Building an Effective Recommendation Model For Students' Academic Pathways Using Machine Learning

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ABSTRACT

Selecting the most suitable academic pathway is critical for students in higher education, as it can significantly impact their future career opportunities and success. This paper proposed a recommendation system for students in the Civil Department at Al-Azhar University's Faculty of Engineering. The system was created using the grades of students who graduated from the department in the period from 2018 to 2022. Different machine learning algorithms such as Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), Naive Bayes (NB), and Support Vector Machine (SVM), are applied to create models for each major in the Civil Department. The models are evaluated using 5-fold cross-validation method, with the F1-measure serving as the performance criterion. The results indicate that the KNN model achieves the best performance for the Structural Engineering and Public Works majors, with an F1-measure of 84% and 87% accuracy, respectively. On the other hand, the NB model achieves the best performance for Irrigation and Hydraulics, with an F1-measure of 69%.The proposed recommendation system can potentially assist students in making informed decisions about their academic careers, by recommending the most appropriate major based on their academic performance.

KEYWORDS: Recommendation system, Machine learning, Educational data mining.

بناء نموذج توصية فعال للمسارات الأكاديمية للطلاب باستخدام التعلم الآلي

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الملخص

يعد اختيار المسار الأكاديمي الأنسب أمرًا بالغ الأهمية للطلاب في التعليم العالي ، حيث يمكن أن يؤثر بشكل كبير على فرصهم الوظيفية المستقبلية ونجاحهم. اقترحت هذه الورقة نظام توصية لطلاب القسم المدني بكلية الهندسة بجامعة الأزهر. تم إنشاء النظام باستخدام درجات الطلاب الذين تخرجوا من القسم في الفترة من 2018 إلى 2022. خوارزميات مختلفة للتعلم الآلي مثل Decision Tree (DT) و Random Forest (RF) و K-Nearest Neighbor (KNN) و Naive Bayes (NB) يتم تطبيق (SVM) Support Vector Machine و لإنشاء نماذج لكل تخصص في الإدارة المدنية. يتم تقييم النماذج باستخدام طريقة 5-fold cross-validation ، حيث يعمل F1-measure كمعيار للأداء. تشير النتائج إلى أن نموذج KNN يحقق أفضل أداء لتخصصي الهندسة الإنشائية والأشغال العامة ، حيث بلغت دقة ٪84 F1-measure و 87٪ على التوالي. من ناحية أخرى ، يحقق نموذج NB أفضل أداء للري والمكونات الهيدروليكية ، مع F1-measure -بنسبة 69٪. يمكن أن يساعد نظام التوصية المقترح الطلاب في اتخاذ قرارات مستنيرة حول حياتهم الأكاديمية ، من خلال التوصية بالتخصص الأكثر ملاءمة بناءً على أدائهم الأكاديمي.

الكلمات المفتاحية : نظام توصية , تعلم الآلة , التنقيب عن البيانات التعليمية.

1. INTRODUCTION

In many universities, students drop out because of choosing educational paths that are not appropriate for their abilities. This happened at the Faculty of Medicine of Assiut University, where more than 60% of the students failed despite performing exceptionally well in secondary education. This is because the students did not select the educational paths that matched their abilities. Therefore, helping students find the educational paths best suited to their abilities will decrease the number of students leaving educational academies. Lowering the number of students who drop out of educational academies will also help improve the quality of instruction. However, to accomplish this, formidable challenges were found. One of the significant challenges is collecting student data to make a history of their educational paths. By analyzing and extracting sufficient information, it is possible to predict the appropriate educational path for a student.

Data mining is a powerful technology that, in its simplest form, can be defined as the automated process of discovering relevant patterns and relationships from data and information [1]. The information obtained through data mining techniques can help higher education institutions in various ways, such as better decision-making, more effective planning for student guidance, more accurate behavior prediction, and more efficient staff and resource allocation. It improves the effectiveness and efficiency of the processes [2-4]. Predicting students' academic paths is one of the main challenges that higher education is currently facing. Many higher education systems are unable to identify student populations who are likely to drop out, due to a lack of intelligent methods to use data and knowledge from the university system. The probability of a current student returning to university the next year or changing his major remains hard to predict with any degree of certainty, despite the existence of several studies that analyze student persistence patterns [5] [6].

