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An intelligent rule-oriented framework for extracting key factors for grants scholarships in higher education

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A B S T R A C T

Education is a fundamental sector in all countries, where in some countries students compete to get an educational grant due to its high cost. The incorporation of artificial intelligence in education holds great promise for the advancement of educational systems and processes. Educational data mining involves the analysis of data generated within educational environments to extract valuable insights into student performance and other factors that enhance teaching and learning. This paper aims to analyze the factors influencing students' performance and consequently, assist granting organizations in selecting suitable students in the Arab region (Jordan as a use case). The problem was addressed using a rule-based technique to facilitate the utilization and implementation of a decision support system. To this end, three classical rule induction algorithms, namely PART, JRip, and RIDOR, were employed. The data utilized in this study was collected from undergraduate students at the University of Jordan from 2010 to 2020. The constructed models were evaluated based on metrics such as accuracy, recall, precision, and f1-score. The findings indicate that the JRip algorithm outperformed PART and RIDOR in most of the datasets based on f1-score metric. The interpreted decision rules of the best models reveal that both features; the average study years and high school averages play vital roles in deciding which students should receive scholarships. The paper concludes with several suggested implications to support and enhance the decision-making process of granting agencies in the realm of higher education.

1. Introduction

Education plays a prominent role in cultural and national development. Improving the educational system substantially enriches students' knowledge and skills, which in turn produces high-quality, specialized leaders. However, students face various difficulties during their education journey, including the burden of paying the tuition fees. Many local and global initiatives and agencies devote their efforts to aiding students with hard life circumstances to pursue their studies. However, they are faced with how to grant scholarships to select smart, persistent, and committed students.

Educational data mining is a field of study that aims to promote education and student performance using intelligent mining tools. The objective is to build models and mining algorithms to interpret and analyze data resulting from educational systems. Data mining is the process of knowledge discovery, where hidden patterns of information in raw data stored in databases or data warehouses are discovered (Baker & Yacef, 2009). Rule-based data mining is a mining method where the output is a set

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of rules that characterize the relationships within the data. These extracted rules have the form of if-then rules, which are easier to comprehend and follow (Cohen, 1995).

Various scholarship and granting agencies are keen on providing equal opportunities for students to pay their tuition fees. However, they find it difficult to select suitable students to receive a grant. This is due to various factors that might influence students' performances conversely. However, automating the process of assessing factors to quantify who is eligible to receive a scholarship has drawn increased attention from researchers worldwide. Various research studies have been conducted to explore factors that influence students and the effect on selecting scholarship recipients.

For instance, Sugiyarti et al. (2018) designed a decision support system (DSS) of a scholarship grantee selection was designed based on the decision tree (C4.5) and for students at senior high school level. Different factors have been studied, including the parents' income, academic achievement, non-academic achievement, and their specialization. The DSS achieved high accuracy (94.7%) in predicting students' performance and recommending scholarship recipients. Furthermore, Susilowati et al. (2019) proposed a machine learning-based DSS for selecting recipients of a doctoral scholarship. The designed DSS was implemented by using a case-based reasoning method, which exhibited very good recommendations.

Also, Khruahong and Tadkerd (2020) utilized a machine learning-based algorithm to analyze individuals who applied for scholarships and who to award. The adopted learning algorithm was the decision tree (J48) algorithm. They also built a web application to ease the use of the developed system, with 77% approximate precision. Moreover, Afrianto et al. (2020) implemented a decision tree algorithm (C4.5) to classify students who are eligible for the Indonesian smart card. The objective of the proposed system was to fairly select and help poor students with their school education. The results of the algorithm showed better selection for poor students with an accuracy of 97%. The authors studied different factors, including the father's and mother's education and occupation, the property tax and electricity bills, and the family size.

Moreover, Aulck et al. (2019) proposed a machine learning-based evolutionary algorithm to optimize the scholarship process. Several ensembles of machine learning algorithms have been used: XGBoost, Random Forest (RF), multilayer perceptron (MLP), support vector machines (SVM), and k-nearest neighbor (KNN). The ensemble model is used to predict students' enrollment, whereas the genetic algorithm (GA) is used to optimize the disbursement strategy. The model significantly enhanced student enrollment yield and increased the annual tuition revenue.

Very few researchers have investigated the effect of having a scholarship on the students' academic performance, but different studies have been conducted on the influence of other aspects. For example, Son and Fujita (2019) proposed a multi adaptive neuro-fuzzy inference system with representative sets for predicting student performance. Alsalman et al. (2019) used a decision tree (J48) and artificial neural network (ANN) to predict students' academic performance in a Jordanian university. Various features have been investigated, including gender, age, family size, whether having a scholarship or not, and others. Another research proposed by (Al Nagi, E., & Al-Madi, N. 2020) discussed the use of machine learning to predict student performance. The authors implemented Decision Tree, ANN, SVM, and K-NN on real data and used four performance measures: accuracy, precision, recall, and F-measure to evaluate the performance, where DT and aNN achieved the best results.

Wang et al. (2021) proposed a deep neural network model for student performance prediction. The model was an adaptive sparse self-attention network that experimented on three public datasets of online learning. Meanwhile Huang et al. (2020) constructed a machine learning model for identifying students at risks to target and improve their performance. Data was collected from three universities in Taiwan and Japan and used to train eight algorithms, which were then evaluated based on accuracy, precision, recall, and f1-score. Based on the findings, the authors concluded that teachers need to involve students in more activities to improve their performance.

