P_cR_c}{P_c + R_c},$$

where P_c and R_c represent precision and recall for class c, respectively. Macro-F1 assigns equal importance to each risk category irrespective of class frequency. High-Risk Recall was also investigated as failing to determine whether students are truly at risk is especially important in an early-warning system.

G. Explainability Analysis

For identifying the influencing variables that may contribute towards making predictions about early-risk, SHapley Additive exPlanations (SHAP) was employed for the tree-based prediction model. SHAP is an approach where each feature contributes to a model prediction, and comparisons can be made globally based on the mean absolute SHAP value [17].

Since the explainability analysis was specifically required for the early-information scenario where G1 and G2 are not available, it becomes possible to understand the influential factors that play a role when prior strong academic indicators are stripped off. The SHAP values have been explained here as contributions to predictions and not as a cause-and-effect relationship.

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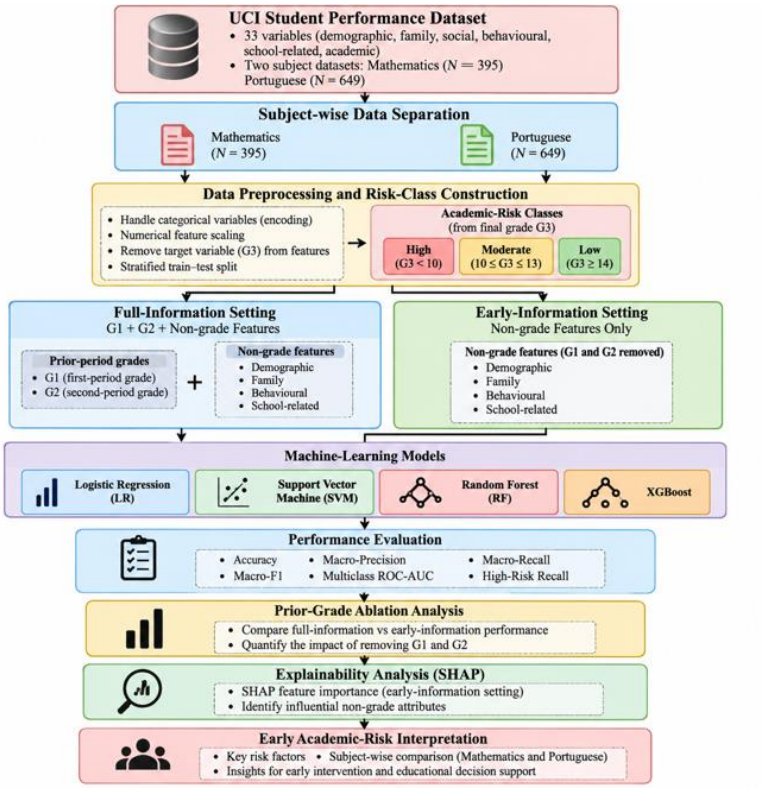


Fig. 1. Proposed explainable machine-learning framework for full-information and early academic-risk prediction.

Figure 1 presents the framework that is proposed to compare the full-information and early academic-risk prediction. First, the datasets of Mathematics and Portuguese subjects undergo pre-processing consisting of categorical encoding, numerical scaling, and creation of risk classes based on the value of G3. In the next step, two parallel prediction scenarios are constructed where students are classified into High, Moderate, and Low academic-risk classes. The full information scenario uses the past-period grades G1 and G2 along with other features, while the early information scenario omits G1 and G2, and uses only demographic, family, behavior and school features. Then, the Logistic Regression, SVM, Random Forest, and XGBoost algorithms are evaluated using several classification metrics, such as Macro F1, ROC AUC, and High-Risk Recall. Additionally, an ablation study with respect to the prior-grades evaluates how much performance changes when G1 and G2 are omitted. Lastly, the SHAP-based explainability determines the important non-grade features used in early-risk prediction. Therefore, the framework distinguishes the classic grade-based performance prediction from early academic-risk prediction.

Methodological innovation, in other words, does not consist of adding yet another classifier; rather, it involves the deliberate elimination of pre-period grades using the same model approach and subsequent analysis across subjects and explanation. The point of such approach is to compare the accuracy of conventional grade-based performance predictions with that of predicting early academic risk.

IV. RESULTS AND DISCUSSION

The experimentally generated results were analyzed using the two defined information contexts mentioned in Section III. In full information context, G1 and G2 grades were used, while in the early information context both these variables were excluded from the model. Four classifiers Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and XGBoost were tested separately on Mathematics and Portuguese datasets. Special attention was paid to Macro-F1 and High-Risk Recall, because accuracy alone may not give an adequate estimation of the classifiers' quality, especially if academic risk classes are imbalanced.

