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PAPER

A Recommendation System Based on Early Academic Performance Prediction and Student Classification: Utilizing Artificial Intelligence and Mobile-Based Application

Zakaria Bousalem[1](✉), Aimad Qazdar[2], Inssaf El Guabassi[3], Abdellatif Haj[4]

[1]Polydisciplinary Faculty, Sultan Moulay Slimane University, Beni Mellal, Morocco

[2]ESTIDMA Laboratory, Ibn Zohr University, Agadir, Morocco

[3]LAROSERI Laboratory, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco

[4]Faculty of Sciences and Technologies, Hassan 1st University, Settat, Morocco

zakaria.bousalem@gmail.com

ABSTRACT

In this paper, we explore the idea that categorizing students according to their early academic results can effectively prevent academic failure and enhance success in schools. Our objective is to offer appropriate educational strategies, learning methods, and resources. We introduce a method designed to improve student learning experiences and increase their high school success. For validation, we gathered a dataset from the School Life Management Software, containing data on the personal information and academic performance of 840 students from 2018 to 2021. Using this data, we developed a predictive model. We then compared the academic outcomes forecasted by our model with the actual results of the students for the 2021–2022 academic year. This comparison showed that our model can accurately predict early student academic performance and outcomes. Integrating our predictive model with a student classification system allows us to suggest effective strategies for enhancing student performance and avoiding academic failure, thereby improving the overall academic experience. In addition to the predictive model, we have developed a mobile application that operationalizes our findings. This application serves as a tool for students and educators, utilizing the predictive model to provide real-time academic performance forecasts. The app not only predicts outcomes but also suggests personalized strategies and resources to support students' learning journeys.

KEYWORDS

Artificial Intelligence (AI), Machine Learning, Predicting Academic Performance, Technologies Enhanced Learning, Mobile Technology

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1 INTRODUCTION

The quality of a country's education system plays a significant role in its economic progress and social development. One of the primary objectives of educational institutions is to offer high-quality education to students. Therefore, enhancing the sustainability, affordability, and quality of education continues to be a major challenge.

Nowadays, the rapid development of disruptive technologies has a profound impact on various sectors, including education [1]. Technology has become an inevitable part of many domains, such as business, healthcare, banking, travel, communication, and particularly education, where significant changes are emerging.

Current disruptive technologies, such as the Internet of Things (IoT), virtual reality (VR), augmented reality (AR), cloud and edge computing, 3D printers, and artificial intelligence (AI), have the potential to transform the entire educational learning process into a learner-centered, innovative, attractive, personalized, fun, collaborative, and inspiring experience. These changes represent a milestone towards achieving higher quality education.

Artificial intelligence and Machine Learning (ML) have introduced innovative research to education, showing promise, but it is still a developing field that requires further progress for fully mature achievements. AI and ML have been utilized in various ways to enhance education, including preventing student dropout rates [2], [3], [4], [5], improving academic performance [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], increasing the role of educational actors (school/university, teacher, pedagogical staff, etc.) [5], [11], [12], and recommending universities and schools, academic paths, programs, courses, and educational resources for learners or teachers [15], [16], [17], [18].

In this paper, we present our approach to building models that predict student academic performance. These models are designed to enable early intervention by providing tailored support to students who are struggling, with the aim of enhancing their academic outcomes. Additionally, we introduce a practical application derived from our study: a mobile application specifically developed to aid students in improving their academic performance. This app leverages our predictive models to identify students at risk of facing learning difficulties at an early stage. By doing so, it empowers teachers and educational institutions to timely and effectively assist these students with the appropriate support. The paper addresses the following research questions:

- RQ1: Can future academic success be identified in the early stages of a student's academic career?
- RQ2: How can ML accurately predict student performance in the study's context?
- RQ3: Can a student's performance in one subject affect their performance in other subjects?
- RQ4: How can recommendations be made based on student performance predictions?

The present paper is arranged in the following manner: Section 2 presents a comprehensive review of the pertinent literature, while Section 3 expounds on the proposed methodology, the sampling of students for this paper, the proposed system, and its ability to accurately predict student performance. Section 4 discusses the experimental validation of the study, while Section 5 provides a discussion of the results obtained, the main questions raised, and some hypotheses to answer these questions. Finally, Section 6 concludes the paper and suggests future directions for study.

2 RELATED WORK

Incorporating information and communication technologies (ICT) in education has led to the accumulation of vast amounts of electronic student data by educational institutions. This wealth of data can be transformed into actionable knowledge and effectively utilized to inform decision-making at various levels, including national, regional, provincial, and local. By leveraging historical student data, predictive models can be constructed to forecast academic performance, thereby facilitating early corrective and preventive interventions. The implementation of predictive models using student data is a critical factor in successful educational management, planning, curriculum development, and other decision-making processes within the academic arena [19], [38].

To enhance comprehension of our study, this section provides a comprehensive review and analysis of previous studies related to the prediction of student performance or grades. Our review presents the academic progress made towards addressing the research questions while identifying areas where researchers should focus their efforts.

Numerous research studies have explored the prediction of student performance or outcomes by utilizing diverse dataset types and employing various machine learning algorithms, as presented in Table 1.

Table 1. Summary of studies addressing students' academic performance

Type of Features	Works
Academic	[2], [4], [5], [6], [7], [9], [12], [13], [14], [19], [21], [22], [24], [25], [26], [30], [31], [32], [37]
Social	[7], [14], [24], [25], [26], [37]
Demographic	[5], [6], [7], [14], [20], [24], [25], [26], [37]
Personal	[14], [26]
Psychological	[26]
Logs/Trace	[5], [6], [14], [28], [33], [37]

Based on our literature review, regression and classification are the most commonly applied modeling strategies for predicting students' academic performance [2], [9], [19], [20], and [37]. Regression models are used to predict continuous variables, while classification models are employed when the predicted variable is categorical. The majority of these studies employed classification algorithms, including decision trees, support vector machines (SVM), restricted Boltzmann machines (RBM), and logistic regression. For regression problems, the multiple regression algorithm was the most frequently utilized. These studies utilized real student data collected from institutional databases [4], [6], [11], [12], [19], [21], [22], or Virtual Learning Environments (VLE) [6], [14], [23], [37]. Other studies employed pre-existing datasets [5], [13], [24], [25].

