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AI-Powered Academic Guidance and Counseling System Based on Student Profile and Interests

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Abstract: Over the past few decades, the education sector has achieved impressive advancements by incorporating Artificial Intelligence (AI) into the educational environment. Nevertheless, specific educational processes, particularly educational counseling, still depend on traditional procedures. The current method of conducting group sessions between counselors and students does not offer personalized assistance or individual attention, which can cause stress to students and make it difficult for them to make informed decisions about their coursework and career path. This paper proposes a counseling solution designed to aid high school seniors in selecting appropriate academic paths at the tertiary level. The system utilizes a predictive model that considers academic history and student preferences to determine students' likelihood of admission to their chosen university and recommends similar alternative universities to provide more opportunities. We developed the model based on data from 500 graduates from 12 public high schools in Morocco, as well as eligibility criteria from 31 institutions and colleges. The counseling system comprises two modules: a recommendation module that uses popularity-based and content-based recommendations and a prediction module that calculates the likelihood of admission using the Huber Regressor model. This model outperformed 13 other machine learning modules, with a low MSE of 0.0017, RMSE of 0.0422, and the highest R-squared value of 0.9306. Finally, the system is accessible through a user-friendly web interface.

Keywords: academic advisor; machine learning; educational counseling; application development; recommendation system; data analytics; admission prediction

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1. Introduction

Educational counseling is a pedagogical and social service that involves orienting students to find the most relevant academic or professional institutions according to their educational background and preferences. Its primary goal is to help students join the right path that aligns with their skills, where they can develop themselves and realize their full potential. It caters to students at all school levels, spanning from primary to higher education [1]. It reinforces their decision-making skills and assists them in finding their own path rather than offering instructions or readymade solutions [2]. Educational counseling has a profound impact on student's lives and futures [3], as the choice of a specific field of study upon entering higher education holds immense weight in shaping a student's career path and can significantly impact the likelihood of securing employment in a related field, as well as the potential for long-term career growth and success [4–6]. This makes educational counseling a fundamental component in establishing a smooth connection between the realms of academia and the professional sphere [7]. Educational counselors hold a critical responsibility in guiding students to make informed decisions regarding their choice of majors [8], especially given the high rates of field of study changes observed among students. Research conducted by the U.S. Department of Education found that approximately 30% of first-time associate and bachelor's degree students changed their majors within three years [9]. Furthermore, a survey conducted in 2014/2015 with 1725 participants revealed that receiving effective academic advising during the first and second years of college can significantly decrease students' likelihood of switching majors [10]. This emphasizes the significance of continuous counseling in aiding students to make informed academic decisions, thereby decreasing the rate of major changes and improving academic retention.

Recently, educational counseling has undergone significant transformations in response to the developments in the education sector. The integration of Information and Communication Technology (ICT) has been a critical driver behind this evolution [11], paving the way for the emergence of online counseling services [12], which have become invaluable for students seeking academic guidance and support, no matter their location [13]. The importance of online counseling services was further highlighted during the COVID-19 pandemic when face-to-face counseling was not feasible [11,14,15]. Since then, it has become necessary to adapt the counseling process to these changing times and encourage counselors to embrace technological tools [16] in order to help effectively meet the evolving needs of students in the current educational landscape and provide them with support that aligns with the contemporary educational paradigm.

Moreover, the use of technology in educational counseling services and tutoring functions has been widely studied, with numerous research [13–18] indicating that it can significantly enhance their effectiveness and accessibility. As a result, many online counseling platforms have been designed and created [19–21] that allow students to connect with educational counselors to receive personalized career guidance and information about universities, programs, degrees, scholarships, and admissions. Certain reputed universities even offer online virtual tours of their campuses [22], and various platforms provide comprehensive information about colleges, universities, and admissions processes to help students make informed decisions about their academic and career paths [23]. These platforms also keep students updated with current educational trends and career opportunities. However, it is essential to mention that, in most cases, and due to the lack of human and financial resources, the educational counseling process still takes place in group sessions at schools [24–26], and some services, like online virtual tours, are only available for a few popular universities worldwide. Additionally, the existing counseling platforms involve certain drawbacks that need to be considered, such as:

- Specialists and certified counselors are not typically involved in non-governmental educational counseling platforms.
- The lack of a free online educational counseling service provided by the government.
- The current platforms operate conventionally and do not incorporate web intelligence techniques [26].
- The number of educational counselors is still insufficient, given the number of students' needs [25].

