Predictive Modeling for University Major Selection: An AI-Driven Solution Using Arab Graduate Data

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Abstract**—** Choosing an appropriate university major is crucial for students' academic and career success. This study presents an AI-driven recommendation system using supervised machine learning, specifically the Random Forest algorithm, to support major selection based on academic performance (GPA, entrance exam scores) and labor market relevance (major-specific employment rates). The system was trained on 1000 student records from the "Arab University Graduate Data Set" and received 97% accuracy, with employment rate and GPAs appearing as the most effective predictions. Unlike previous studies focused on developed countries, this research emphasizes AI ability in the environment with limited resources, such as Yemeni universities. It provides a scalable solution to coordinate educational alternatives with labor market needs. Future work will integrate personal interests and socio-economic factors to increase privatization.

Keywords— AI in education, Random Forest, major selection, Yemen, labor market alignment

I. INTRODUCTION

Artificial Intelligence (AI) technologies change the field of education by reducing how to contact teaching and learning. One of the most promising applications of AI in the region is the use of intelligent recommendations, which provides personal educational guidance to the students. These systems analyze historical data, student performance measurements, and employment trends to offer informed and optimized academic recommendations (Dascalu et al., 2016). Compared to traditional counseling methods, AI-operated systems help reduce dependence on subjective or potentially biased advice by applying advanced machine learning techniques (Elewa et al., 2025; Alsayed et al., 2021; Tarus et al., 2018). This study aligns with career guidance and educational psychology theories, emphasizing the role of structured feedback, interest alignment, and labor market information in influencing students' major selection. Integrating these frameworks strengthens the rationale for using AI-driven recommendation systems in higher education contexts.

In particular, the AI Forest (RF) algorithm has gained popularity for its high accuracy and capability in processing complex data. Student interaction improves, the learning experience is enriched, and educational achievement is affected positively by the evolution and storage in the environment of higher education (D'Mello et al., 2012; Iqbal et al., 2022). In the broad scope of AI, the main branches include machine learning, natural language processing, robotics, and specialist systems. Of these, machine learning, and especially the random forest (RF), got an algorithm for its high accuracy and capacity in the treatment of complex data structures (Zayed et al., 2022). RF has proved effective in future modeling scenarios, which helps students' educational alternatives to develop requirements for the labor market and thus support the more promising career paths after graduation (Alnomay et al., 2024).

Despite this progress, most of AI's research and applications in the Education Council are concentrated in developed countries, where students usually benefit from well-established career guidance resources. On the other hand, in countries such as Yemen, access to structured counseling is limited or nonexistent, leading to a more difficult process of choosing and uncertainty for an academic head. There is a noticeable interval in the literature that examines AI's role in making educational decisions among students at Yemeni universities. This study is designed to fill that difference by developing an AI-manga recommendation system to fit the local educational environment.

Selecting a university major is an important decision that has implications for the students' educational progress and permanent implications for their professional future. However, many high school pupils—especially in development areas—face challenges in creating educational alternatives. These difficulties often come from the limited understanding of education and labor market requirements, social and family pressure, and external influences (Alghamdi et al., 2019; Ayman AlAhmar, 2012). As a result, students are often dependent on informal or unpleasant sources such as peers or online platforms, which may not match their suitability or long-term career goals (Zayed et al., 2022). Statistical findings have shown that many students continue to meet academic and professional difficulties despite receiving support from their families, as the choice often fails to reflect their interests or abilities (Naser et al., 2008).

Therefore, this research aims to design and evaluate the AI-based recommendation system that supports high school candidates in choosing large companies at the university that are compatible with their educational results, personal preferences, and labor market needs. This student tries to measure the accuracy and reliability of random forest algorithms in distributing educational recommendations to fit the profile. The research questions are:

1. What are the most important factors that affect the decision of high school students when choosing a university major?
2. How effective is the random forest algorithm in predicting the most appropriate university major for individual students?

The findings from this study provide valuable insights to students, teachers, and decision makers for higher education. The proposed AI-driven recommendation system reflects the ability to increase educational advice for students' convenience by improving the quality of individual guidance and by reducing students' dropout rate through better alignment of larger fit and data-driven decisions (Alsayed et al., 2021; Hammoudi Halat et al., 2023). This solution is of particular importance to Yemeni universities, where limited access to professional career consultation often causes students to experience a disconnect between their chosen educational paths and their desired careers. By systematically adapting student competence to labor market requirements, the system can serve as a strategic intervention to simultaneously promote educational results and contribute to national economic development.