A significant academic challenge is to develop learning and teaching strategies to enhance retention and progression in the educational process, which largely depend on monitoring student performance and utilizing student feedback. The main sources for examining student feedback and development are grades and achievements, but universities and educational institutions can also use these data to predict student performance, dropout rates, and study paths. The primary objective of this study is to help students choose an educational path that matches their talents and abilities. Providing them with this guidance as soon as possible enables students to select the educational path that suits them, reducing the number of university dropouts and improving the quality of education. This paper focuses on some departments within Al-Azhar University's Faculty of Engineering.

Section 2 of this article reviews many of the related research works, while Section 3 represents the proposed recommendation model and an overview of the developed solution. Section 4 presents and discusses the experimental implementation and its results, while Section 5 concludes and suggests some future research directions.

2. RELATED WORK

Choosing the appropriate educational path for one's abilities and skills is essential for students to achieve their academic goals successfully. Many students struggle with practical education due to poor choices of educational paths that do not suit them. Therefore, this topic aims to help students

choose the suitable paths for their skills to complete their education successfully. By proposing a data mining model for the higher education system in the university, B. K. Baradwaj and S. Pal demonstrated the potential of data mining techniques in the context of higher education. Among the various methods for data classification, the decision tree method is used in this study to assess student performance on the classification problem. This work enables them to obtain information about students' exam performance at the end of the semester. It helps in the early detection of dropouts and students who need special attention, allowing the instructor to provide appropriate advising and counseling [7]. Li et al. explored the influence of attributes on students' academic achievement by applying various common data mining methods, such as Naive Bayesian (NB), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Decision Tree Classifier (DT), to predict students' performance. They discovered that SVM technique performed better than others and that behavioral features had a positive effect on students' performance [8].

Francis et al. have developed a novel prediction system that combines classification and clustering methods to evaluate students' academic performance. It has been tested using student datasets from various academic fields at higher education institutions in Kerala, India. The results showed that a hybrid algorithm that combines clustering and classification methods produces results that are much higher in terms of achieving accuracy in predicting the students' academic progress [9].

Rahman et al compared J48 with the baseline performance evaluation and analysis of Naïve Bayes, Bayes Net, Multilayer Perceptron, SVM, REPTree, and Random Forest with Two Datasets provided. According to EDM research, classification performs better than other mining techniques. Therefore, they suggested a comprehensive investigation of Classification Models in their research. In addition to this, Weka is used for the calculations of baseline performance. The results of their investigation indicate that while many models are very efficient, only a few are not; performance of tuned J48 attracts attention because its outcomes are the most realistically superior to others. It is evident that combining models or using a better and more effective J48 classification algorithm would be a great choice [10]. The model proposed by K. J. Somaiya tries to predict student performance in an academic institution. The algorithm used is a type of machine learning method known as neural networks. Moreover, the importance of various different attributes or "features" is considered to identify which of these are related to student success [11]. Zafar Iqbal et al thoroughly analyzed real data collected from the Information Technology University (ITU), Lahore, Pakistan, using Collaborative Filtering (CF), Matrix Factorization (MF), and Restricted Boltzmann Machines (RBM) methods. They evaluated the academic status of ITU students who were admitted into the Electrical Engineering department's bachelor's program. When predicting the students' success in a certain course, the RBM method was found to be superior to the other methods [12]. Ansar Siddique et al. identified the critical factors that have a major impact on student's performance at the secondary level and integrated single and ensemble-based classifiers to produce an efficient classification model for the prediction of academic success. First, three different single classifiers—a Multilayer Perceptron (MLP), a J48, and a PART—as well as three well-known ensemble algorithms—Bagging (BAG), MultiBoost (MB), and Voting (VT)—were investigated. To improve the performance of the above classifiers, nine additional models were created by combining single and ensemble-based classifiers. MultiBoost with MLP outperformed the others in the evaluation, achieving 98.7% accuracy, 98.6% precision, recall, and F-score. This study suggests that the recommended approach may be useful for determining secondary-level students' academic progress [13].