As part of the ongoing efforts to improve the efficacy of educational counseling, particularly in terms of career and academic guidance [27–29], a novel web-based counseling system has been designed and developed as a supportive resource to aid students in making informed decisions pertaining to their university and major preferences. The system is aimed to support and help high school students who are navigating college applications in selecting the most appropriate college or university [27] by considering each student's academic background and interests, as well as the requirements of their selected university.

The framework is designed to analyze various data inputs, including subject grades and academic setbacks. It works principally in two distinct scenarios; the first step involves predicting a student's chances of gaining admission into their preferred institution [30] from the available universities on the platform. In the second step, the framework utilizes a recommendation engine to suggest alternative universities [31] based on a description matching the career paths and opportunities those universities offer [32]. The recommendation option goal is to empower students by providing them with insights into similar academic opportunities at other universities, especially if their chances of admission are low at their first-choice institution.

To generate the prediction scenario, 13 machine learning algorithms were investigated, including Decision Tree, Linear Regression, Random Forest, K-Neighbours, Support Vector Machine (SVM), AdaBoost Regressor, Gradient Boosting Regressor, XGBoost, CatBoost, Lasso, Ridge, Bayesian Ridge, and Huber Regressor. These algorithms were employed to identify the most accurate model for predictions suiting the collected educational data [33]. In addition, the recommendation scenario was based on content-based recommendations, which suggests similar universities to students, and a popularity-based approach on the home page to address the cold start problem [34] by informing students about their peers' preferences.

2. Research Contributions

In the context of educational counseling, we propose a web-based application for academic advising that combines a recommendation module and prediction module with the following advantages:

- High predictive accuracy: The system provides the student with a credible percentage of his admission chance based on past experiences of other students from the training dataset.
- It addresses the lack of human resources in educational counseling by eliminating the need for direct face-to-face counselor interaction.
- Accessibility: An alternative option for the student to meet with the counselor is through remote means, ensuring convenience and accessibility.
- Saves research time: Comparing multiple universities with similar programs allows students to save time. The system provides tailored and relevant content-based recommendations based on university descriptions.
- User-friendly web-based interface.

3. Related Works

3.1. The Impact of Educational Counseling on Individuals and Society

Receiving guidance from an educational counselor can be immensely beneficial in determining the optimal academic trajectory and career path based on one's interests, strengths, and shortcomings. It is an essential component of the education system, as research has demonstrated its positive influence on students' academic accomplishments and social integration. Research by Turner et al. [35] highlights the significance of availing professional counseling services at the university level, as it can culminate in higher student retention and graduation rates.

Tyilo, N. and Shumba, J. [36] highlight the importance of life orientation for South African students. It provides teachers with new strategies to promote learning autonomy and decision-making skills and address social issues among learners despite challenges in the local educational system.

Oigara and Lyimo [37] emphasize in their study the importance of combining modern and indigenous career counseling approaches to tackle students' challenges in promoting community-based career development and facilitating the process of decision-making.

St. Clair KL [38] published an overview of the research literature related to middle school counseling, including a list of resources and studies for educational counselors working with middle school students.

Dar et al. [39] highlight different approaches and practical techniques for school counselors to support individual and group student assistance; they also underscore the primary rule of counseling services to promote students' well-being and academic progress.

Al-Masarwah [40] led a study of 112 counselors to determine the attitudes of educational counselors towards the use of counseling by playing in their remote counseling work during the period of Coronavirus.

Shahin [41] conducted a comprehensive analysis of the existing educational counseling services in Palestinian public schools, identifying the strengths and weaknesses of the current system and recommending improvements.

In many countries, including Morocco, counseling services are unavailable in schools, and counselors can only visit schools once or twice a year due to limited human resources [25]. This lack of support leads to many students facing confusion, depression, and other mental health challenges as they struggle to pave a path toward a prosperous future [42,43]. Making an ill-informed decision about one's academic or career pursuits can result in severe consequences, such as dropping out of school [5], poor job performance, decreased community involvement, and, ultimately, the hindrance of society's growth.