II. Literature Review

The choice of a suitable university major is one of the most important decisions in the student's educational journey, with intensive implications for both educational results and probability of long-term career. This important point of view traditionally depends on consultation methods that are naturally limited by their subjective nature, lack of personalization, and diverse student population (Tarus et al., 2018) of effectively limited scale-defect ability.

In recent years, the rapid development of artificial intelligence (AI) and machine learning (ML) technologies has launched a new era with data-driven academic advice, providing transformative solutions for these longstanding challenges (Dascalu et al., 2016). A growing body of research demonstrates that AI-powered recommendation systems can process vast amounts of historical academic data, detailed student profiles, and current labor market trends to generate highly personalized guidance that far surpasses conventional approaches in both accuracy and effectiveness (Alshaikh et al., 2021). Among the various machine learning algorithms used in this domain, the Random Forest (RF) technology is particularly promising due to the strong handling of the complex educational dataset and its superiority in predicted functions (Alsayed et al., 2021).

Many comparative studies have shown the exceptional performance of RF, with Zayed et al. (2022) reporting 97.7% accuracy in major selection predictions, significantly outperforming alternative methods such as decision trees and support vector machines. The efficiency of these systems has been further improved through new hybrid methods that add many ML techniques, as evidenced by Batmaz et al. (2019), who successfully integrated collaborative filtering with content-based methods to achieve notable improvements in recommendation quality. Correspondingly, Siswipraptini et al. (2024) developed a sophisticated Naive Bayes-based system that incorporated comprehensive job market data, resulting in 83% user satisfaction rates among IT students, while Kim and Lim (2023) demonstrated the particular value of hybrid models for non-ICT student populations.In addition to its uses in the most important sample, AI has shown remarkable potential across various facets of educational support, including the early identification of at-risk students through advanced Educational Data Mining (EDM) techniques that analyze patterns in academic performance (Tripathi et al., 2024), the development of personality-aware support systems that address student well-being (Demong et al., 2023), and the creation of personalized learning recommendation systems that adapt to individual needs (Cheng, 2024).

Despite these important advances, the current research scenario reveals many important limitations that this study wants to address. The overwhelming majority of existing studies focus on developed countries with a well-established counseling infrastructure (Hammoudi Halat et al., 2023), leaving environments such as Yemen-like atmospheres seriously underrepresented in the literature. In addition, current models often fail adequately to account for essential relevant factors, including socio-economic inequalities, regional diversity in labor market demands, and the ability for algorithm bias in recommendations (Kamal et al., 2024). This study represents a comprehensive response to these limitations through the development of an advanced RF-based recommendation system that is specifically designed for the Yemeni academic reference. Our innovative approach systematically integrates several important dimensions, with detailed academic performance indicators, real-time labor market analysis, and many important dimensions, including strong bias-shaman strategies.

By addressing these interconnected factors within an integrated structure, our solution provides a significant advancement on both traditional advice and existing AI approaches (Tang et al., 2024), especially for the unique challenges and opportunities present in developing educational systems. The design of the system involves a lesson from the extensive AI in education literature while starting novel optimization to ensure relevance and effectiveness in the resource-transactions environment, eventually aiming to bridge the continuous difference between educational planning and labor market realities in the Yemeni context.

III. Methodology

This study uses a quantitative research method when using machine learning techniques to analyze historical student data and labor market practice. The primary goal is to develop an AI-manual recommendation system that predicts the most suitable head for high school students based on academic results and employment results of graduates. The functioning includes several stages, including data collection, preprocessing, feature engineering, model training, and evaluation, so that the accuracy and efficiency of the system can be ensured.