In Table 2, the types of features used to predict student academic performance are presented. These features were derived from datasets containing student academic data, social data, and demographic data, as well as personal and psychological data in some studies [26]. Virtual learning datasets were mainly composed of logs and traces [5], [6], [14], [23], [27], [28], [29], [37]. The use of student academic data was the most prevalent feature type [6], [7], [9], [14], [24], [26], [37], and demographic data [6], [7], [14], [20], [24], [37] were also used in several studies.

Table 2. Type of features used to predict student academic performance

Modeling Strategies	Dataset Origin	Dataset Source	Works
Classification	Inst	Collected	[2], [4], [6], [7], [9], [12], [26], [30], [31], [32]
Classification	Inst	Downloaded	[5], [25]
Classification	VLE	Downloaded	[5], [24]
Classification	VLE	Collected	[26], [28], [29], [37]
Regression	Inst	Collected	[19], [21], [22]
Regression	VLE	Collected	[14], [33], [37]
Regression	Inst	Downloaded	[5], [13], [20]
Regression	VLE	Downloaded	[5], [14]

In terms of the number of observations, the sample sizes used in the reviewed studies range from around 100 to 500, as reported in several works [2], [4], [13], [14], [19], [20], [21], [22], [25], [27], [28], [29], [30], [37]. However, there are exceptions, such as [31], who used a sample of less than 50, and [5], [23], whose samples were greater than 10,000.

In these works, various metrics were used to validate the performance of the models, depending on the type of the used modeling strategies (classification or regression). Among the most commonly used validation metrics were MAE, RMSE, TP, Recall, and the ROC-curve, among others. However, only a small number of these studies utilized the K-fold cross-validation technique, as seen in the works by El Aissaoui et al. [20], Nespereira et al. [27], and Hussain et al. [29].

Compared to previous studies discussed, our study aims to utilize the multivariate regression machine learning algorithm to predict students' final grades in subjects using real student data collected from the institute database. In contrast to the related work mentioned above, we assess the model's performance during both the modeling and validation stages. Furthermore, we validate our model's performance on two levels: first, using validation metrics such as MAE, RMSE, RAE, RSE, R^2, and ten repetitions of random cross-validation; second, by consulting experts in the field represented by the pedagogical committee established by the school administration.

3 CONTEXT AND DATASET

The following sections describe the context of this study and the used dataset.

3.1 Context

The study presented in this paper concerns students in the last year of secondary school (Baccalaureate or Bac). The Bac certificate is obtained after a two-year academic program, during which students are evaluated through a regional examination at the end of their first year. This assessment aims to evaluate their proficiency in secondary subjects. At the end of the second year, a national examination (NE) is administered to assess the students' knowledge in their respective fields of specialization, such as mathematics, physics, and science.

Throughout the stages of business and data understanding, we conducted various studies and analyses to evaluate student performance at the end of each first semester for the academic years of 2019–2020, 2020–2021, and 2021–2022. Our efforts yielded a comprehensive comprehension of the underlying problem and enabled us to identify the different calculation formulas utilized.

In Morocco, the calculation formula for determining the Grade of the Bac (*GB*) is presented in Formula (1):

$$GB = \frac{(CA + RE + (NE \times 2))}{4} \tag{1}$$

Where *CA* represents the Continuous Assessment score (25%), *RE* represents the Regional Examination score (25%), and *NE* represents the National Examination score (50%).

Additionally, the calculation formula for *CA* is presented in Formula (2):

$$CA = \frac{(CA1 + CA2)}{2} \tag{2}$$

As shown in Formula (2), the *CA* component of the Grade of the Bac (*GB*) formula comprises two averages, namely *CA*1 and *CA*2. These averages correspond to the continuous assessment scores for the first and second semesters of the second year of the Bac program, respectively.

To calculate the average continuous assessment score (*CA*) for each semester, the scores for each subject are multiplied by their respective coefficients, and the products are summed. This sum is then divided by the total number of coefficients for that semester Formula (3).

$$CA1 = \frac{\sum(Score\_Subject \times Coef\_Subject)}{\sum Coef\_Subject} \tag{3}$$

As indicated in Formula (4), the National Examination Score (*NE*) is computed by multiplying the scores achieved in the subjects assessed by their corresponding coefficients, summing the resulting products, and dividing this total by the sum of the coefficients.

$$NE = \frac{\sum(Score\_Subject \times Coef\_Subject)}{\sum Coef\_Subject} \tag{4}$$

Table 3. Merits

Performance	Categories
[10–12]	Passed, with Standard Pass (wSP)
[12–14]	Passed, with Honors (wH)
[14–16]	Passed, with High Honors (wHH)
[16–20]	Passed, with Highest Honors (wHstH)

Each student is assigned a category (merit) based on their grade of the Bac, as shown in Table 3.

3.2 Participants and datasets

The present study utilized a dataset composed of real-world student data obtained from the School Life Management Software of the HBMK High School. Specifically, the data pertained to 1160 students enrolled in the Physics (P) stream during the 2018–2019, 2019–2020, 2020–2021, and 2021–2022 school years. It should be noted that these data represent the complete set of available information for the Physics stream.