Moreover, a model based on logistic and multiple linear regression methods was developed by Ranawaka and Rajapakse (2020) to predict grade 5 students' performance in scholarship examination in Sri Lanka. The model achieved good accuracy in predicting the talented students who require personalized education to promote further their abilities. Also, a meta-classifier approach was created by Hassan et al. (2019) to predict the students' performance. The base algorithms used were SVM, neural network (NN), and decision tree, while the multi-classifiers included bagging, stacking, AdaBoost, and the majority vote. The model achieved optimal accuracy by optimizing the hyperparameters, while the results showed that demographics with behavior learning features were the most influential in predicting students' performance. Delima (2019) used a data mining approach to predict scholarship grantees, first using the k-means algorithm to analyze the data and then the autoregressive integrated moving average (ARIMA) method for the prediction. Yet, a fuzzy-based model was proposed in (Nechvoloda & Shevchenko, 2019) for the distribution of academic scholarships in higher institute in Ukraine. The proposed model achieved good results in eliminating decision-making biases when granting scholarships.

Furthermore, Tsai et al. (2020) proposed and studied different statistical and deep learning models to inspect the reasons for students' withdrawal and predicting it in Taiwan. Three features were found significant in predicting the drop-out rate: the number of absences, and if they took loans, and the number of altered subjects. Rivas et al. (2019) used different machine learning techniques (i.e., decision tree, and neural networks) to predict if students would pass or fail based on online learning. Interestingly, the most influential feature for predicting (fail/pass) status was the number of clicks.

Further, Sharma et al. (2020) conducted a study based on machine learning methods to study the most influential predictor on students' performance. The used algorithms were the SVM, KNN, RF, and logistic regression (LR), which showed that the number of absences is the most influential factor in students' performance. In Cambodia, a study was conducted to analyze the most influential features affecting students' performance in the mathematics class in high school. Several statistical, machine learning, and deep learning methods were used to analyze the data. However, the association rule algorithm showed that various factors affect students' performance in mathematics, classified originally into domestic, individual, and school factors. Such significant factors are the students' interest in mathematics, the amount of time to self-study, the homework completion rate, the mother's education level, the father's employment status, the level of anxiety in the class, and others. Furthermore, Rebai et al. (2020) used random forest and regression trees to study the factors affecting students' performance of high school in Tunisia. The study found that school size, competition, class size, parental pressure, and percentage of girls were the most important factors. Alshanqiti and Namoun (2020) asserted the influence of different students' skills on their performance, such as time management, self-esteem, the level of anxiety, high school grades, and their attendance. Besides, Frank and Witten (1998) found that gender, race, and having lunch were the most crucial features in impacting the students' performance in school. Meanwhile, there are very few research studies on the performance of students on scholarships, especially in the Arab region. Inspired by this problem, the objective of this paper is to ascertain the potential factors that affect the decisions of granting agencies and construct a set of supporting decision rules in the Arab context and especially in Jordan. The rules are to help the responsible party when taking the final decision about applicants. Hence, the problem was formulated as a rule-based system using data collected from the University of Jordan that encompasses characteristics from undergraduates from all fields of study. The methodology was divided into two parts: the first part; to study the effects of the first four-year averages, the first two-year averages, and when no university averages are included. The second part; considered the utilization of the first two-year averages and a special investigation of the five most common types of granting reasons. The data is grouped into five clusters of students: students who did not receive any grant, who received it from the Ministry of Education, those who received it from the High Royal Honorable, those exempted from paying, and those who had loans. Three rule induction methods were used (PART, JRip, and RIDOR) and evaluated based on accuracy, recall, precision, and f1-score. They were used to extract hidden information from many observations in the form of interpretable rules. The rules of the best-obtained models are explained and presented in the paper.

This contribution of this paper is the application of a rule-oriented framework in the Arab context (Jordan) to aid the decision-making of organizations. There is no model built and deployed to automate such an application in the Arabic educational environment, especially in the University of Jordan.

The rest of the paper is organized as follows. Section 2 presents the problem description in detail. Section 3 explains the methodology, including the dataset, methods and implementation, and evaluation results. Section 4 discusses the obtained results. Finally, Section 6 concludes the paper and lists some future work.

2. Problem description

Education plays a significant role in societal development. Hence, advancing educational systems and students' ability to cope with the constantly evolving science and technology is critical. Students face different challenges during their educational journey. Different local agencies and organizations offer scholarships and grants to help students continue their education. However, the problem such agencies encounter is how to decide on suitable students to receive this grant. Various cases were observed at the university level, including how receiving a grant has a significant effect on students' performance. However, the objective of granting agencies is to give the grants to students who perform and develop consistently well over their study period. Therefore, the objective of this paper is inspired by this problem. A rule-based model is developed to analyze students' attributes and infer the characteristics of students who received grants and maintained their excellent academic performance over the study period. This paper investigates factors influencing four different granting agencies in the University of Jordan and compares them with performance factors of students who received no grants during their study. Thus, the developed model suggests the characteristics of students or factors to consider when awarding the grants.

3. Methodology

In this section, the dataset used to build the proposed is discussed and mainly the preparation steps implemented to make it ready to be used by the rule-based models. In addition to the three implemented models which are: Jrip, PART, and RIDOR, and how this research implemented them. Lastly, a description of the evaluation measures used to compare the performance of the models.