A. Predictive Performance Analysis

Table II provides the results of all four classifiers under both information contexts. It is evident that there was a marked difference between full-information and early-information predictions. In the case of the usage of G1 and G2 variables, all four classifiers gave much better results.

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TABLE II. PERFORMANCE COMPARISON UNDER FULL- AND EARLY-INFORMATION SETTINGS

Dataset	Setting	Model	Accuracy	Macro-F1	ROC-AUC	High-Risk Recall
Math	Full	LR	0.830	0.834	0.955	0.892
Math	Full	SVM	0.800	0.808	0.937	0.777
Math	Full	RF	0.851	0.858	0.956	0.846
Math	Full	**XGBoost**	**0.863**	**0.870**	**0.963**	0.869
Math	Early	LR	0.468	0.474	**0.662**	**0.500**
Math	Early	SVM	0.468	0.470	0.654	0.408
Math	Early	RF	0.463	0.457	0.653	0.377
Math	Early	**XGBoost**	**0.473**	**0.476**	0.639	0.415
Portuguese	Full	LR	0.795	0.781	0.933	**0.800**
Portuguese	Full	SVM	0.797	0.776	0.931	0.730
Portuguese	Full	RF	0.823	0.778	**0.947**	0.510
Portuguese	Full	**XGBoost**	**0.846**	**0.825**	0.946	0.720
Portuguese	Early	LR	0.529	0.519	0.725	**0.600**
Portuguese	Early	**SVM**	0.556	**0.545**	0.742	**0.600**
Portuguese	Early	RF	0.593	0.464	**0.752**	0.170
Portuguese	Early	XGBoost	**0.607**	0.522	0.739	0.260

XGBoost performed best in full-information with an accuracy of 0.863, a Macro-F1 score of 0.870, and a ROC-AUC of 0.963 for Mathematics. The second best was RF with a Macro-F1 of 0.858. It is notable that LR had the best High-Risk Recall of 0.892, hence the overall strongest-performing model was not the best performer in all risk criteria.
The same was true for Portuguese. In full-information, XGBoost got the best accuracy and Macro-F1 scores of 0.846 and 0.825, respectively. RF had the best ROC-AUC of 0.947, while LR performed best in terms of High-Risk Recall at 0.800. The variations prove the importance of considering the behaviour of an academic-risk model in the high-risk category beyond the overall accuracy.

The performance dropped sharply in early-information. In the case of Mathematics, XGBoost had the best Macro-F1 of 0.476, although LR came very close with 0.474 and gave the best High-Risk Recall of 0.500. In the case of Portuguese, the highest accuracy was achieved by XGBoost with an accuracy of 0.607, but the highest Macro-F1 was accomplished by SVM, along with significantly higher High-Risk Recall at 0.600, while that of XGBoost was just 0.260. Hence, it would not be correct to state that XGBoost is always better.

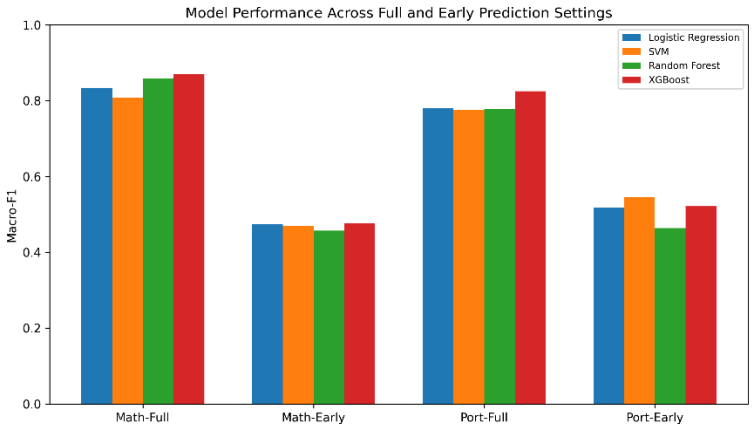


Fig. 2. Macro-F1 comparison of machine-learning models under full- and early-information prediction

As shown in Fig. 2, the two information scenarios further differ in their levels of performance through visual evidence. Full information always led to high values of Macro-F1 for both subjects. Conversely, the lower and clustered results attained under early prediction reveal that the lack of grades makes it more challenging to classify the three groups.

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B. Effect of Previous Grades on Early Predictive Risk Estimation

The most significant experiment conducted for this study is the one where G1 and G2 are controlled and removed. Table III shows the effect based on the best Macro-F1 for each information condition.