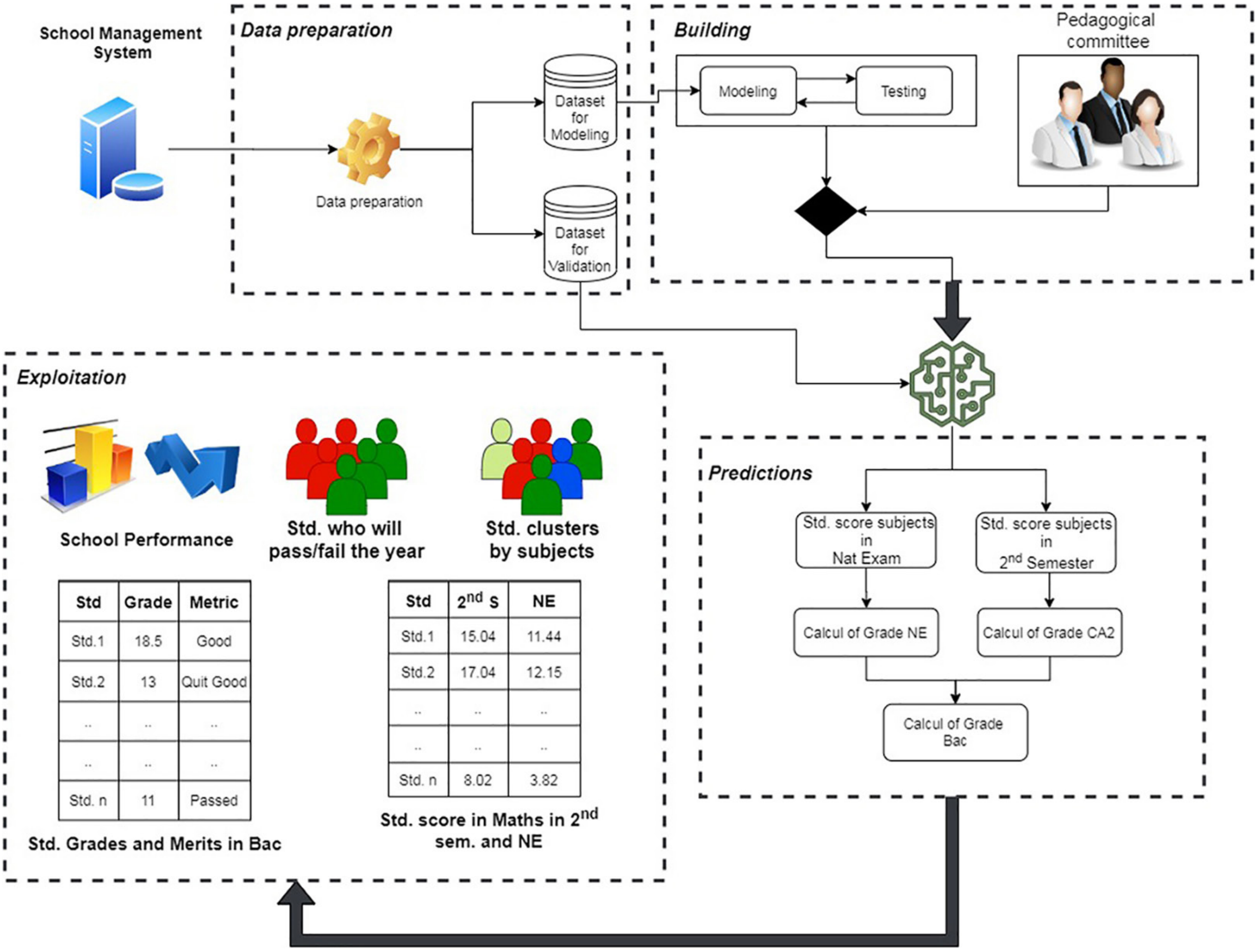


Fig. 1. Overarching system architecture

The study population comprised second-year high school baccalaureate students between the ages of 16 and 19. For the modeling phase of the study, a sample of 840 students was selected from the dataset representing the 2018–2019, 2019–2020, and 2020–2021 school years. Of these, 496 were girls and 344 were boys. Notably, 91 of the students included in the sample were repeaters, with 44 being girls and 47 being boys.

Table 4. Used features

Feature	Feature Details	Data Type
stdId	Represents the unique identification numeral allocated to each student	Nominal
Sex	Denotes the Sex classification of the student.	Nominal
Age	Denotes the precise numerical representation of the student's age	Quantitative
RE_Scr	Refers to the numerical score obtained by students in the Regional Examination.	Quantitative
Math_1S	Indicates the academic score in Mathematics achieved during the initial semester	Quantitative
PC_1S	Represents the academic performance in Physics and Chemistry in the first semester.	Quantitative
SVT_1S	Signifies the academic achievement in Life and Earth Sciences during the opening semester	Quantitative
Philo_1S	Designates the academic score acquired in Philosophy in the first semester	Quantitative
Ang_1S	Denotes the linguistic performance score in the English subject during the initial semester.	Quantitative
Trad_1S	Refers to the academic marks achieved in Translation during the first semester.	Quantitative
Ed_Ph_1S	Represents the accomplishment score in Physical Education in the first semester.	Quantitative
Ed_Is_1S	Indicates the academic marks received in Islamic Education during the first semester.	Quantitative
Fr_1S	Specifies the linguistic academic score in the French language in the initial semester.	Quantitative
Arab_1S	Denotes the academic performance in the Arabic language during the first semester.	Quantitative
Disc_1S	Represents the evaluative score associated with Discipline in the opening semester.	Quantitative
CA_1S	Indicates the overall performance rating achieved in the Continuous Assessment during the first semester.	Quantitative

Regarding the validation phase, the dataset consisted of 320 students for the 2021–2022 school year, comprising 216 girls and 104 boys. Out of the sample used in this phase, there were only eight repeaters, comprising six girls and two boys. It should be noted that the privacy of the student data used in this study was maintained by assigning them unique codes. Table 4 provides a comprehensive overview of all the variables included in the analysis.

4 THE PROPOSED SYSTEM

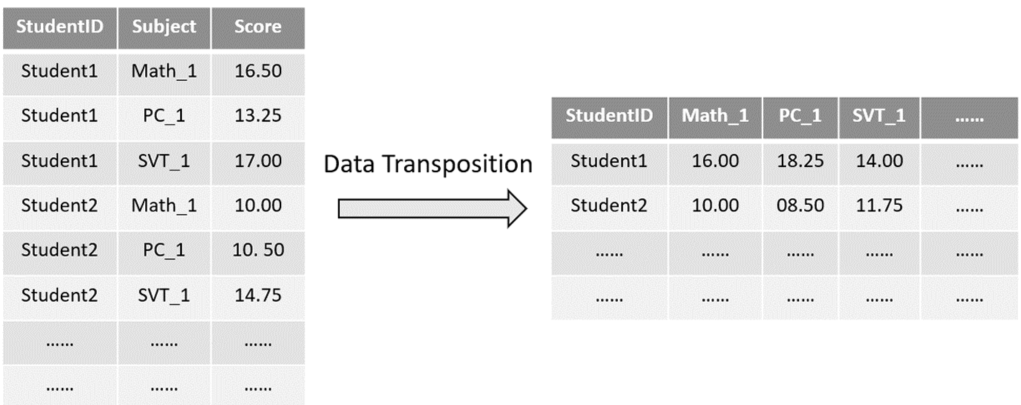
The proposed system is illustrated in Figure 1, which comprises four main steps: **Data Preparation, Model Building, Results Prediction**, and **Predictions Exploitation**.

4.1 Data preparation

In the domain of data science, the preliminary step of data preparation is of paramount importance. This is because it facilitates the conversion of raw data into insightful knowledge and ensures the removal of biases and disturbances that might compromise the integrity of the data [34]. This intricate process usually demands a considerable temporal investment and encompasses four principal procedures, delineated in Figure 2.