3.1. Dataset preparation

The data was collected from the University of Jordan registration unit, which contains various information about undergraduate students. It consists of the students' attributes in the period from 2010 to 2020 with 68,068 records and 78 features. The features include diverse information about undergraduates, such as their demographics; passed, repeated and completed courses; their averages; and information about their high schools. Also, the data types of the features are different, some being binary, numerical, or categorical. Table 1 contains a description of the features.

Many records in the dataset have missing values that were handled by removing these records. The categorical features were either encoded into numeric features or removed if they presented other numerical features. The dataset after preprocessing had 29,082 records and 51 features. However, five datasets were consolidated from this dataset: the first was related to students who did not receive any grant, and accounts for 17,283. The second relates to students who received a grant from the high royal honor, accounting for 4,231. The third represents students who took the Ministry of Education grant as an honor for only teachers' children, and accounts for 2,060. The fourth is related to students receiving grants due to the Exemption for the children of employees, which is 1,211. Finally, the students who received student support fund loans account for 893.

Some features were removed from the constructed datasets if they had a constant value. Therefore, the number of used features was 46, 44, 46, 45, and 42 for the datasets of students who did not receive any grant (Grant_SRC_0), the high royal honorable (Grant_SRC_3), the ministry of education/honor the children of teachers(Grant_SRC_181), those exempted for being the children of employees (Grant_SRC_94), and the student support fund loans (Grant_SRC_105), respectively. The Class label is the final student's rate, which is a multi-class output. The classes are *Excellent*, *Very Good*, *Good*, and *Satisfactory*. Table 1 shows the records and features of these five datasets, whereas Figure 1 shows the distribution of the classes based on the datasets.

Table 1
Description of the dataset

No.	Feature Name	Description
1	FACULTY	Faculty
2	MAJOR	Major
3	STUDYTYPE	Study Type
4	ADMITYPE	Type Of Student Admission In The University
5	ADMITYPEO	Initial Type Of Student Admission In The University
6	LEVEL	Student Level
7	TRNS_FLG	IS The Student Transferred From Another College?
8	PUNISH_FLG	Did The Student Get A Disciplinary Punishment?
9	FINSUPCO	Fees Payment Way
10	GRNTSOUR	Payment Side
11	REGSTAT	The State Of Student's Registration
12	DECLARECODE	Clearance Flag
13	GRADYEAR	Graduation Year
14	GRADSEM	Graduation Semester
15	ENROLYEAR	Enrollment Year
16	ENROLSEM	Enrollment Semester
17	PLNYER	Plan Year
18	PLNSEM	Plan Semester
19	DISABILITY	Does The Student Have Disabilities?
20	SEX	Sex
21	NAT	Nationality
22	GEAVE	High School Rate
23	GEYEAR	High School Year
24	GEBRANCH	High School Branch
25	GECERTIF	Nationality Of High School Certificate
26	CERTIFTYPE	Type Of High School Certificate
27	GESCHOOL	High School
28	GEREGION	High School Region
30	BIRTHMONTH	Month of Birth
31	BIRTHYEAR	Year of Birth
32	RELIGION	Religion
33	AGE	Age
34	REPEATED_CORS_FLAG	Does The Student Have Repeated Courses?
35	QUALIFICATION_EXAM_FAILS_FLAG	Did The Student Fail In The Qualification Exams?
36	CORS_FAILS_FLAG	Does The Student Have A Failure In His Courses?
37	REGISTRATION_FEES_FLAG	Does The Student Have A Registration Fees?
38	PLAN_CRDTS	The Total Number Of Student Plan During The Bachelor Degree
39	CRIDITSEM1	Accumulative Hours In 1st Semester
40	CRIDITSEM2	Accumulative Hours In 2nd T Semester
41	CRIDITSEM3	Accumulative Hours In 3rd Semester
42	CRIDITSEM4	Accumulative Hours In 4th Semester
43	CRIDITSEM5	Accumulative Hours In 5th Semester
44	CRIDITSEM6	Accumulative Hours In 6th Semester
45	CRIDITSEM7	Accumulative Hours In 7th Semester
46	CRIDITSEM8	Accumulative Hours In 8th Semester
47	CRIDITSEM9	Accumulative Hours In 9th Semester
48	CRIDITSEM10	Accumulative Hours In 10th Semester
49	AVG_YR1	Accumulative Average In 1st YEAR
50	AVG_YR2	Accumulative Average In 2nd YEAR
51	RATE	Final Student Rate

Table 2
Dataset features and records after preparation

Dataset/ Grants	Features after selection	Records
Grant_SRC_0	46	17,283
Grant_SRC_3	44	4,231
Grant_SRC_181	46	2,060
Grant_SRC_94	45	1,211
Grant_SRC_105	42	893

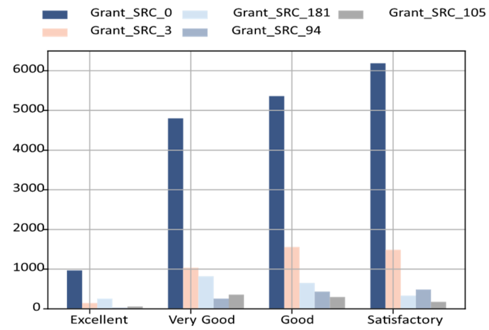

Fig. 1. The class distribution for five datasets.

3.2. Methods

In this research, we have implemented three models JRip, PART, and RIDOR. The description of each of them is explained in the following subsections.