Mohamed Ezz and Ayman Elshenawy presented an adaptive recommendation system. They proposed to determine the best educational path(s) for a student in the college-preparatory year. By

automatically using various data mining methods to extract relevant variables and create a customized model for each educational course, adaptability is achieved. The dataset was automatically transformed into one-versus-all (for binary classification) and the problem was stated as a multi-label multi-class binary classification problem. The proposed model is used as a case study to predict students' academic performance in the engineering faculty at Al-Azhar University. Based on each student's academic achievement, it suggests one of the seven engineering departments that are best for them [14]. Also Mohamed Ezz proposed a predictive model for students to help them choose the most suitable faculty based on their grades for different subjects in high school. Moreover, the model considers the country state, where the student is located, and the gender of the student. The proposed model serves as an advisory and recommendation system for the student, helping them make an informed decision. The model is applied to selected case studies, namely, the student enrollment process in the faculty of Engineering, at Al-Azhar University in Egypt [15].

This study was motivated by previous research that explored ways to enhance student performance and support the development of education. To recommend the best educational path for a student, this study used his academic data and applied artificial intelligence algorithms. It analyzed student data from the civil departments of Al-Azhar University to predict the suitable educational path for a student.

3. PROPOSED RECOMMENDATION MODEL

This section describes the methodology used to develop an effective recommendation model that can help students choose the most suitable academic paths for them. For example, in a college like the college of engineering that consists of multiple departments and majors, students need to choose a specialization that matches their interests and abilities. Within the civil department, for instance, there are three majors to choose from: structural engineering, public works, and irrigation and hydraulics. Therefore, students need guidance to help them select the most appropriate major for their goals and aspirations. To develop a model that can assist students in this process, a large amount of data was collected and analyzed, extracting key insights that could inform the development of the model. By analyzing academic performance data, it is possible to create a model that can provide personalized guidance to students seeking to select a major inside the Civil Department. Overall, this methodology was designed to ensure that the model developed was robust and reliable and that it could provide students with the guidance they need to make informed decisions about their academic and professional futures. By leveraging data and insights in this way, this paper can help students to realize their full potential and achieve their goals.

3.1 Data Set Collection

This research used the Civil Department at Al-Azhar University's Faculty of Engineering as a case study to develop this model. The dataset used in this study contains test results for all years from first-year engineering courses to bachelor's for the Civil Department at Al-Azhar University. This dataset includes details for 1343 students who graduated from the Civil Department between 2018 and 2022. These students are divided into three majors: structural engineering has 532 students, public works has 554 students, and irrigation and hydraulics has 257 students. It is worth noting that students in this department choose their major in the third year based on their results from the first and second years.

3.2 Building Recommendation Model

The process of building a recommendation model will be conducted in two stages. In the first stage, a robust and accurate recommendation model will be built for each major. This will involve analyzing the students' data for each major using different machine-learning algorithms to identify patterns and relationships that can be used to make recommendations. The objective is to develop a model for each major that can effectively predict if a specified major is suitable or not for the student based on his performance in the first and second years.

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Once the recommendation model for each major has been developed, the second stage will involve building an overall recommendation model for the department's majors. This model will incorporate individual recommendation models for each major to provide a comprehensive recommendation for each student by recommending one or more majors for the student based on predictions of each major model.