Fig. 2. Data preparation process

- **Data collection:** The methodology involves systematically gathering information from each student enrolled at HBMK High School during the period extending from 2018 to 2022. The exportation of the collated data is executed in a relational model. Conforming to prevalent national and international regulatory norms [35] pertinent to the safeguarding of personal information, identifiable student data elements are meticulously obfuscated or encrypted.
- **Data filtering:** In this operative phase, emphasis is concentrated on scores derived from the Physics discipline. Incorporated within this framework are the Regional Examination (RE) outcomes, exemplifying students' scholarly accomplishments in subsidiary subjects at the conclusion of the preliminary Baccalaureate annum, coupled with the Continuous Assessment (CA) results, and the scores amassed in eleven subjects during the initial semester of the subsequent Baccalaureate annum.
- **Data transposition:** The initial data structure, as procured, was not amenable for the deployment of machine learning algorithms. To rectify this, the Talend Open Studio software was employed to modify the data structure, associating it aptly with the relevant student codes. A visual comparison of the data pre- and post-transposition is delineated in Figure 3.
- **Data cleaning:** The prepared dataset may comprise data that are irrelevant to this study, such as regional exam scores of students who have transferred schools or those who are exempted from physical education. Consequently, we employed two distinct techniques to cleanse our dataset: (i) imputation of missing values using the mean of the observations (in the case of students excused from physical education) and (ii) removal of observations with missing values (in the case of student absences during the exam).



StudentID	Subject	Score
Student1	Math_1	16.50
Student1	PC_1	13.25
Student1	SVT_1	17.00
Student2	Math_1	10.00
Student2	PC_1	10. 50
Student2	SVT_1	14.75
......	......	......
......	......	......

StudentID	Math_1	PC_1	SVT_1	......
Student1	16.00	18.25	14.00	......
Student2	10.00	08.50	11.75	......
......	......	......	......	......
......	......	......	......	......

Fig. 3. Data transposition example

4.2 Model building

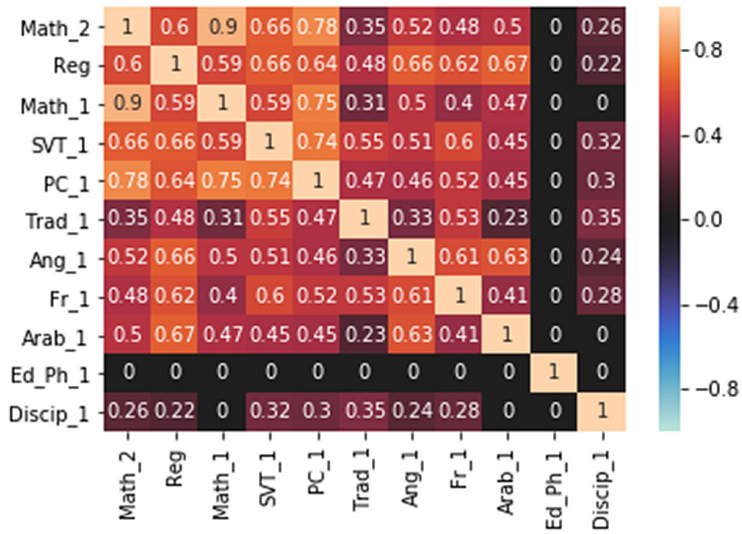


Fig. 4. Correlation matrix between Math of second semester, Regional Exam and subjects of 1st semester

The models built in this study utilized the multiple regression machine learning algorithm. This modeling phase was developed in two stages: 1) **the creation of a model for predicting the scores of subjects in the second semester**, and 2) **the development of a model for predicting the scores of subjects in the national exam**. To select the variables from the dataset for building the models, we employed a correlation matrix. Figure 4 depicts the correlation matrix utilized between Math in the 2nd semester, the Regional Exam, and the subjects of the 1st semester. This approach enabled us to identify, for each subject, the variable (subject) with which the correlation was the highest and establish the relationship of influence among the various subjects (see Figure 5).

Figure 5 presents a part of the influence relationship graph for Math, Physics, and SVT for the second semester and the National Exam.

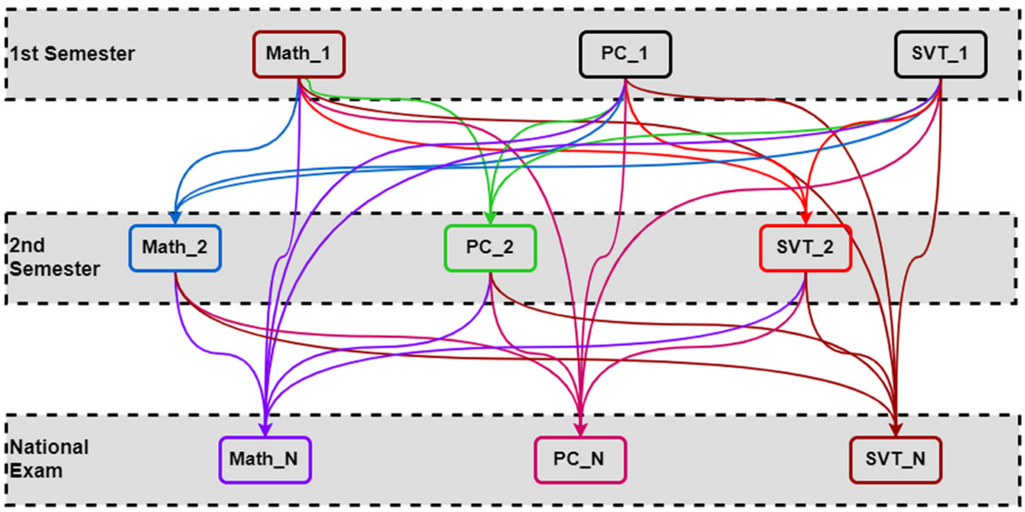


Fig. 5. Influence relationship graph between subjects

It is important to note that this relationship aids in identifying a student's performance in a particular subject, as well as the topics (subjects) that have an impact on it. This knowledge enables the determination of the type of reinforcement and additional assistance required to enhance the student's performance.

The performance of the model was validated on two distinct levels. The first level involved several performance indicators, namely mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), relative squared error (RSE), and coefficient of determination (R^2), which were calculated, analyzed, and interpreted. The second level involved a pedagogical committee established by the school administration, comprising 11 teachers representing all the baccalaureate school subjects and headed by the school principal. The committee evaluated the model's predictions against the actual grades obtained by students at the end of each academic year, thereby validating or rejecting the final model.