3.2.1. JRip

JRip, created by William W. Cohen, is the Java implementation in the Weka software (Waikato Environment for Knowledge Analysis) (Eibe et al., 2016) of the propositional rule learner based on repeated incremental pruning to produce error reduction (RIPPER) (Cohen, 1995). The JRip algorithm consists of two stages: building and optimization stages. The former, iteratively, has two phases: a growing phase and a pruning phase. The growing phase builds one rule at a time, starting with an empty rule set and greedily adding conditions to it until it is 100% accurate. In this phase, all the potential conditions of every attribute are tried and the condition with the highest information gain is selected. The information gained is given by Eq. (1) (Cohen, 1995).

$$IG(S,F) = H(S) - \sum_{f \in F} \frac{|S_f|}{|S|} \times H(S_f) \tag{1}$$

where S is a set of all features. S_f are the elements of S having feature F with value f, and H(S) is the entropy of S.

3.2.2. PART

PART is an implementation of a rule induction algorithm in Weka software (Eibe et al., 2016). It is based on partial decision trees, using the separate-and-conquer method to create decision tree lists. The PART algorithm constructs a partial decision tree classifier (C4.5), looks for the best generated branch, and converts it into a rule. The C4.5 classifier develops a classification tree model using information entropy. The features with the maximum information gain are used to split the tree and create subsets. Iteratively, the algorithm recurses over the constructed subsets until the optimal rules are generated (Frank & Witten, 1998).

3.2.3. RIDOR

The Ripple Down Rule learner (RIDOR) is a rule-based classification method that initially generates default rules. Exceptions to default rules are generated using incremental reduced error pruning (IREP) algorithm, where the exceptions are of minimum error rate. Exceptions are sets of rules that iteratively the algorithm tries to find the best by constructing tree-like exceptions (Gaines & Compton, 1995).

3.2.4. Implementation

The training parts of the datasets were used during the training phase to build the models, and the testing parts were used for the performance evaluation phase. Each dataset was experimented with three rule-based classification methods (i.e., JRip, PART, and RIDOR), and evaluated in terms of accuracy, recall, precision, and F1-score. The best performing classification model per dataset was selected to analyze its generated classification rules. Fig. 2 shows the implemented methodology. Initially, the experiments were conducted to investigate the effect of the university grade point average (GPA) where the first four years were considered, then first two years, or without any GPA included. Hence, three datasets were constructed and fed into PART, JRip, and RIDOR, and evaluated based on accuracy, recall, precision, and f1-score. Based on the obtained results, the GPA in the first two years was included in the subsequent experiments for the five common granting sources as classified by the University of Jordan. All the datasets were divided into training and testing by a ratio of 66%, and 34%, respectively. The default hyperparameters settings of JRip, PART, and RIDOR as in WEKA software (Eibe et al., 2016) were utilized.

All the experiments were conducted and implemented in the WEKA software (Eibe et al., 2016) and carried out on a PC with macOS operating system, 2.3 GHz processor, dual-core intel core i5, and 8 GB memory.

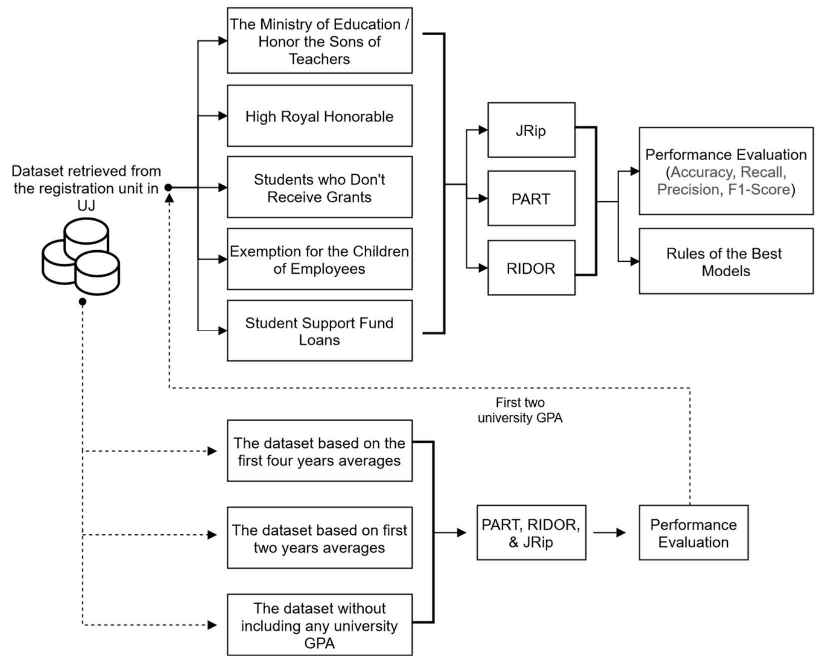

Fig. 2. A description of the proposed methodology

3.3. Evaluation measures

Four evaluation measures were used to assess the created models: the classification accuracy, recall, precision, and f1-score. All the metrics were computed based on the confusion matrix, where *TP* is the true positive, *TN* is the true negative, *FN* is the false negative, and *FP* is the false positive. This is represented and given by the confusion matrix as given in Table 3.