3.2. The Use of Machine Learning in Educational Counselling

Machine learning techniques have been widely adopted in the education sector in recent years. These techniques have shown significant improvements in students' educational experiences and have been helpful in addressing decision-making challenges. As a result, several research papers have been published that explore the potential of machine learning in addressing the challenges of educational counseling.

Tran, T.Y. et al. [44] proposed a data mining-based model with WEKA software 3.8.3 developed by the University of Waikato in Hamilton, New Zealand, to extract knowledge from educational data and support students in selecting the most suitable courses from the extracted knowledge.

Charleer et al. [45] presented a learning analytics dashboard for student assistance called LISSA to facilitate the dialogue between advisers (counselors) and students by visualizing grade data.

Joachim et al. [46] lodged a multimedia program based on a vocational encyclopedia to foster relevant career decisions by making use of expert advice based on the same user input.

Zayed et al. [27] have developed a system that utilizes supervised machine learning techniques, including Decision Trees, Random Forests, and Support Vector Machines to predict the undergraduate majors of MBA students. They examined various input features, including the student's academic background and the job market, to ensure a high academic degree and employment prospects for students.

Alsayed et al. [47] conducted a study to determine suitable undergraduate majors for students based on current job markets and prior experiences before admission. Several models were evaluated. The findings revealed that Random Forest and Gradient Boosting Classifiers were the most accurate models in suggesting the most fitting undergraduate major. Additionally, higher secondary school marks, university degree marks, and entry test scores were significant criteria for the prediction.

Elahi et al. [31] created a university recommender system, utilizing user preferences as ratings. The system was evaluated through offline and online assessments, employing various algorithms to generate personalized university ranking lists. The findings show that the Singular Value Decomposition (SVD) algorithm performs exceptionally well in terms of accuracy and perceived personalization. Meanwhile, the k-Nearest Neighbors (KNN) algorithm is better in terms of novelty.

Unfortunately, the majority of current models do not take into account student interests or preferences beyond their academic background. Additionally, many papers do not fully utilize machine learning algorithms in this area. The educational counseling process is still being carried out in a traditional manner or through static educational websites that offer only general information about universities and colleges, such as graduation rates, admission requirements, and study costs based on student research.

4. Materials and Methods

4.1. Data Collection

Data collection is a crucial step in the development of any machine-learning model [48]. Our study used an online self-administered questionnaire through Google Forms distributed through scholarly groups on social media. The questionnaire requested information from students on their academic interests, graduation exam scores, and the university or college they were accepted to. We also obtained eligibility criteria and requirements from 31 Moroccan institutions and colleges.

The research considered the experiences of 500 graduates from 12 public high schools in 5 cities throughout Morocco. Our participants represented diverse backgrounds, including urban and rural areas, as indicated in Table 1. Among the rural population, 220 individuals were surveyed, including 100 females (20.0%) and 120 males (24.0%). 280 participants were included in the urban cohort, featuring 157 females (31.4%) and 123 males (24.6%).

Table 1. Demographic description.

	Female		Male		
Area	**Count**	**Percentage**	**Count**	**Percentage**	**Total**
Rural	100	45.45%	120	54.55%	220
Urban	157	56.07%	123	43.93%	280

4.2. Data Analysis

The dataset was generated by consolidating tables containing university admission criteria and students' responses. Following this, the data underwent translation, cleansing, and preprocessing to ensure consistency before being refined for analysis. This refined data was then used to develop a machine-learning model that can predict the probability of eligibility for each student profile in the future.

During the data preprocessing step, we analyzed and selected a specific group of features, as outlined in Table 2. These selected features exhibit diverse levels of impact on the target variable, admission chance.

Table 2. Description of the Dataset.

Columns/Variable Name	Type	Predictor/Response
Gender	Categorical	Predictor
Field	Categorical	Predictor
Repeated in Baccalaureate	Categorical	Predictor
Math	Numeric	Predictor
French	Numeric	Predictor
Physic	Numeric	Predictor
Computer science	Numeric	Predictor
Arabic	Numeric	Predictor
English level	Categorical	Predictor
Your desired School	Categorical	Predictor
University ID	Numeric	Predictor
Admission Chance	Numeric	Response

During the data analysis, we examined the relationship between admission chances and various academic features such as the grades for math, French, Arabic, and physics. We used a pair plot [49], as shown in Figure 1,to visually represent scatter plots of these features against the target variable, admission chance, which provided us with valuable insights into their correlations.