4.3 Results predictions

Following the model building, the third step involves predicting the students' results by subject in the second semester and the National Examination. Using the formulas Formula 1, Formula 2, Formula 3, and Formula 4 described in the section Context, the results of these two models are used to calculate the grade of the second semester, the National Exam, and the Bac for each student.

4.4 Predictions exploitation

Finally, utilizing the predictions allows for the presentation of indicators based on the forecasted performance of the school at the end of the academic year, statistics on the rates of success and failure, merits and grades of each student in the Bac, as well as the proficiency level of each student per subject in the national exam, etc.

5 EXPERIMENTS AND RESULTS

Various methods for evaluating the success of models exist. However, the evaluation of each model is highly dependent on the domain of study and the expected outcomes of the system.

In our case, the aim is to predict students' scores in each subject in Bac and make decisions based on whether a student needs reinforcement, support, or needs to work harder to succeed in the subject. These decisions are meaningful if the predictions are accurate.

The model used in this study was generated by using the multiple regression algorithm through the scikit-learn Python library. The model comprises two sub-models: Model S2 for predicting the student's scores for each subject in the second semester and Model NE for predicting the scores for each subject in the National Exam. The final grade of Bac for each student is predicted by utilizing the results from both models and applying the calculation formula for GB Formula (1). To evaluate the model's performance, the predicted GB for each student was compared to the actual GB. Various performance metrics were utilized, such as MAE, RMSE, RAE, RSE, and Coefficient of determination (R^2).

5.1 Global results

Table 5 compares the overall performance results of the model evaluation between the modeling and validation phases. As shown in Table 5, we observe that the values of the metrics (MAE, RMSE, RAE, RSE, and R^2) used for the calculation of CA2 were almost identical in both phases. For the calculation of NE, our model showed consistent metric values in both phases, except for RMSE, which was reduced by 0.37 in the validation phase.

Table 5. Evaluation of model performance in modeling and validation in calculating grade in second Semester, National Exam and Bac

Phase	Calcul of CA2		Calcul of NE		Calcul of GB	
	M	V	M	V	M	V
MAE	0.28	0.00	0.00	0.00	0.00	0.03
RMSE	0.94	0.90	1.27	0.90	1.25	0.92
RAE	0.66	0.65	0.62	0.65	0.51	1.17
RSE	0.60	0.60	0.66	0.60	0.75	1.80
R^2	80%	80%	80%	80%	57%	90%

Finally, the MAE and RMSE values obtained for the calculation of GB are consistent in both the modeling and validation phases. However, the RAE and RSE values increased by 1.02 and 0.61, respectively. Moreover, we note that the coefficient of determination represents 90% in the validation compared to 57% in the modeling.

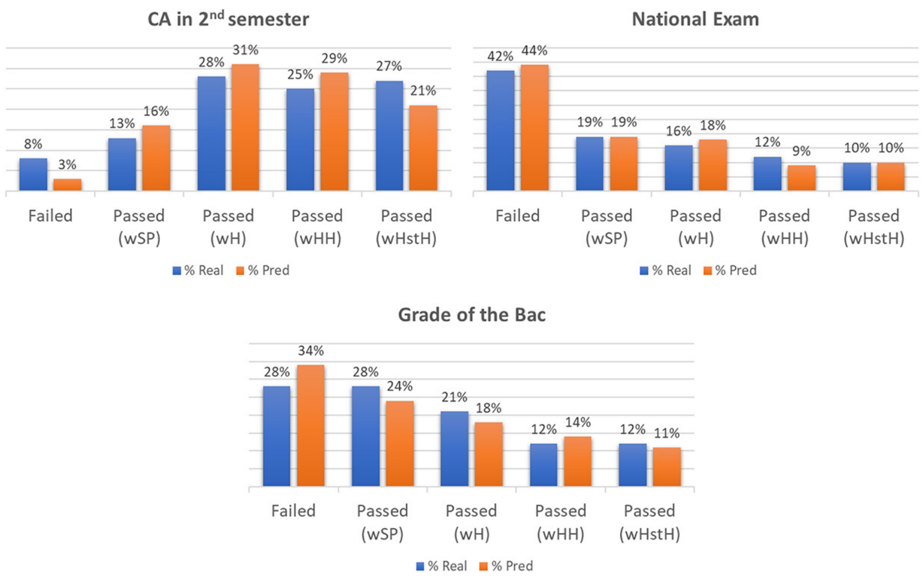


Fig. 6. Comparison of real results and predictions for the 2021–2022 school years

Figure 6 presents a comparative analysis of the actual values and the predicted values for the 2021–2022 academic year.

In terms of CA2, the model predicted that 3% of students (approximately 10 students) would fail in the second semester, while 97% would pass with the following merit distributions: wSP: 16%, wH: 31%, wHH: 29%, and wHstH: 21%. However, an analysis of student results at the end of the semester showed that

8% of students (equivalent to 26 students) did not pass the second semester, while 92% of students passed with the following merit distributions: wSP: 13%, wH: 28%, wHH: 25%, and wHstH: 27%.

Regarding the prediction of National Examination results, our system predicted that 44% of students (141 students) would fail, while 134 students (equivalent to 42%) actually failed, with a negligible difference of 2% (6 students). Figure 6 illustrates that our system predicted that 34% of the promotion was at risk of failing the year, which is 6% higher than the actual percentage (28%). The system also predicted that 24% of students would pass with Standard Pass (wSP), while 28% of students actually did. Furthermore, the system predicted that 18% of students would pass with Honors (wH) merit, while 21% of students actually obtained this merit. In terms of With High Honors (wHH) merit, the system predicted that 14% of students would pass, while 12% actually did. For the With Highest Honors (wHstH) merit, the system predicted 11%, while the actual percentage was 12% (a difference of 1%).

5.2 Prediction in the second semester

As previously mentioned, the calculation of the continuous assessment (CA) scores for each semester involves adding the score of each subject multiplied by its coefficient and dividing the total by the sum of the coefficients. To accomplish this, it is necessary to predict the score of each subject.