3.2.1 Building Major recommendation model

The process of building a major recommendation model consists of three steps, as illustrated in **Figure 1**. The first step is the preprocessing step, which involves preparing the data for analysis. This includes cleaning the data by removing any errors or inconsistencies, discarding any irrelevant data, and transforming the data into a format that can be used for analysis. This step is essential for ensuring that the data is accurate and suitable for building the recommendation model. The second step is the feature selection step, which involves selecting the most relevant features from the data for use in the recommendation model. The third step is the building model step, which involves building different models using different machine-learning algorithms. The objective is to build a model that accurately predicts the most suitable educational path for each student based on their abilities and performance. Once the models have been built, the best model is chosen based on its accuracy and performance.
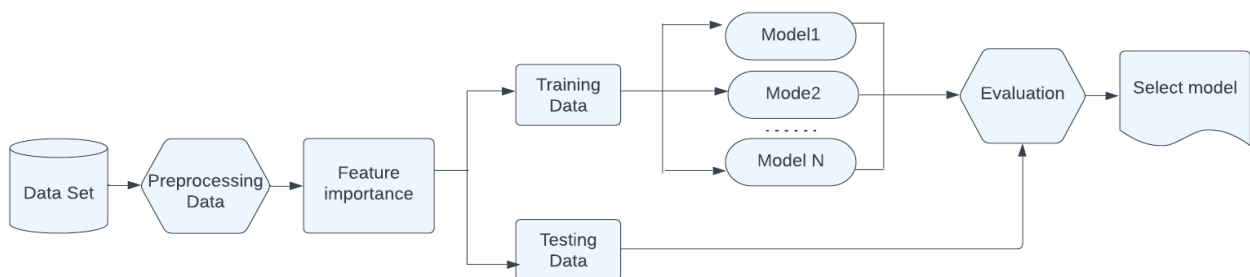

**Fig. 1: Building Major recommendation model**

Preprocessing Phase

The purpose of the preprocessing phase is to prepare the data in a suitable format for building a proper model. Since the maximum scores for the courses are different (100, 150, and 200), a normalization was made for the students' scores in the courses by converting them into percentages of the maximum score. Since students specialize in their major starting from the third year, the percentage of total result of both third and fourth years combined was considered as the student's performance in their major. To facilitate analysis, it was classified students into two groups:

outstanding and non-achieving students. To do this, it set a threshold of 70% for outstanding students and 65% for non-achieving students. It was ignored the scores fell between 65% and 70% to create a clear distinction between the two groups.

Figure 2 provides an overview of the number of students in each class for each major. **Figure 2.a** shows that there are 425 students in the Public Works major, with 301 outstanding students and 177 non-achieving students. **Figure 2.b** shows that there are 395 students in the Structural Engineering major, with 266 outstanding students and 126 non-achieving students. Lastly, **Figure 2.c** shows that there are 195 students in the Irrigation and Hydraulics major, with 88 outstanding students and 107 non-achieving students.