TABLE III. EFFECT OF PRIOR-GRADE REMOVAL ON PREDICTIVE PERFORMANCE

Dataset	Best Full Macro-F1	Best Early Macro-F1	Absolute Reduction	Relative Reduction
Mathematics	0.870	0.476	**0.394**	**45.3%**
Portuguese	0.825	0.545	**0.280**	**33.9%**

The removal of previous grades has brought down the highest value of the Mathematics Macro-F1 from 0.870 to 0.476, indicating an absolute difference of 0.394 and a relative difference of about 45.3%, while the variable Portuguese has declined from 0.825 to 0.545, meaning a difference of 33.9%.

Such results constitute the primary empirical finding of this study. The high value of grade performance that is observed for grades G1 and G2 cannot be predicted in a similar manner independent of grades. Therefore, grades constitute a significant share of information on which discrimination between risk groups is based.

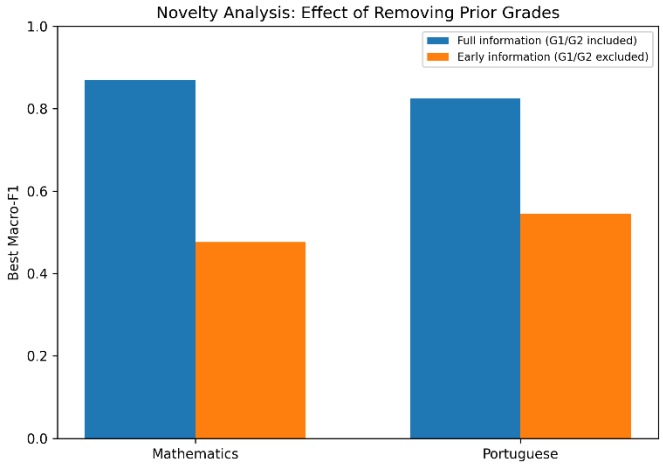


Fig. 3 – Prior-Grade Ablation / Novelty Graph

This point is illustrated well in Fig. 3. While both samples show some degradation in performance, the decline is more noticeable in the case of the mathematics sample. The Portuguese sample maintains a higher predictive power even after removing G1 and G2, meaning that the non-G factors retained have higher discriminative power with respect to the risk categories considered.

Notably, this reduced predictive power does not imply model failure but rather highlights the challenge of detecting future academic risks prior to having any data from earlier tests. This difference is vital in assessing educational early-warning models since high performance obtained from late-stage academic factors may not be of the same intervention value as moderate performance derived from truly early-stage factors.

C. Explainability and Academic Risk-Factor Analysis

Based on the explainability results, it is clear that in cases where prior period grades are not available, there is a greater tendency of the models to rely on the historical, behavioral, demographic, and educational features. This is especially the case with the importance of failures and absence, which have been consistently featured in both datasets. However, SHAP values measure the contribution of features to model outcomes and not the causal relationship of the features with academic performance in Fig 4.

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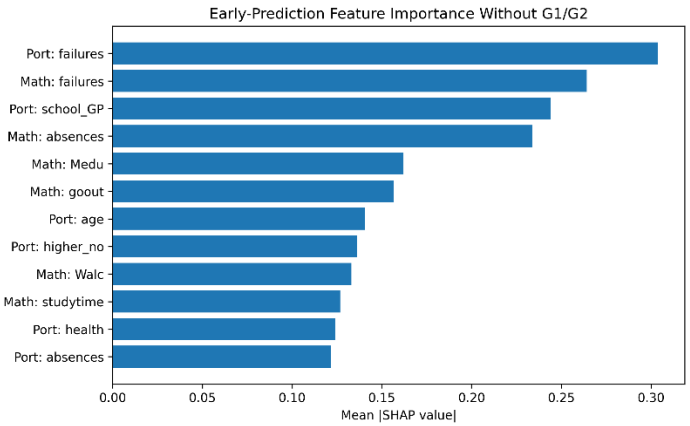


Fig. 4. SHAP-based feature importance for early academic-risk prediction after excluding prior-period grades G1 and G2.

V. CONCLUSION

This research has introduced an explainable machine learning framework to detect academic risk early using the datasets for Mathematics and Portuguese. Four classifiers were compared under both full and early information frameworks. The classifier that produced the best results was XGBoost with Macro-F1 values of 0.870 and 0.825 for full and early information, respectively. The exclusion of grades led to a decline in accuracy by 45.3% and 33.9%, respectively, indicating the importance of grades. SHAP analysis revealed previous failure, absence from classes, and behavior as significant early risk features. This paper highlights the need for timely and explainable intervention in academic risk detection.

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