Table 6. Model S2 performance evaluation in modeling and validation

Phase	Math		PC		SVT		Philo		Ang		Arab		Fr		Ed_Is		Trad	
	M	V	M	V	M	V	M	V	M	V	M	V	M	V	M	V	M	V
MAE	0	–0.1	0	–0.1	0	–0.1	0	–0.1	0	–0.1	0	–0.1	0	–0.1	0	–0.1	0.00	–0.10
RMSE	1.1	1.38	1.1	1.29	1.2	1.33	1.1	1.31	1.2	1.29	1	0.99	1	1.2	1	1.51	0.92	1.09
RAE	0.6	0.53	0.6	0.57	0.6	0.55	0.6	0.54	0.6	0.58	0.7	0.64	0.6	0.6	0.7	0.51	0.62	0.54
RSE	0.6	0.71	0.6	0.63	0.7	0.75	0.7	0.81	0.7	0.75	0.6	1.15	0.6	0.82	0.7	1.27	0.68	0.86
R^2	81%	72%	82%	82%	76%	72%	72%	63%	69%	70%	80%	38%	81%	53%	78%	20%	65%	53%

Table 6 displays the results of the model performance evaluation by comparing the actual and predicted values for each student in the second semester, during both the modeling and validation phases.

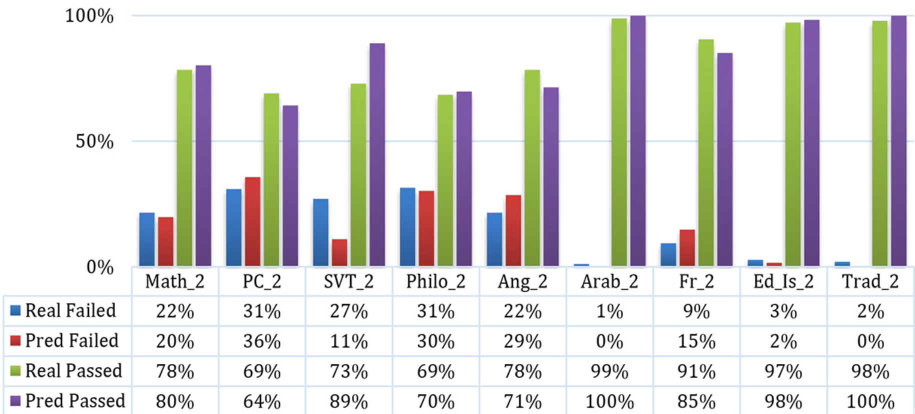


Fig. 7. Comparison of real results and predictions for the 2021–2022 school years

The results in Table 6 indicate that there is minimal change (≤ 0.57) in the values of the metrics MAE, RMSE, RAE, and RSE between the modeling and validation phases for all subjects.

Regarding the coefficient of determination, we observed that it remains relatively stable between the modeling and validation phases, particularly for the subjects that will be evaluated in the national exam, namely: Math, PC, SVT, Philo (philosophy), and Ang (English). Specifically, for PC and Ang, the R^2 remained constant, while it decreased by 4% for SVT and by 9% for Math and Philo. However, the R^2 values for these subjects remained substantial in both phases. For instance, in the case of PC, R^2 was 82% in both the modeling and validation phases.

For the other subjects, we noticed a significant decrease in R^2 values, such as a decrease of 42% for the Arab subject, 28% for Fr, 58% for Ed_Is, and 12% for Trad.

Figure 7 provides a comparison between the actual pass/fail percentages and the predicted percentages for each subject in the second semester of the 2021–2022 school year.

5.3 Prediction in the National Exam

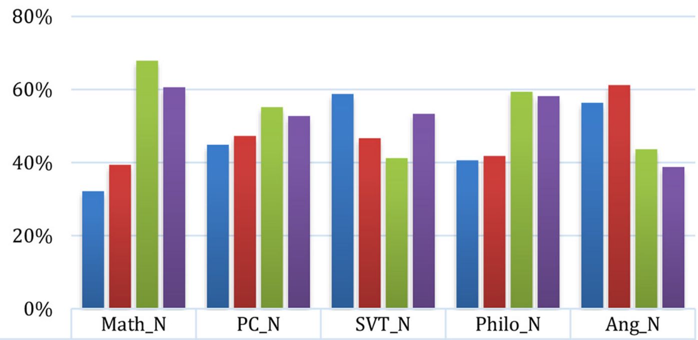
Table 7 displays the comparison of the NE model's performance evaluation metrics between the modeling phase and the validation phase. As previously mentioned, the national exam assesses the main subjects of each stream in the second year of the baccalaureate, including Math, PC, and SVT for the PC stream. Alongside these three subjects, students are also tested on English (Ang) and Philosophy (Philo), which are common subjects across most streams. Table 7 presents a comparison of the metrics values used between the development phase of the model and the validation phase.

Table 7. Comparison of the model NE performance in the modeling and validation phases

Phase	Math		PC		SVT		Philo		Ang	
	M	V	M	V	M	V	M	V	M	V
MAE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	1.60	1.56	1.53	1.44	1.41	1.51	1.62	1.60	1.60	1.50
RAE	0.48	1.97	0.51	1.79	0.55	1.84	0.49	2.04	0.52	1.82
RSE	0.72	1.38	0.70	1.49	0.75	1.15	0.85	1.11	0.79	1.31
R^2	70%	71%	73%	79%	65%	53%	45%	30%	61%	67%

The results presented in Table 7 indicate that our model can provide accurate predictions of student performance in National Exam subjects, especially Math and PC. The evaluation metrics used in both the development and validation phases showed negligible changes. Specifically, the MAE and RMSE remained nearly constant across all subjects, while the RAE and RSE showed slight increases of 1.49 and 0.66 for Math, 1.28 and 0.79 for PC, 1.29 and 0.40 for SVT, 1.55 and 0.26 for Philo, and 1.30 and 0.52 for Ang, respectively. Additionally, the coefficient of determination (R^2) increased by 1% for Math, 6% for PC, and Ang, but decreased by 12% for SVT and 15% for Philo.

Figure 8 displays a comparison between actual pass/fail rates and predicted rates for each National Exam subject.