The pair plot, Figure 1, highlighted distinct patterns, revealing that higher admission chances were associated with higher grades in French and math, indicating a significant positive correlation. Moreover, commendable performance in Arabic and physics also showed a positive correlation with admission chances.

This analysis, confirms that academic excellence, as reflected in higher grades, is strongly correlated with increased admission chances.

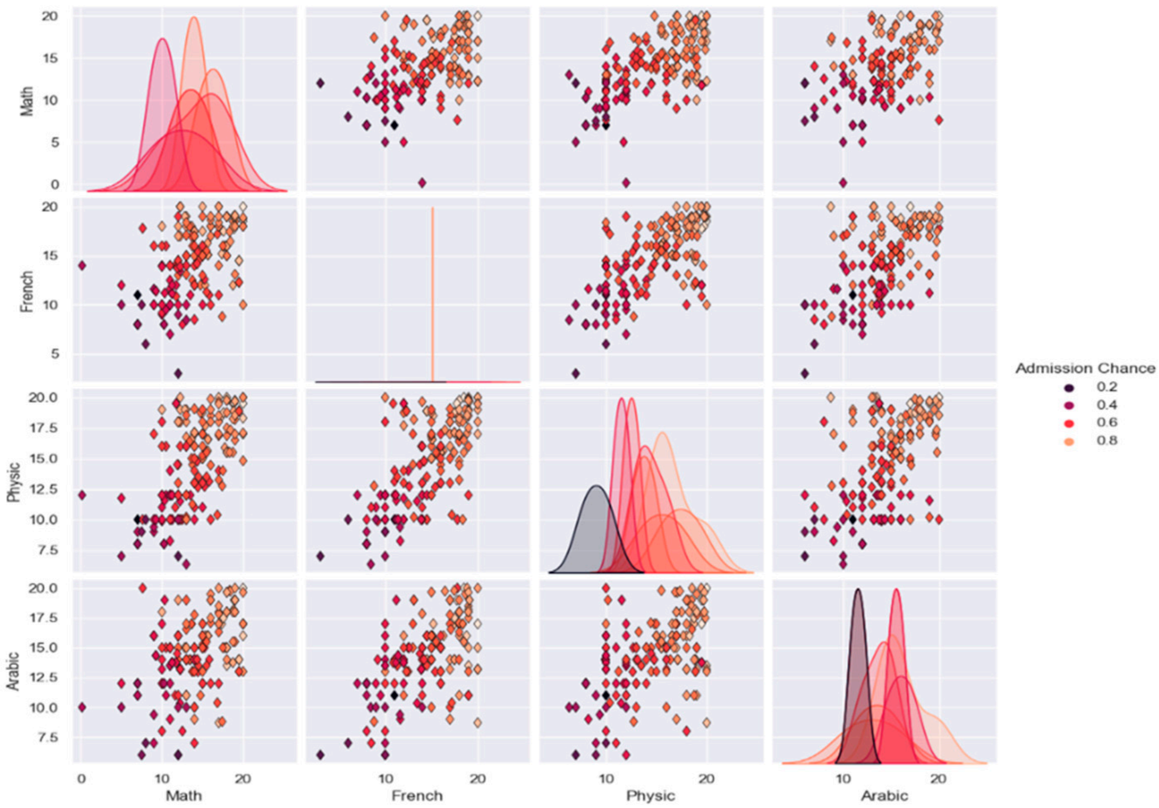


Figure 1. The correlation between school subject and admission chance.

Based on the analysis of the dataset, Figure 2, it has been noted that students who have pursued mathematics during their high school education demonstrate a greater likelihood of gaining admission to their preferred universities. This suggests that selecting mathematics as a field of study may enhance the probability of a student's acceptance into their desired academic institution.