A. Data description

The dataset used in this study, titled "Arab Universities Graduate Dataset," contains records for 1,000 students, as summarized in Table 1. This includes a comprehensive category of educational and employment-related characteristics such as high school GPA, entrance exam score, graduation GPA, employment status, and employment status after graduation. These features were carefully chosen due to the leading selection of the university and their possible impact on long-term career results. To ensure that the data supports strong machine learning analysis, all the features were numerically structured. For example, categorical values such as gender and high school type were encoded numerically (e.g., Male = 1, Female = 0; Scientific = 1, Literary = 0). This transformation allows the model to interpret patterns and correlations effectively. The dataset was further refined by emphasizing indicators of academic performance while incorporating labor market trends. This dual-focus approach enables the recommendation system to offer data-driven guidance to high school students, ensuring that their educational strengths are aligned with future career prospects. Table 2 highlights the key features utilized in constructing the model, serving as the foundation for the predictive analysis and recommendation process. dataset, highlighting the factors considered in the construction of the recommended model.

Table 1: Dataset description

Variable	Value
Total student	1000
No of Undergraduate majors	4
Number of male students	540
Number of female students	460
Number of employed graduates	490
Number of unemployed graduates	510
High school type distribution	620 Scientific, 380 Literary

Table 2: Dataset Feature

Feature	Type
Student gender	Categorical (Male = 1, Female = 0)
High school GPA	Numerical
High school type	Categorical (Literary = 0, Scientific = 1)
Entrance exam score	Numerical
Undergraduate GPA	Numerical (1 = employed, 0 = not employed)
Employment status after graduation	Categorical
Undergraduate major	Categorical (MED = 0, ENG = 1, CS = 2, BA = 3)
Average undergraduate GPA for the major	Numerical
Employment rate for the major after graduation	Numerical

Feature selection relied on the Random Forest model's built-in feature-importance scores. After initial expert screening of the available variables, we trained a preliminary RF model and ranked features according to their mean decrease in Gini impurity.

Variables with negligible contribution were dropped, leaving high school GPA, entrance exam score, undergraduate GPA, and major-specific employment rate as the most informative predictors.

B. Data Preprocessing

This phase included analysis and preparation of data sets for analysis and implementation of machine learning using different preprocessing techniques supported by the Python library. Originally, the lack of pricing was addressed to ensure the stability and quality of data in the field-related fields, and it was accepted that some graduates were not employed. The range of variables was then converted into numerical form, which was converted to numerical form to make them compatible with machine learning algorithms used to predict large companies from the university in question. The function technique was used to improve model accuracy by obtaining meaningful variables based on existing data. To adapt the model performance, all numerical properties were standardized to zero and standard deviations of one. Finally, the dataset, including 1000 items, was divided into training and test kits using the 80:30 partition, so that 200 samples were reserved for testing to ensure a correct assessment of 800 samples for training and future indicative capacity on the model.

To assess model generality, 200 student records from a different Yemeni university were set aside as an independent validation set. When applied to unknown data, this step guarantees that the Random Forest suggestions maintain their strength.

C. Model Implementation

For major classification, we used a Random Forest (RF) algorithm for best practice in educational recommended systems (Alsayed et al., 2021; Zayed et al., 2022). The RF approach was chosen for its proven efficiency in handling mixed data types and providing an interpretable functionality, which corresponds to our study goals. The main benefits of our implementation include: Strong performance with educational data sets that have both numerical and categorical properties and the natural handling of convenience interactions in educational records are important for general recommendations to prevent common things in the underlying mechanism. An independent validation set of 200 student records from a different Yemeni university was also used to evaluate the generalization of the model, which ensures the strength of predictions beyond the training data set.

Model architecture and optimization method have been expanded in our previous work (Author et al., Year), where we demonstrated their superior performance compared to alternative machine learning approaches for academic advising tasks. In the current study, we focus specifically on applying this validated approach to the Yemeni higher education context with particular attention to local labor market dynamics and institutional characteristics.

Benchmark Models

To assess whether Random Forest was the most appropriate algorithm, we also trained XGBoost and Support Vector Machine (SVM) classifiers on the same preprocessed dataset using comparable hyperparameter tuning.