	Math_N	PC_N	SVT_N	Philo_N	Ang_N
Real Failed	32%	45%	59%	41%	56%
Pred Failed	39%	47%	47%	42%	61%
Real Passed	68%	55%	41%	59%	44%
Pred Passed	61%	53%	53%	58%	39%

Fig. 8. Comparison of real and predict success rates by subject for the NE of the 2021–2022 school years

5.4 Design result

In this section, we present a mobile application developed from our study. This app uses our predictive models to help students forecast their academic performance across different subjects. It provides predictions on students' performance and recommends assistance for subjects in which students may face challenges. Additionally, the application offers teachers insights into their students' potential academic progress, allowing them to intervene with suitable support measures. Our aim is to proactively support education by anticipating and addressing students' needs early on. Here, we will showcase select interfaces of the application.

a) Student Interfaces Overview

- **Academic Performance Prediction Submission Form**

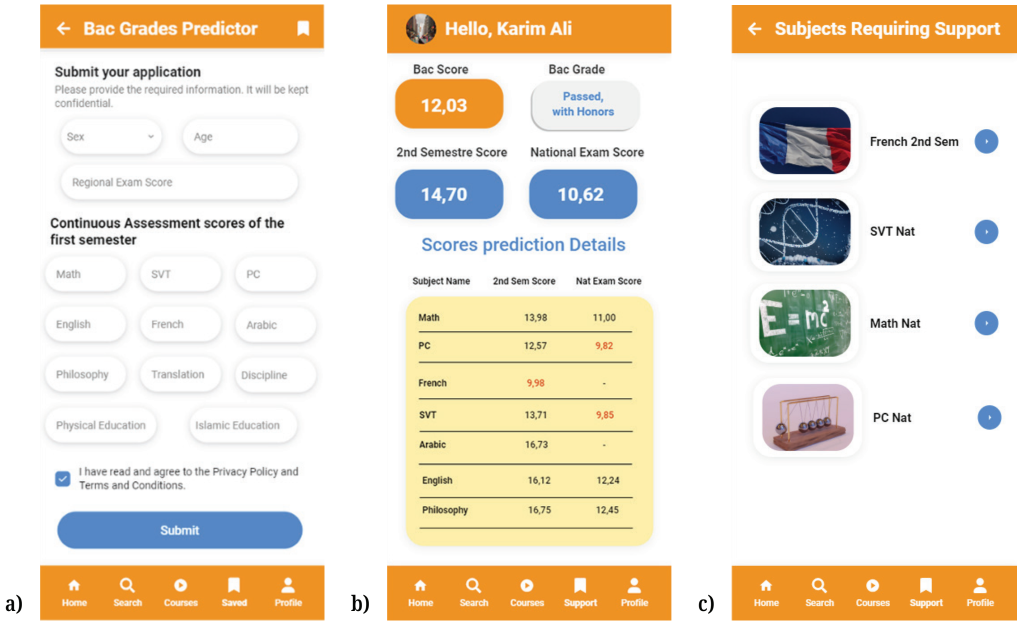


Fig. 9. Student Interfaces

Figure 9a depicts our mobile application's submission form interface, where students enter personal and academic details to obtain predictions of their academic performance. This form requires inputs such as sex, age, regional exam score, and first semester subject scores. By agreeing to the Privacy Policy and Terms and Conditions and clicking the 'Submit' button, students can proceed to have their academic outcomes predicted by the application.

- **Academic Performance Prediction Results**

Figure 9b presents an output screen from our mobile application, which visualizes the predicted academic outcomes for a student. Post-submission, the application processes the student's inputted data to generate a comprehensive academic forecast.

The output is methodically organized into several sections, each providing a distinct category of information.

  - The "Bac Score" and "Bac Grade" sections display the overall predicted score and the corresponding Baccalaureate merit.
  - "2nd Semester Score" and "National Exam Score" provide specific numerical predictions for these assessments.
  - The "Scores Prediction Details" section provides a detailed forecast of the expected scores for a range of subjects in the second semester and national exam, each paired with its respective predicted score. This comprehensive list is not exhaustive and includes, but is not limited to, subjects such as Math, Physical Chemistry, French, and others.

- **Subjects Requiring Support**

Figure 9c shows a structured list from our mobile application, categorized under "Subjects Requiring Support." It serves as a tailored recommendation system, providing a selection of subjects for which a student is predicted to need additional assistance based on prior performance forecasts.

Each subject is represented by a distinct icon and label, indicating the focus area of the supplementary lessons.

b) Stakeholders Interfaces Overview

- **Bulk Students' Data Upload for Academic Prediction**

Figure 10a presents a data upload interface within our mobile application, tailored for educational stakeholders. The functionality presented is a form allowing the upload of a CSV (Comma-Separated Values) data file. This specific form is engineered to accept a dataset comprising both personal and academic information of students enrolled in the Physics stream.

Once the file is uploaded, stakeholders can initiate the predictive analysis by clicking the 'Submit' button. This action triggers the application's algorithms to process the uploaded data and generate academic predictions for all students in the physics stream.

- **Academic Performance Analytics Results Interface**

Figure 10b depicts a visualization of the aggregated predictive analytics for students in the Physics stream. It is structured into distinct sections, each offering a different perspective on the predicted academic results.

  - The upper section of the interface displays overall success metrics, indicating the percentages of "Successful" and "Unsuccessful" predicted outcomes for the student cohort.

- A histogram titled "Predicted Bac Grades" displays the distribution of projected grades, categorizing them into various academic distinctions such as "Failed," "With Standard Pass" (wSP), "With Honors" (wH), "With High Honors" (wHH), and "With Highest Honors" (wHstH).
- The "Detailed results" section provides functional options for stakeholders. It includes the ability to download the comprehensive results file in Excel format, facilitating further analysis and reporting. Additionally, there is a sharing feature, designed to distribute the results via email for collaborative review or to transfer the data to a computer for in-depth work.

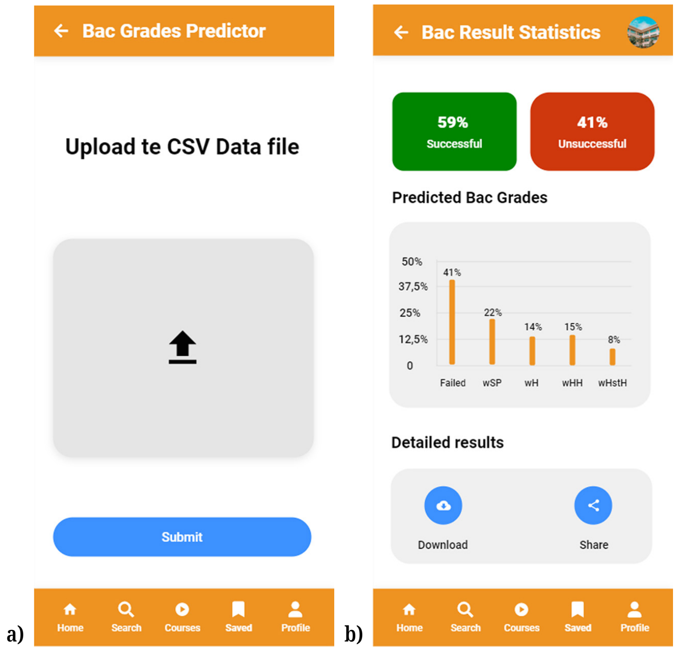


Fig. 10. Stakeholders interfaces

The downloaded Excel file is expected to contain the full scope of predicted results for students enrolled in the Physics stream, specifying which students may require educational support and in which subjects. This file will also include visual charts to enhance the interpretability of the data, providing a clear and immediate understanding of the academic projections.