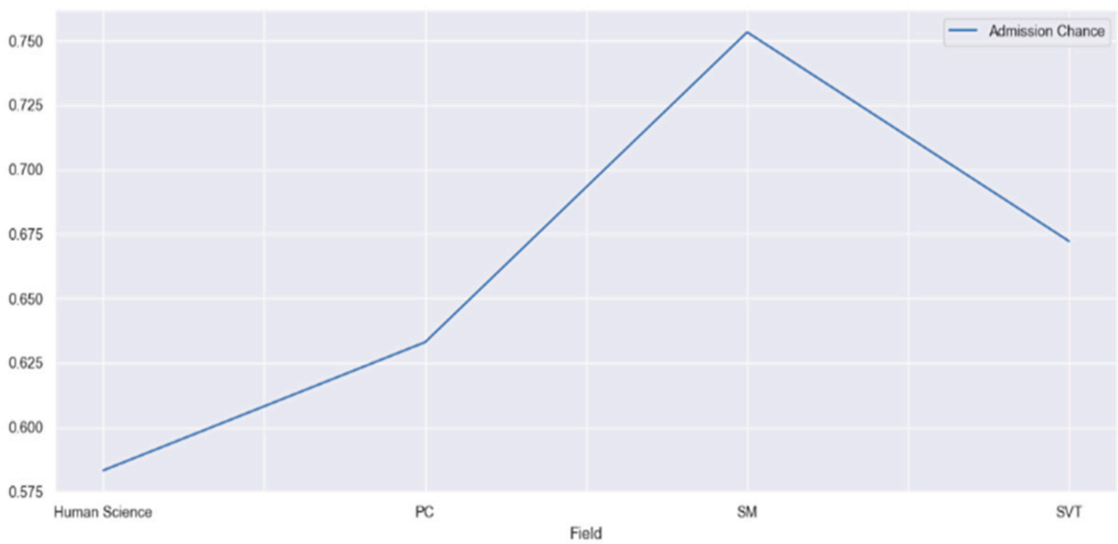


Figure 2. The correlation between field and admission chance.

To effectively exploit this data and add it to the model, we utilized the label encoding [50] approach to transform the key categorical characteristics, Field and Desired University, into a unique scalar numerical value to be utilized as input with other features.

We determined the input variable and output variable as below:

Upon the student inputting his information, including field, school subject grade, and desired university, the system will display a message box indicating the student's field of study, desired university, and admission chances. The system will also suggest the five most similar universities based on the student's desired university (Table 3, Figure 3).

Table 3. Input and Output Result.

Input	Output			
Field	Field	Admission Chance	Desired University	Similar Universities
School Subject Marks				
Desired University				

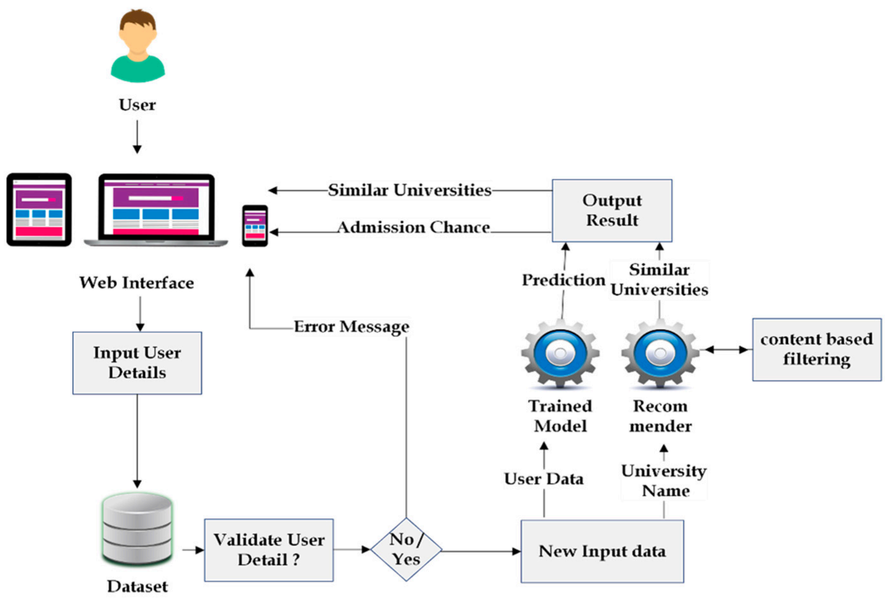


Figure 3. System architecture.