Table 3
Confusion matrix for multi-classes

		Predicted classes			
	Classes	a	b	c	d
Actual classes	a	**TN**	FP	TN	TN
	b	FN	**TP**	FN	FN
	c	TN	FP	**TN**	TN
	d	TN	FP	TN	**TN**

The accuracy is the ratio of correctly classified instances from all classes to the correct and incorrect classified instances, regardless of the type of the class (Eq. 2).

$$Accuracy = \frac{1}{C}\sum_{i \in C}\frac{TP_i+TN_i}{TP_i+TN_i+FP_i+FN_i} \quad (2)$$

Recall is known by sensitivity, which means how much the classifier can identify the instances of class_i, which is defined by Eq. (3). The precision is also known as positive predictive value, which is identified as the ratio of the instances that are correctly identified of class_i over the number of all class_i instances, which is represented in Eq. (4). In contrast, the f1-score or the f-measure presents the ability of the model to balance precision and recall, calculated as Eq. (5).

$$Recall_i = \frac{TP_i}{FN_i + TP_i} \quad (3)$$

$$Precision_i = \frac{TP_i}{FP_i+TP_i} \quad (4)$$

$$F1 - Score_i = 2 \times \frac{Precision_i \ X \ Recall_i}{Precision_i+Recall_i} \quad (5)$$

The macro-average of all metrics is also calculated and reported, every metric per class is computed and then averaged across classes.

4. Results

This section discusses the results obtained using JRip, PART, and RIDOR from the extracted dataset and the five constructed datasets. The rules of the best obtained models are then interpreted to extract useful decision rules for each of the employed granting agencies. Both quantitative analysis and performance evaluation are discussed in the following subsections.

4.1. Quantitative analysis

Generally, quantitative analysis is divided into two sections: the first studies the effect of including the study-years averages on performance, while the other interprets the performance of the models per the five most common granting agencies.

4.1.1. Part I

This subsection presents the performance evaluation of JRip, PART, and RIDOR over the total extracted dataset in terms of classification accuracy, precision, recall, and f1-score. Table 4 presents the performance evaluation results of PART, JRip, and RIDOR when the first four-year averages are considered. In terms of accuracy, there is a slight variation between them, however, the JRip algorithm achieved the highest accuracy of 95.237. Regarding recall and precision, JRip and RIDOR performed alternatively similarly. For instance, JRip was better in terms of recall at the "Excellent" and "Good" classes, whereas the RIDOR class was better at "Very Good" and "Satisfactory" classes. The JRip algorithm obtained the best precision and f1-score in 75% of the classes, which grants it merit over the other algorithms, especially when using a relatively reasonable number of rules. Moreover, the PART algorithm did not achieve any outperforming results compared to JRip and RIDOR algorithms.

Table 5 shows the performance of the algorithms when two-year averages were considered. Regarding accuracy, the JRip algorithm achieved the highest at 75.42%, while the RIDOR and PART obtained 74.96% and 71.61%, respectively. Regarding recall, the JRip algorithm gained outperforming results at the "Excellent" and "Good" classes with scores of 0.814 and 0.645, respectively, whereas the RIDOR algorithm obtained the best recall in "Very Good" with 0.850, and in "Satisfactory" with 0.833. Regarding precision, JRip obtained the best values in the "Very Good", and "Satisfactory" classes by having 0.785 and 0.800, respectively. The RIDOR algorithm achieved 0.866 of precision in the "Excellent" class, and 0.690 in the "Good" class. Furthermore, regarding the f1-score, the JRip algorithm obtained the best scores in "Excellent," "Good," and "Satisfactory" classes by having 0.793, 0.658, and 0.808, respectively. Generally, the JRip algorithm performed PART and RIDOR algorithms.

However, when comparing the results when considering the four-year averages and the first two-year averages, it is clear that the former achieved better as explained by Table 3. For example, when the four-year averages are considered, the accuracy of the JRip algorithm was 95.24%, while it was 75.42% for the two-year averages.

Table 4
The performance measures when considering the first four averages over the study year

Class	Metric	PART	JRIP	Ridor
	Accuracy	93.922	**95.237**	94.873
Excellent	Recall	0.973	**0.985**	0.983
	Precision	0.965	**0.969**	0.966
	F1-score	0.969	**0.977**	0.974
Very Good	Recall	0.958	0.969	**0.974**
	Precision	0.957	**0.974**	0.957
	F1-score	0.957	**0.972**	0.965
Good	Recall	0.911	**0.932**	0.892
	Precision	0.913	0.930	**0.957**
	F1-score	0.912	**0.931**	0.923
Satisfactory	Recall	0.944	0.952	**0.975**
	Precision	0.945	**0.952**	0.933
	F1-score	0.944	0.952	**0.953**
	#Rules	359	**39**	705

Table 5
The performance measures when considering the first two averages over the study years

Class	Metric	PART	JRIP	Ridor
	Accuracy	71.612	**75.415**	74.960
Excellent	Recall	0.724	**0.814**	0.689
	F1-score	0.742	**0.793**	0.768
Very Good	Recall	0.754	0.792	**0.850**
	F1-score	0.748	0.788	**0.794**
Good	Recall	0.610	**0.645**	0.586
	F1-score	0.615	**0.658**	0.634
Satisfactory	Recall	0.784	0.817	**0.833**
	F1-score	0.782	**0.808**	0.808
	#Rules	2271	**58**	1834

In contrast, Table 6 presents the performance results when no study-year averages are included. Performance degrades as no study-year averages were involved. This is clearly presented for example, in the 46.13% accuracy measure recorded by the JRip algorithm when no averages are included, which is far lower than the 75.42% and 95.24% recorded for the two-year and four-year averages, respectively. It can be observed from the table that the RIDOR algorithm achieved the highest accuracy at 50.44%. Regarding the recall measure, RIDOR obtained the highest results at the "Excellent" and "Very Good" classes by obtaining 23.3% and 57.5%, respectively. Whereas the best recall of the "Good" class was obtained by the PART algorithm by having 37.9%, and for the "Satisfactory" class, it was obtained by the JRip algorithm by having 96.7%. Regarding the precision, the JRip algorithm achieved the highest precision in 75% of the classes at "Excellent," "Very Good," and "Good" by having 53.3%, 54.1%, 58.7%, respectively, whereas, for the f1-score, the RIDOR algorithm achieved the best results in 75% of the classes. It achieved 28.9% in the "Excellent" class, 50.7% in the "Very Good" class, and 66.0% at the

"Satisfactory" class. Generally, the RIDOR algorithm obtained the best performance results though lower than when the two- and four-year averages were included. The experiments in the second part relied on including only the first two-year averages.