By preprocessing the data in this way, it is possible more easily analyze and interpret the results and create a model that can accurately predict which students are likely to excel in their chosen major. This information can be used to develop strategies that help students achieve their full potential and succeed academically.
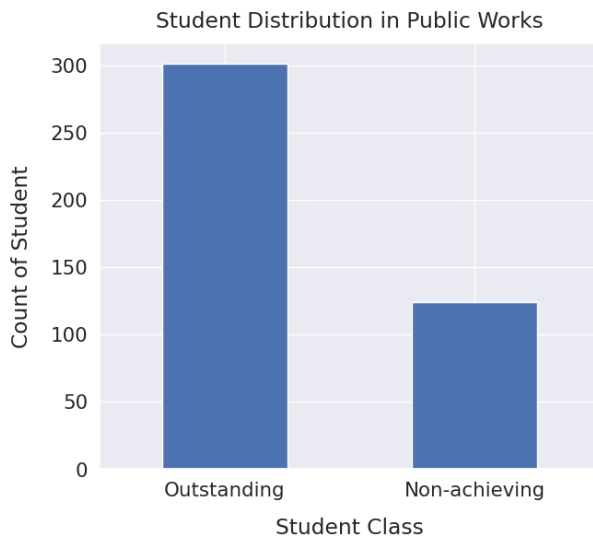
a) Student class distribution in Public works
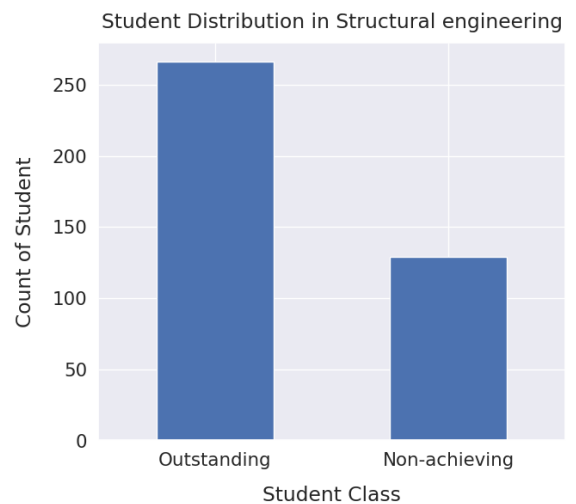
b) Student class distribution in structural engineering
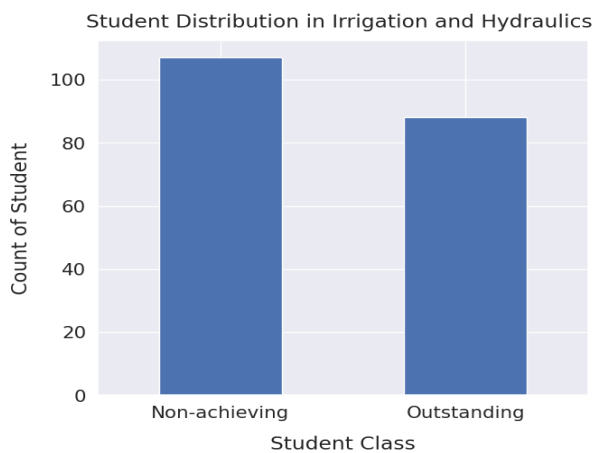
c) Student class distribution in Irrigation and Hydraulics.

Fig. 2: Student class distribution

Once the student data has been collected and preprocessed, the next step is to encode the student groups. This involves assigning a value of 1 for outstanding students and a value of 0 for non-achieving students. The encoding process is necessary to make the student data suitable for use with machine learning algorithms.

Feature Selection and Building Model Phases

The feature selection phase involves selecting the most relevant features from the data to reduce the dimensionality of the data and improve the accuracy and efficiency of the model. In this phase, the Decision Tree algorithm is employed to determine the important features [16]. After selecting the most relevant features, the next phase is the building model phase. In this phase, different machine learning algorithms will be used to build models that accurately predict the most suitable educational pathway for each student. These algorithms include Decision Tree, Random Forest, K-Nearest neighbor, Naive Bayes, and Support Vector Machines. These algorithms were chosen because they are the most widely used in this field.

The goal of the building model phase is to select the best model based on its accuracy and performance. This involves training the different models using the selected features and evaluating their performance using metrics such as accuracy, precision, and recall. The model with the highest accuracy and performance is selected as the final recommendation model.

3.2.2 Building Overall Recommendation Model

After building a recommendation model for each major, the next step is to build an overall recommendation model by aggregating the results of all the individual models. The overall recommendation model provides one or more recommended majors to the student based on their academic performance as shown in **Figure 3**.
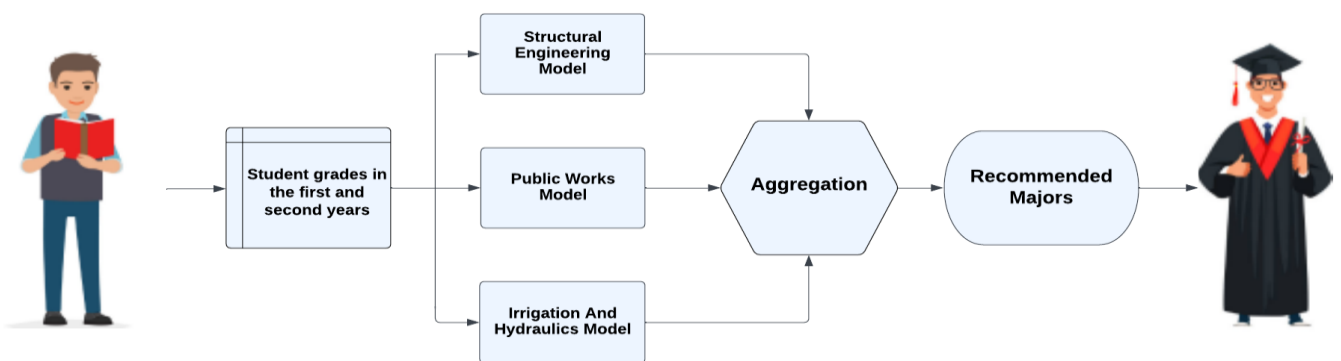