4.3. System Architecture

The counseling system consists of two modules: The recommendation module and the prediction module.

4.3.1. Recommendation Module

The architecture of the proposed system includes two types of recommendations that aim to enhance the student counseling experience. The first type of recommendation is prominently displayed on the application's home page and is especially useful in addressing the "cold start" problem [34]. This issue arises when a newly registered user has no existing information in the system and is unaware of the range of available universities. In such cases, students can explore the most popular universities based on the searches and preferences of their peers.

The second type of recommendation is triggered when a student inputs the name of their preferred university through an interactive form. Using the content-based filtering algorithm, the system generates a list of five similar universities. This algorithm selects universities based on various factors, including university descriptions and information about career options and available academic fields. This type of recommendation offers students the opportunity to explore other universities that match their interests and preferences, opening up new opportunities for them.

4.3.2. Prediction Module

Upon logging into the platform, students can complete a prediction form (Figure 3) by submitting their grades for each subject and choosing their preferred university from a drop-down list. Subsequently, the system employs this data, in conjunction with the university's admission threshold from its dataset, to calculate the student's likelihood of admission as a percentage.

This prediction is generated through several iterations. We tried to identify the optimal machine-learning model capable of accurately predicting student admissions chances. We tested 13 models (Table 4) and evaluated their performance using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared metrics. The model that exhibited superior performance was selected and further optimized by adjusting the learning rate hyperparameters. Ultimately, we validated the model by splitting the dataset into training and testing sets to ensure it could produce accurate predictions on new data. The goal was to find our case's most precise and accurate model.

Table 4. Machine Learning Models.

Model	Description	References
LASSO	Penalizes regression coefficients, useful for feature selection.	[51]
Ridge Regression	Adds a penalty term to prevent overfitting and manages multicollinearity.	[52]
Bayesian Ridge	Incorporates Gaussian prior to variable selection and multicollinearity.	[53]
Elastic Net	Combines Lasso and Ridge regularization with a balance parameter.	[54]
Huber Regressor	Robust to outliers, uses a combined loss function.	[55]
Linear Regression	Models the relationship between variables using a linear equation.	[56]
Logistic Regression	Models the probability of a binary outcome or event based on one or more independent variables.	[57]
SGD Regressor	It uses stochastic gradient descent for optimizing large-scale data.	[58]
AdaBoost Regressor	Boosts regression model performance by aggregating weak learners to create a more robust and precise predictor.	[59]
Gradient Boosting Regressor	Improves the accuracy of regression models by combining multiple weak models, typically decision trees, and minimizing the loss function using gradient descent.	[60]
XGB Regressor	It employs decision trees as base learners and utilizes gradient descent to optimize boosting.	[61]
CatBoost Regressor	Handles datasets with mixed feature types and provides multiple hyperparameters to enhance model performance.	[62]

5. Results and Discussion

We evaluated all used Machine learning models using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared metrics [63] to evaluate the performance of each model and to determine the most performant model. The results obtained from this evaluation are presented in the table below:

Based on the results obtained (Table 5), we can notice that the most performant model is the Huber Regressor, which has the lowest Mean Squared Error (MSE) of 0.0017, Root Mean Squared Error (RMSE) of 0.0422 and the highest R-squared value of 0.9306.

The Huber Regressor model is less sensitive to outliers compared to ordinary linear regression. It performs well in our case.

It is also important to note that the SGD Regressor model has extremely high MSE and RMSE values and a negative R-squared value, indicating that it should be avoided in this study.

Other models such as Linear Regression, Ridge, Bayesian Ridge, Random Forest, XGBoost, and CatBoost also perform well with relatively low MSE, RMSE, and high R-squared values, indicating good accuracy.

Table 5. Models Evaluation 1.

Model	MSE	RMSE	R-Squared
Decision Tree:	0.0079	0.0888	0.6931
Linear Regression:	0.0034	0.0583	0.8675
Random Forest:	0.0035	0.0595	0.8622
K-Neighbours:	0.0070	0.0839	0.7265
SVM:	0.0053	0.0733	0.7907
AdaBoost Regressor:	0.0059	0.0774	0.7672
Gradient Boosting Regressor:	0.0033	0.0582	0.8680
XGBoost:	0.0045	0.0672	0.8244
CatBoost:	0.0035	0.0598	0.8609
Lasso:	0.0258	0.1606	−0.0028
Ridge:	0.0023	0.0485	0.9085
Bayesian Ridge:	0.0022	0.0473	0.9129
Elastic Net:	0.0258	0.1606	−0.0028
Huber Regressor:	0.0017	0.0422	0.9306

6. Implementation

We implemented a simple and user-friendly interface using PyCharm [64] software to facilitate students' interactions and explore the application's services, enhancing the counseling experience with innovative functionalities.