This interface serves as a crucial tool for stakeholders to evaluate the effectiveness of educational strategies and implement necessary interventions.

6 DISCUSSION

Based on the performance evaluation of our model, we find that our system can accurately predict student performance in the second semester (CA2) and the National Exam (NE). Furthermore, the overall results of the Baccalaureate (GB) are also precise and validated according to the employed metrics (e.g., R^2 = 0.9%, RMSE = 0.92, MAE = 0.03), which are presented in Table 5.

Figure 6 displays statistical forecasts for the overall performance of the PC section, showing the percentages of failures, successes, and merits that students are likely to achieve by the end of the year. Furthermore, our system enables the prediction of student performance by subject in the second semester and the National Exam, as illustrated in Figures 7 and 8. This feature provides teachers with insight into their students' future levels and enables them to take appropriate measures to support their progress.

The availability and timing of these statistics and predictions are crucial. Typically, schools organize support sessions for national exam subjects for all students for about a month at the end of the second semester. However, in our opinion, these sessions are insufficient in terms of time and not targeted, as they do not account for the diverse levels of students. In contrast, our system's predictions are available at the end of the first semester, providing stakeholders (e.g., school directors, teachers, supervisors, and pedagogical administrators) with approximately four months to take necessary measures and apply targeted support for students at different levels (e.g., school-wide, class-wide, group-wide, subject-specific, and student-specific) to improve their performance and increase their chances of success in the Baccalaureate.

Based on the performance evaluation of our models, the accuracy of predictions for scientific subjects like Math, PC, and SVT in the second semester is higher. For literary subjects, the prediction accuracy of the Philo score is higher compared to Ed_IS. In terms of languages, the accuracy of predictions for Ang marks is higher compared to Fr, Arab, and Trad. Concerning the National Exam, we observed that the predictions of scores for scientific subjects like Math and PC are more accurate compared to SVT. Similarly, the predictions for the Ang language are also accurate. However, the predictions for Philo scores are not very accurate.

Based on the interpretation of our findings, several questions arise. Among them, we cite:

a) Why are the predictions of the model in the 2nd semester (Model_S2) more precise for the subjects of the national exam like Math, PC, SVT, Philo, and Ang?

b) Why are the predictions of the model in S2 for literature subjects more precise for Philosophy than for Islamic Education?

c) Why are the predictions of the model in S2 for languages more precise for English than for Arabic, French, and translation, knowing that the teaching of English only starts, in the majority of cases, in Morocco at high school; on the other hand, the teaching of French and Arabic starts from the primary school?

d) Why are the predictions of the model of the national exam (Model_NE) more precise for the scientific subjects Math and PC compared to SVT?

e) Why are the predictions of the Model_NE not precise for the SVT, Philo, and Ang, unlike the predictions of the Model_S2 for the same subjects?

To answer these questions, several hypotheses arise. Among these hypotheses, we propose that:

- Hypothesis 1: According to questions 1, 2, and 3, we suppose that the students in the second year of Bac are more interested in the subjects of the national exam compared to the other subjects, which will be evaluated only by Continuous Control in the classroom.
- Hypothesis 2: According to question 4, we assume that this is due to the coefficients of the subjects since the coefficient of Math and PC is equal to 7 for this section, which is higher than that of the SVT (coef. SVT = 5). This means that the degree of student engagement in a subject may depend on the coefficient.
- Hypothesis 3: According to question 5, we assume that there are other parameters that we must take into consideration in the Model_NE to have more accurate predictions.

In order to validate our hypotheses, we must augment our dataset with additional features that detail the academic trajectory of students from their Common Core curriculum year to their Bac second year. These features may include scores for all subjects throughout their three years of high school, scores for the subjects of the Regional Exam, information regarding their teachers' profiles, and so forth.

7 CONCLUSIONS AND FUTURE WORK

The prediction of students' performance in various subjects is an efficient approach for evaluating student progress and making decisions about additional support or intervention. In this paper, we present a machine learning-based methodology for predictive analysis of high school students' performance in Morocco. The methodology is based on CRISP-DM [36] and employs a real dataset obtained from the adopted School Life Management Software. Initially, we comprehended the problem and the data, and subsequently, for model development, we constructed the dataset using real data from high school students from the school years 2018–2019, 2019–2020, and 2020–2021. Finally, in the validation phase, we evaluated the model's effectiveness by comparing the system's predictions with the actual student results in the 2021–2022 academic year.

The predicted scores for each subject in the second semester and national exams (S2 and NE type), the scores for regional exams, and the first semester are utilized to calculate Bac scores. We evaluated the prediction performances at two levels. The first level involved calculating the most used indicators (e.g., MAE, RMSE, RAE, and RSE), while the second level involved a pedagogical committee led by the school principal. Our results demonstrate that our system can accurately predict student performance. Complementing our predictive model, we have developed a mobile application based on these models. This application is designed to bring our predictive capabilities to a more accessible and user-friendly platform, enabling schools, teachers, and parents to easily interact with our system. Through this mobile application, users can receive tailored recommendations and insights, aiding them in making informed decisions to enhance student academic performance.

In future studies, our aim is to enhance our dataset with additional features such as academics, socials, demographics, and other relevant factors to improve the precision of our predictions for all subjects. We also plan to extend our study by testing our model on other school majors, applying alternative regression and classification machine learning algorithms, and evaluating our model's performance at various levels, including provincial, regional, and national.

In the long run, we aspire to publish our model as a Cognitive Web Service, which will empower schools, teachers, and parents to predict their students' or children's performance accurately. This service will provide actionable recommendations and assist in planning the necessary actions required to improve their academic performance.

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9 AUTHORS

Zakaria Bousalem is with the Polydisciplinary Faculty, Sultan Moulay Slimane University, Beni Mellal, Morocco (E-mail: zakaria.bousalem@gmail.com).

Aimad Qazdar is with the ESTIDMA Laboratory, Ibn Zohr University, Agadir, Morocco.

Inssaf El Guabassi is with the LAROSERI Laboratory, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco.

Abdellatif Haj is with the Faculty of Sciences and Technologies, Hassan 1st University, Settat, Morocco.