**Fig. 3: Overall Recommendation Model**

4. EXPERIMENTAL RESULTS

The proposed recommendation system was evaluated using data from students who successfully graduated from the civil department at the faculty of engineering at Al-Azhar University in the

period from 2018 to 2022. The system was implemented using Python3 and various libraries were utilized for this purpose.

In the first step, the student data was read and prepared for building the model using the panda's library. The historical data from the students' first- and second-year course scores percentage were used as features, and the percentage of overall result in the third and fourth year was used as a benchmark. Each instructional major was represented as a separate specialization, and the feature importance for each major was obtained using decision tree [16]. The value of each attribute in each major was shown in **Fig. 4**, where **Fig. 4a** shows the relevant courses for successful students in the public works major, where these courses are Geotechnical Engineering (1), Properties and Testing of Materials, Plane Surveying, Fluid Mechanics, Drainage and Reinforced Concrete Structure, Reinforced Concrete Structure, Mechanics, Building Structural, Structural Materials, Computer Applications.

While **Fig. 4b** shows that Geotechnical Engineering (1), Properties and Testing of Materials, Plane Surveying, Fluid Mechanics, Drainage and Reinforced Concrete Structure, Reinforced Concrete Structure, Mechanics, Building Structural, Structural Materials, and Computer Applications are the most relevant courses for success students in the structural engineering. The most relevant courses for the Irrigation and Hydraulics major are Applied Statistics, Civil Engineering Drawing, Drainage and Irrigation, Mechanics, Structural Materials, Plane Surveying, and Structural Analysis (1) in irrigation and hydraulics as shown in **Fig. 4c**.
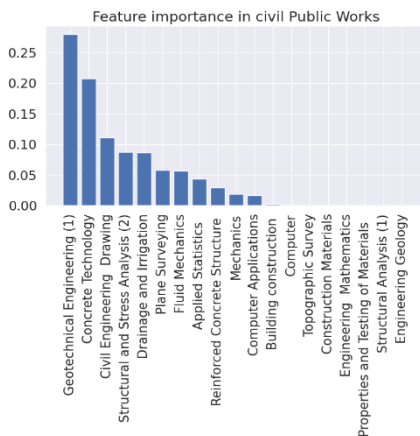
a) Important features for Public Works
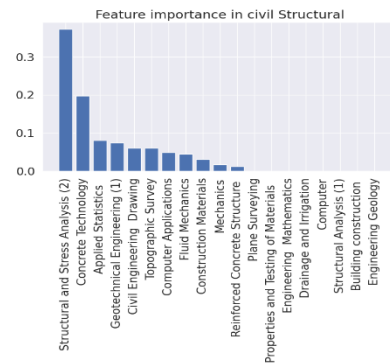
b) Important features for Structural Engineering
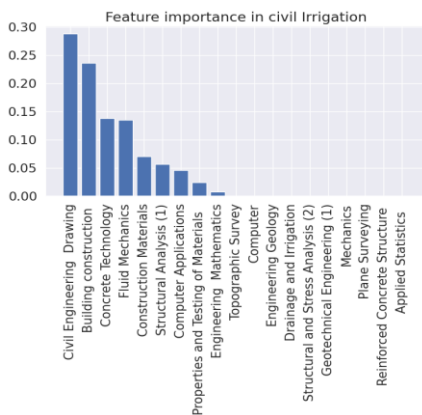
c) Important features for Irrigation and Hydraulics.