6.1. Home Page

Upon accessing the home page of the educational guidance platform, as illustrated in Figure 4 below, students will be able to view the universities that are most frequently searched, as well as the preferences of other students. This is intended to aid students who may be uncertain about their preferences.

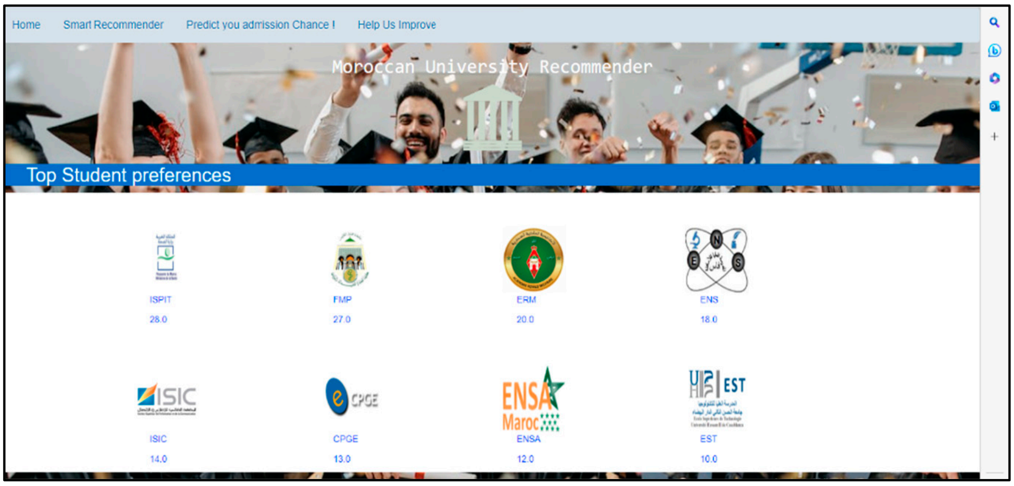
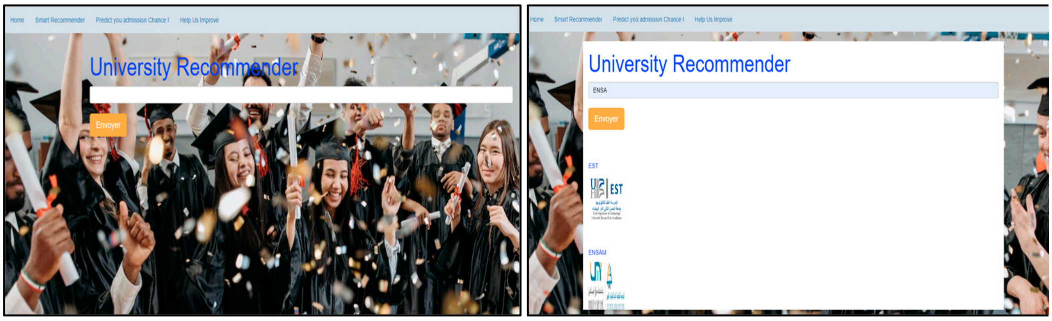


Figure 4. The home page.

6.2. Recommendation Module

The platform offers a user-friendly recommendation service to students who are seeking universities with similar options for their academic pursuits, Figure 5. With this system, students can perform comprehensive searches that offer pertinent results, enabling them to explore various universities that offer similar study areas and career paths.



(a) (b)

Figure 5. (**a**,**b**) Content-based recommendation.

6.3. Prediction Module

As indicated in Figure 6 and Table 3, the system allows students to enter their academic scores and field of study to determine the probability of their admission to universities. Using a content-based filtering approach, the system also suggests five institutions with similar features to the student's preferred university [65].