Table 6
The performance measures without considering any of the study years averages

Class	Metric	PART	JRIP	Ridor
	Accuracy	49.129	46.042	**50.438**
Excellent	Recall	0.167	0.064	**0.233**
	F1-score	0.195	0.114	**0.289**
Very Good	Recall	0.512	0.409	**0.575**
	F1-score	0.495	0.466	**0.507**
Good	Recall	**0.379**	0.02	0.191
	F1-score	**0.387**	0.039	0.265
Satisfactory	Recall	0.631	**0.967**	0.778
	F1-score	0.622	0.601	**0.660**
	#Rules	3401	**22**	2859

Table 7
The performance indicators for the *Grant_SRC*_0

Class	Metric	PART	JRIP	RIDOR
	Accuracy	71.801	**75.460**	73.792
Excellent	Recall	0.705	**0.805**	0.724
	F1-score	0.737	**0.787**	0.773
Very Good	Recall	0.745	0.773	**0.884**
	F1-score	0.744	**0.778**	0.776
Good	Recall	0.633	**0.645**	0.449
	F1-score	0.615	**0.650**	0.550
Satisfactory	Recall	0.772	0.825	**0.874**
	F1-score	0.787	0.820	**0.825**
	#Rules	1341	29	1183

4.1.2. Performance Evaluation

This subsection presents the performance evaluation of the JRip, PART, and RIDOR algorithms over the five datasets used in terms of classification accuracy, precision, recall, and f1-score. Table 7 shows the results of the three algorithms after analyzing and predicting the performance of students who received no grants during their study period (*Grant_SRC*_0). The JRip algorithm performed the best in terms of accuracy with 75.46%, whereas PART and RIDOR performed slightly more poorly with 71.8% and 73.8%, respectively. Also, the JRip algorithm obtained the best performance in terms of recall and f1-score for the "Excellent" and "Good" classes by having (80.5%, 64.5%), and (78.7%, and 65%), respectively. The RIDOR algorithm attained the best precision for the "Excellent" and "Good" classes with 82.9%, and 71%, respectively. It also gained the highest recall for the "Very Good" and "Satisfactory" classes with 88.4%, and 87.4%, respectively. Generally, JRip and RIDOR performed better than the PART algorithm, however, the JRip algorithm had the lowest number of rules (29).

Table 8
The performance indicators for the *Grant_SRC*_3 dataset

Class	Metric	PART	JRIP	RIDOR
	Accuracy	69.145	**75.469**	72.550
Excellent	Recall	0.647	**0.784**	0.745
	Precision	0.673	**0.755**	0.704
	F1-score	0.66	**0.769**	0.724
Very Good	Recall	0.707	0.741	**0.776**
	Precision	0.699	**0.811**	0.780
	F1-score	0.703	0.775	**0.778**
Good	Recall	0.658	**0.746**	0.563
	Precision	0.63	0.687	**0.730**
	F1-score	0.644	**0.715**	0.636
Satisfactory	Recall	0.722	0.771	**0.868**
	Precision	0.762	**0.802**	0.694
	F1-score	0.742	**0.786**	0.771
	#Rules	352	26	310

Table 9
The performance indicators for the *Grant_SRC*_181 dataset

Class	Metric	PART	JRIP	RIDOR
	Accuracy	71.143	**76.000**	71.571
Excellent	Recall	0.689	0.811	**0.944**
	F1-score	0.747	**0.802**	0.783
Very Good	Recall	**0.826**	0.822	0.756
	F1-score	0.781	**0.800**	0.771
Good	Recall	**0.675**	0.645	0.541
	F1-score	0.667	**0.695**	0.628
Satisfactory	Recall	0.523	**0.807**	0.798
	F1-score	0.585	**0.752**	0.680
	#Rules	140	18	108

Table 8 shows the performance results of the three models when trained on data of students who received the grants from High Royal Honorable (*Grant_SRC*_3). The table shows that the JRip attained the best-obtained classification accuracy with 75.5%, while the PART algorithm obtained the lowest accuracy at 69.12%. The JRip algorithm obtained the best of recall, precision, and f1-score for the "Excellent" class with 78.4%, 75.5%, and 76.9%, respectively. Also, attained the highest precision of class "Very Good" (81.1%), the best recall and f1-score of the "Good" class 74.6% and 71.5%, respectively, and the best precision and f1-score for the "Satisfactory" class, 80.2% and 78.6%, respectively. The PART algorithm failed to achieve any outperforming results over the classes and in comparison, with JRip and RIDOR. Meanwhile, the RIDOR algorithm obtained the best recall and f1-score for the "Very Good" class 77.6% and 77.8%, respectively, the best precision of the "Good" class (73%), and the best recall of the "Satisfactory" class (86.8%). Furthermore, the JRip algorithm gained the lowest number of rules (26), then RIDOR (310), and PART (352).