Fig. 4: Important Features for each major

In the second step, models were built for each major using Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN) with k= 7, Naive Bayes (NB), and Support Vector Machine (SVM) machine learning algorithms, and the one with the highest accuracy was chosen. The result is evaluated by use splitting 5-fold cross-validation. The F1-measure (F1) was used as the performance criterion. F-measure is calculated using precision and recall, and the formula is shown in equation (1), where precision is calculated using equation (2), and recall is calculated using equation (3).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{1}$$

$$Where\ Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$And\ Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

Table 1 presents the results of using cross-validation on various models in a recommendation system. The table shows the best-performing model for each major based on their F1-measure. For example, in the Structural Engineering major, the KNN model achieved the highest accuracy with an F1-measure of 84%. Similarly, in Irrigation and Hydraulics major, the NB model had the highest accuracy with an F1-measure of 69%. For the Public Works major, the KNN model had the highest accuracy with an F1-measure of 87%.

Table 1: Performance for different majors and models using 5-fold cross-validation method

Major	Modele	Precision (%)	Recall (%)	F1-score (%)
Structural Engineering	Decision Tree	83	79	79
	Random forest	84	80	81
	KNN	**86**	**83**	**84**
	NB	90	75	78
	SVM	83	82	79
Irrigation and Hydraulic	Decision Tree	61	48	52
	Random forest	56	57	56
	KNN	67	49	52
	NB	**71**	**70**	**69**
	SVM	56	50	49
Public Works	Decision Tree	85	84	84
	Random forest	85	90	87
	KNN	**88**	**87**	**87**
	NB	90	75	81
	SVM	83	84	83

The confusion matrix results for the best model in each major are presented as follows: **Table 2** presents the confusion matrix results for KNN model in the Structural Engineering major, followed by **Table 3** for NB in the Irrigation and Hydraulics major, and then **Table 4** for KNN in the Public Works major. These tables provide detailed information on the performance of different machine learning models in different majors, based on the metrics provided in the confusion matrices.

Table 2: The confusion matrix results for KNN model in the Structural Engineering major

	Confusion Matrix			Performance Evaluations		
	Predicted Class					
	Non-achieving	Outstanding	Total	Precision (%)	Recall (%)	F1-score (%)
Non-achieving	20	6	26	74	76	75
Outstanding	7	46	53	88	86	87
Total /W. Avg.	27	52	79	86	83	84

(Actual Class)

**Table 3: The confusion matrix results for NB model in the Irrigation and Hydraulics majors**

	Confusion Matrix			Performance Evaluations		
	Predicted Class					
	Non-achieving	Outstanding	Total	Precision (%)	Recall (%)	F1-score (%)
Non-achieving	16	5	21	69	76	72
Outstanding	7	11	18	68	71	74
Total /W. Avg.	23	16	39	71	70	69

(Actual Class)

Table 4: The confusion matrix results for KNN in the public works majors

|	Confusion Matrix			Performance Evaluations		
	Predicted Class					
	Non-achieving	Outstanding	Total	Precision (%)	Recall (%)	F1-score (%)
Non-achieving	18	7	25	85	72	78
Outstanding	3	57	60	89	95	91
Total /W. Avg.	21	64	85	88	87	87

(Actual Class)