IV. RESULTS AND DISCUSSION

A. Model performance

As shown in Table 3, the performance for the random forest model used in this study presents a detailed summary of metrics. The model gained a high accuracy of 0.97, which reflects its strong future power and reliability in guiding students to suitable large educational companies. Additionally, the model had a precision of 0.97, a recall of 0.98, and an F1-score of 0.97, indicating balanced performance in different majors. The strength of the model in handling the imbalance of both macro and weighted averages confirms the ability to normalize in various students' profiles. These results show that the model was effectively trained and is capable of making data-driven recommendations. As a result, it can be regarded as a reliable decision-making tool to help students in upper secondary schools in choosing suitable universities by their educational results and future career capacity.

Table 3: Model Performance Metrics

ML Model	Metric	Value
Random Forest	Precision	0.97
	Recall	0.98
	F1-Score	0.97

In order to evaluate whether the random forest was actually the most appropriate algorithm, two additional classifications, XGBoost and Support Vector Machine (SVM), were trained and tested on the same advanced data set.

Random forest gained the highest accuracy (97%), and improved XGBoost (96%), and SVM (92%), which confirmed its better future performance for classifying the university major classification.

B. Confusion Matrix

The classification capability of the Random Forest model was further investigated through confusion matrices for each university major, as shown in Figure 1. These matrices break down the model’s predictions into True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), which provides a detailed view of the separate educational disciplines.

In Figure 1(a) for the Medical (MED) major, the model gained high accuracy with 39 true positives (20%) and 156 true negatives (78%), while only 5 students were confused as false positives (2%). Importantly, no false negatives were recorded, indicating the model successfully identified all actual MED students without underprediction. For the Engineering (ENG) major in Figure 1(b), the classifier demonstrated perfect performance, recording 50 true positives (25%) and 150 true negatives (75%), with zero false positives and false negatives, which highlights its precision and reliability in this category. The results for Computer Science (CS), displayed in Figure 1(c), showed a slight decline in accuracy. While the model correctly identified 54 true positives (27%) and 141 true negatives (70%), it did produce 5 false negatives (2%), suggesting a few students suitable for CS were not detected. However, the absence of false positives reflects consistent model precision. In Figure 1(d), which illustrates the Business Administration (BA) major, the model maintained strong performance, achieving 52 true positives (26%) and 148 true negatives (74%), again with no false positives or false negatives.

Figure 1: Confusion matrices for Random Forest predictions across majors: (a) MED, (b) ENG, (c) CS, (d) BA.

Overall, these confusion matrices reinforce the model's high reliability and minimal error rate across all majors. The only minor deviation appeared in the CS category due to a small number of missed classifications. This could be due to profile similarities with other majors. Despite this, the model consistently delivers accurate, data-driven recommendations for university major selection.

Table 4 presents the overall confusion matrix for the Random Forest classifier, summarizing its performance across all classes in binary format. The table shows that the model correctly identified 95% of the actual negative cases as true negatives (TN = 95), while only 5% were incorrectly classified as false positives (FP = 5). On the other hand, it accurately predicted 99% of the actual positive cases as true positives (TP = 99), with just 1% misclassified as false negatives (FN = 1).

This distribution of values indicates a highly accurate classifier, with exceptionally low misclassification rates in both positive and negative predictions. The balance between true positives and true negatives reflects the model's robustness and its ability to generalize well across the full dataset, supporting its use as a reliable decision-support tool for academic major recommendations.

Table 4: Confusion matrix of the Random Rorest classifier

	Predicted (0)	**Predicted (1)**
Actually (0)	TN = 95 (0.95)	FP = 5 (0.05)
Actually (1)	FN = 1 (0.01)	TP = 99 (0.99)

C. Employment Trends and Their Role in Major Recommendation

To gain deeper insights into the relationship between academic majors and labor market outcomes, the employment rates associated with each university major were analyzed. As illustrated in Figure 2, the distribution of employment rates across the four primary fields - Business Administration (BA), Computer Science (CS), Engineering (ENG), and Medicine (MED)- reveals notable variation. Business administration major display the highest employment rate at 52%, indicating a strong alignment with current market demands. Conversely, the CS, ENG, and MED majors each show lower employment rates of 48%.