Table 10
The performance indicators the *Grant_SRC*_94 dataset

Class	Metric	PART	JRIP	RIDOR
	Accuracy	64.563	**71.117**	70.874
Excellent	Recall	**0.778**	0.667	0.667
	F1-score	0.609	**0.632**	**0.632**
Very Good	Recall	0.710	0.790	**0.840**
	F1-score	0.676	**0.756**	0.750
Good	Recall	**0.493**	0.486	0.424
	F1-score	0.528	**0.571**	0.542
Satisfac-	Recall	0.736	0.868	**0.887**
	F1-score	0.727	0.786	**0.792**
	#Rules	103	11	48

Table 11
The performance indicators for the *Grant_SRC*_105 dataset

Class	Metric	PART	JRIP	RIDOR
	Accuracy	67.763	71.053	**73.355**
Excellent	Recall	**0.875**	**0.875**	0.792
	F1-score	0.808	0.808	**0.826**
Very Good	Recall	0.770	**0.877**	0.828
	F1-score	0.758	0.796	**0.811**
Good	Recall	0.468	0.394	**0.560**
	F1-score	0.540	0.531	**0.629**
Satisfactory	Recall	0.816	**0.918**	0.857
	F1-score	0.672	**0.720**	0.706
	#**Rules**	78	8	88

JRip algorithm performed the best in the “Excellent” and “Good” classes with 63.2%, and 57.1%, respectively. The RIDOR algorithm achieved the same as the JRip algorithm in the “Excellent” class but outperformed the PART and JRip algorithms in the “Satisfactory” with 79.2%. Furthermore, the JRip algorithm generated the lowest number of decision rules (11), while RIDOR and PART generated 48 and 103, respectively.

Table 11 presents the performance results of PART, JRip, and RIDOR when trained on students’ data regarding who received the student support fund loans (*Grant_SRC*_105). The table shows that the best-obtained classification accuracy was by RIDOR by having 73.4%. JRip and PART obtained 71.1%, and 67.8%, respectively. Regarding the recall, the JRip algorithm obtained the best results in classes “Excellent,” “Very Good,” and “Satisfactory” with 87.5%, 87.7%, and 91.8%, respectively. However, in the “Good” class, the RIDOR algorithm achieved the best (56%). For precision, JRip achieved the highest in the “Good” class (81.1%). However, for the rest of the classes, the RIDOR algorithm performed the best with 86.4%, 79.5%, and 60%, respectively. Regarding f1-score, the RIDOR algorithm performed better than the other algorithms in the first three classes with 82.6%, 81.1%, and 62.9%, respectively. The JRip algorithm achieved the best in the “Satisfactory” class with 72%. The PART algorithm did not perform better than JRip and RIDOR; even in the “Excellent” class, it performed similarly to the JRip in terms of recall, precision, and f1-score. In terms of the number of rules, the JRip algorithm obtained 8, PART 78, and RIDOR 88.

Table 12 shows the macro-average of all metrics of PART, JRip, and RIDOR across the five datasets. Regarding the accuracy and f1-score, the JRip algorithm achieved the best results for *Grant_SRC*_0, *Grant_SRC*_3, *Grant_SRC*_181, and *Grant_SRC*_94 with 75.5%, 75.5%, 76%, and 71.1%, and 75.9%, 76.1%, 76.2%, and 68.6%, respectively. Whereas, at the last dataset (*Grant_SRC*_105), the RIDOR algorithm accomplished the highest results in accuracy and f1-score with 73.4% and 74.3%, respectively. Similarly, for the recall and precision, the JRip algorithm achieved the best results for *Grant_SRC*_0, *Grant_SRC*_3, and *Grant_SRC*_181 with 76.2%, 76.1%, and 77.1% and 75.5%, 76.4%, and 75.7%, respectively. However, for *Grant_SRC*_94, the RIDOR algorithm achieved a better recall (70.5%), and for *Grant_SRC*_105, it achieved better precision (74.4%). Fig. 3 shows results of f1-score metric over the datasets, where JRip outperformed PART and RIDOR for 80% of the datasets.

Table 12
Summary of the macro-average of recall, precision, and F1-score

Algorithm	Dataset	Accuracy	Recall	Precision	F1-score
JRip	Grant_SRC_0	75.460	0.762	0.755	0.759
	Grant_SRC_3	75.469	0.761	**0.764**	0.761
	Grant_SRC_181	**76.000**	**0.771**	0.757	**0.762**
	Grant_SRC_94	71.117	0.703	0.684	0.686
	Grant_SRC_105	71.053	0.766	0.720	0.714
PART	Grant_SRC_0	**71.801**	0.714	**0.729**	**0.721**
	Grant_SRC_3	69.145	0.684	0.691	0.687
	Grant_SRC_181	71.143	0.678	0.720	0.695
	Grant_SRC_94	64.563	0.679	0.608	0.635
	Grant_SRC_105	67.763	**0.732**	0.676	0.695
RIDOR	Grant_SRC_0	**73.792**	0.733	**0.753**	0.731
	Grant_SRC_3	72.550	0.738	0.727	0.727
	Grant_SRC_181	71.571	**0.760**	0.700	0.716
	Grant_SRC_94	70.874	0.705	0.687	0.679
	Grant_SRC_105	73.355	0.759	0.744	**0.743**