To assess the presence of overfitting, a comprehensive analysis was performed on three prominent models: The Structural Engineering KNN Model, Public Work KNN Model, and Irrigation and Hydraulic NB Model. These models were specifically chosen for their exceptional performance in recommendation systems. The findings from the evaluation, as depicted in **Figure 5**, unequivocally indicate that overfitting did not occur in any of these models.
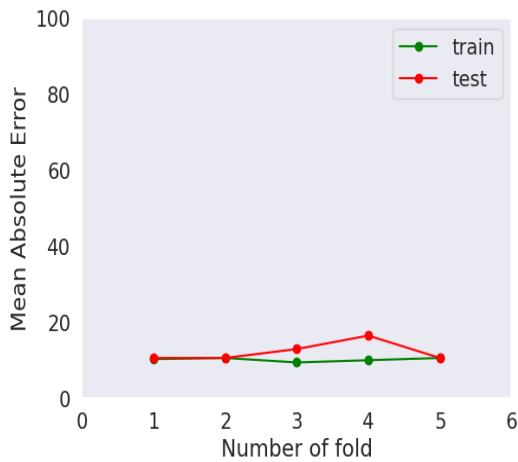
a) The result of the overfitting assessment for Public
Works KNN Model
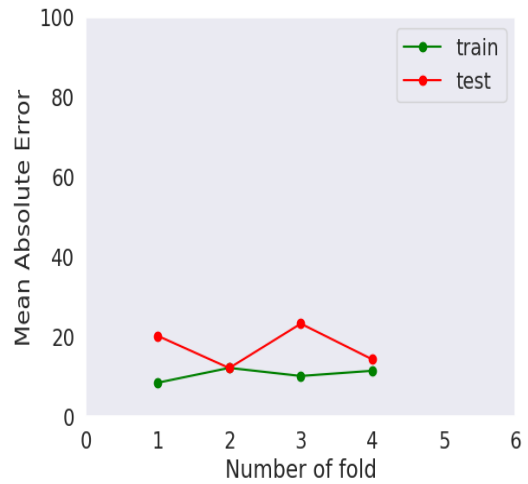
b) The result of the overfitting assessment for
Structural Engineering KNN Model
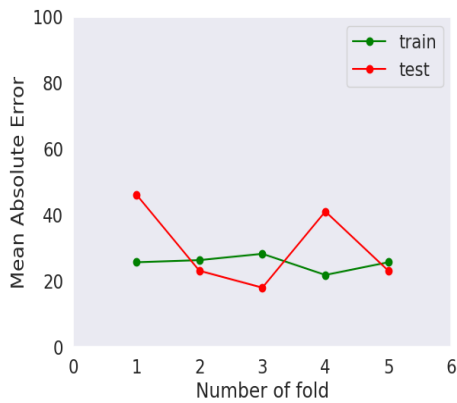
c) The result of the overfitting assessment for Irrigation
and Hydraulics NB Model.

Fig. 5: The result of the overfitting assessment for each major model

Based on the results obtained, the system can recommend the most appropriate major to a student based on the best F1-measure. This information is valuable in guiding students to choose the academic pathway that is most suitable for their individual needs and goals. By recommending the most appropriate major, students can make more informed decisions about their academic careers, which can lead to better outcomes in the long run.

CONCLUSION AND FUTURE WORK

This study presents a recommendation system designed specifically for students in the Civil Department at Al-Azhar University's Faculty of Engineering. The system utilizes historical grades of students who graduated from the department in the period from 2018 to 2022, along with the feature importance obtained using decision tree. Different machine learning algorithms, such as decision tree, random forest, KNN, NB, and SVM, were employed to build models for each major in the Civil Department. The models were assessed using a 5-fold cross-validation method, with the F1-measure serving as the performance criterion. The results showed that the KNN model

achieved the highest accuracy of 84% for Structural Engineering. Similarly, Public Works majors achieved an F1-Measure of 87%. However, in the field of Irrigation and Hydraulics, the NB model outperformed others with the highest accuracy, achieving an F1-Measure of 69%. The proposed recommendation system has the potential to provide valuable guidance to students in making informed decisions about their academic careers. By suggesting the most suitable major based on their academic performance, students can select the pathway that aligns with their individual needs and goals.

One potential area for future work is to incorporate additional features into the recommendation system, such as extracurricular activities and interests. This would provide a more comprehensive view of each student's profile and could lead to more accurate recommendations. Another area for future work is to expand the dataset to include more students and majors. This would provide a more diverse set of data to train the models and could lead to better performance. In addition to working on developing the system so that a score is determined for each major that is recommended for the student.

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