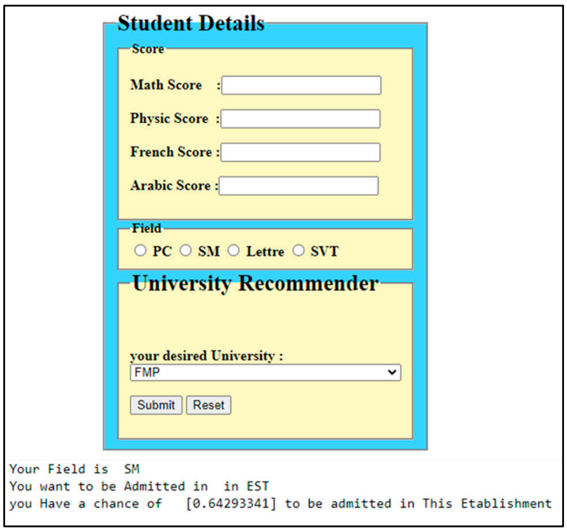


Figure 6. Admission chance prediction.

6.4. User Feedback

Gathering user feedback is critical to this project, as it is a vital connection between the counseling team and the student community, Figure 7. Their thoughts, suggestions, and opinions provide invaluable insights that we can use to enhance the platform and continuously improve the educational counseling experience.

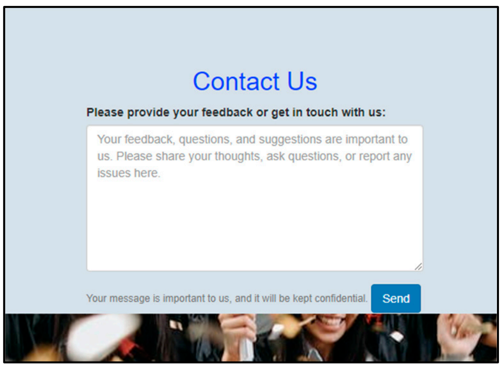


Figure 7. Feedback form.

7. Conclusions

This research presents a novel educational counseling system that offers enhanced support to high school seniors while they navigate the college application process. The system's primary objective is to aid students in selecting the most suitable college or university based on their academic background and the institution's requirements. It functions as an informative resource, providing students with valuable insights into their chances of being accepted to their preferred institution while also suggesting alternative academic opportunities at similar universities based on their interests, thereby alleviating the burden of extensive research.

To determine the most accurate model for the prediction task, thirteen machine learning algorithms were evaluated, including Decision Tree, Linear Regression, Random Forest, K-Neighbours, Support Vector Machine (SVM), AdaBoost Regressor, Gradient Boosting Regressor, XGBoost, CatBoost, Lasso, Ridge, Bayesian Ridge, and Huber Regressor. After careful consideration, the Huber Regressor was deemed the most accurate model.

In addition to the prediction task, the system also incorporates a recommendation algorithm that offers alternative university options to students when they realize their chances of being admitted to their preferred university are low or when they wish to save time searching for universities that offer similar career paths. The recommendation scenario uses a content-based approach that suggests similar universities to students based on a university description available in the dataset. Additionally, it utilizes a popularity-based approach implemented on the system's homepage to provide students with information on their peers' preferences.

This project aims to provide easily accessible educational guidance services to all students, given its significance in both the academic and social aspects of their lives. By automating this process, the system can address the shortage of human resources in educational counseling and save time and cost for students who would otherwise have to travel to obtain university information.

The proposed work will continue to be refined with a more extensive database of universities to cover national and international institutions and add more student experiences, as well as work to improve the web interface of the system to make it a more informative and user-friendly resource.

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Institutional Review Board Statement: Ethical Approval for the study was not required as it falls under the category of non-interventional research, specifically a social survey, in accordance with local legislation, NOTE DE PRESENTATION DU PROJET DE LOI RELATIVE A LA PROTECTION DES PERSONNES QUI PARTICIPANT AUX RECHERCHES BIOMEDICALES. This underscores the country's commitment to international standards in research generally, including the Universal Declaration of Human Rights (1948).

Informed Consent Statement: Informed consent was obtained from all subjects involved.

Data Availability Statement: The data is available upon request only, due to privacy restrictions.

Conflicts of Interest: The authors declare no conflicts of interest.

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