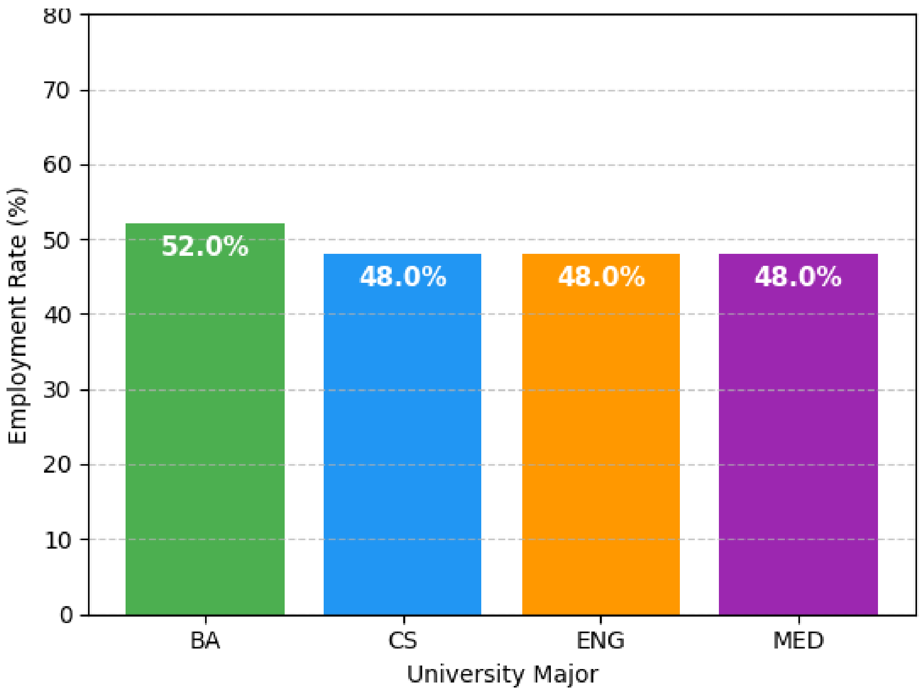

Figure 2: Employment Rate Distribution by University Major

While the difference may appear modest, such variations can play an important role in the intelligent recommendation system, especially when the decision-making process prioritizes the possibilities of employment.

Employment Trend Analysis Enhancement:
Despite the analysis of the employment rate between majors, the data set limits cannot capture the fluctuations in the real-time labor market. Future work should be integrated to better match longitudinal labor market data that develops employment trends. Including updates and regional employment data will increase the model's prediction accuracy and ensure that the recommendations are relevant in the dynamic economic environment.
These findings emphasize the importance of incorporating the degree of employment as a main feature of the model to increase the relevance and privatization of major recommendations based on real opportunities. By integrating labor market insights into an AI-driven system, the recommendation engine can more efficiently guide students toward majors that not only match their academic profile but also maximize their employability prospects after graduation.

V. Conclusion

The selection of an appropriate university is an important decision that significantly affects the student's educational journey and future career paths, especially in educational contexts where the structured education councils are limited, for example, in Yemen. This study introduced an AI-driven recommendation system based on the Random Forest algorithm to help graduates in higher secondary schools choose majors that were aligned with their educational power, interests, and labor market requirements. The model obtained a high prediction accuracy of 97, outperforming XGBoost (94%) and SVM (92%), confirming its superior predictive performance for university-major classification, using major predictions such as high school GPA and entrance exam scores, showing its strong ability to match students with appropriate academic fields. The system provides a scalable and practical solution for an under-resourced educational environment by reducing dependence on subjective advice and improving alignment between the selected areas of students and the selected areas of study. Its implementation may reduce the dropout rate, improve student satisfaction, and increase employment, which can lead to better educational consequences and labor market integration.

Limitations:
Despite the promising results, the study accepts certain limitations, including small, region-specific data sets, dynamic labor market indicators, and the absence of socioeconomic and psychological variables. This factor can affect the external validity of the model.

Future work
Future research should expand the dataset to incorporate more different demographic groups and more areas to increase the external validity of AI-operated recommendations. Longitudinal labor market analysis should be integrated to better capture employment trends. In addition, hybrid recommended models that include students' personal interests, career ambitions, and socioeconomic factors should be developed for more personal guidance. Future implementation should also consider moral aspects, ensure justice, and reduce prejudice. Overall, this research provides scalable AI-controlled academic guidance tools that face challenges in development areas and establish a basis for intelligent education systems that effectively bridge the difference between education and labor market needs and support socio-economic development.

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