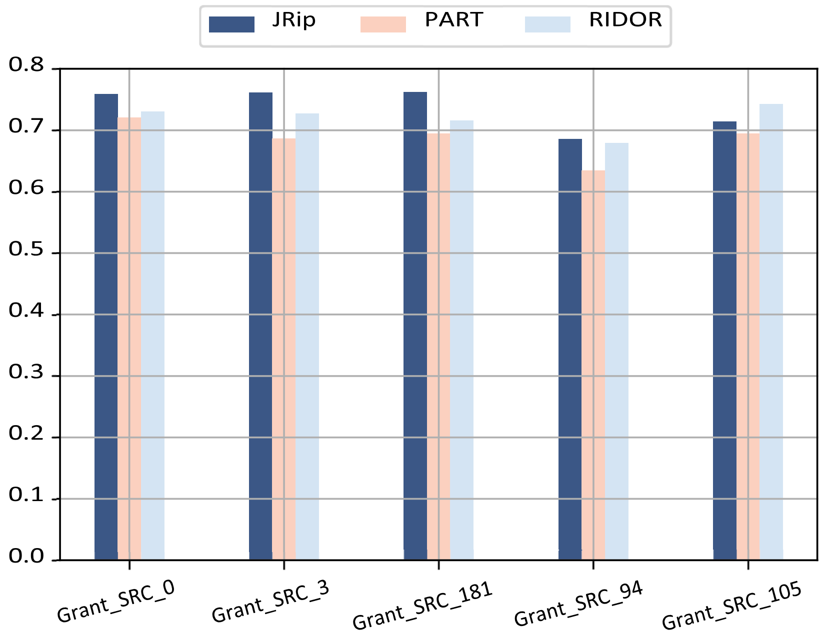

Fig. 3. F1-score Results for JRip, PART, and RIDOR for the five constructed datasets

Fig. 4 shows the confusion matrices of the best obtained models across the datasets. The x-axis presents the predicted classes, while the y-axis presents the actual classes. JRip performed the best for datasets *Grant_SRC*_0, *Grant_SRC*_3, *Grant_SRC*_181, and *Grant_SRC*_94, where it was better than the other algorithms in recognizing the “Satisfactory” classes. For *Grant_SRC*_105, the RIDOR algorithm was the best classifier and was the most efficient in identifying the “Very Good” class.

Excellent	**297**	**72**	**0**	**0**
Very Good	**86**	**1264**	**267**	**19**
Good	**2**	**260**	**1154**	**372**
Satisfactory	**1**	**19**	**344**	**1719**
	Excellent	**Very Good**	**Good**	**Satisfactory**

(a) ***Grant_SRC*_0 (JRip)**

Excellent	**40**	**11**	**0**	**0**
Very Good	**13**	**258**	**76**	**1**
Good	**0**	**46**	**408**	**93**
Satisfactory	**0**	**3**	**110**	**380**
	Excellent	**Very Good**	**Good**	**Satisfactory**

(b) ***Grant_SRC*_3 (JRip)**

Excellent	**73**	**17**	**0**	**0**
Very Good	**19**	**222**	**28**	**1**
Good	**0**	**46**	**149**	**36**
Satisfactory	**0**	**0**	**21**	**88**
	Excellent	**Very Good**	**Good**	**Satisfactory**

(c) ***Grant_SRC*_181 (JRip)**

Excellent	**6**	**3**	**0**	**0**
Very Good	**4**	**79**	**15**	**2**
Good	**0**	**22**	**70**	**52**
Satisfactory	**0**	**5**	**16**	**138**
	Excellent	**Very Good**	**Good**	**Satisfactory**

(d) ***Grant_SRC*_94 (JRip)**

Excellent	**19**	**5**	**0**	**0**
Very Good	**3**	**101**	**18**	**0**
Good	**0**	**20**	**61**	**28**
Satisfactory	**0**	**1**	**6**	**42**
	Excellent	**Very Good**	**Good**	**Satisfactory**

(e) ***Grant_SRC*_105 (RIDOR)**

Fig. 4. Comparison of the confusion matrices for the best obtained models across the five datasets

4.2. Rules analysis

This subsection shows the generated rules of the best-obtained models from the extracted datasets. The JRip algorithm was considered for the total dataset with only the first two-year averages; the JRip algorithm is also considered for *Grant_SRC*_0, *Grant_SRC*_3, *Grant_SRC*_181, and *Grant_SRC*_94. The RIDOR algorithm was analyzed for the *Grant_SRC*_105 dataset. The generated rules are accompanied by a ratio of two numbers (A/B). The first (A) indicates the number of rules that were correctly classified by the rule, while the other (the denominator) presents the number of instances that were misclassified by the rule. Hence, the selected rules are the rules of the maximum value of ($A - B$).

The best generated rules of the whole dataset with two averages are as follows:

1. (2^{nd}_Year_Average >= 3.16) and (Repeated_Courses = 0) −⟶ Student_Rate = Very_Good (5353/628)
2. (2^{nd}_Year_Average >= 2.54) and (Repeated_Courses = 0) and (Fees = 0) −⟶ Student_Rate = Good (4355/1107)
3. (2^{nd}_Year_Average >= 3.71) −⟶ Student_Rate = Excellent (1481/224)
4. (2^{nd}_Year_Average >= 3.24) −⟶ Student_Rate = Very_Good (564/146)
5. (2^{nd}_Year_Average >= 2.6) and (High_School_Avg >= 91.5) −⟶ Student_Rate = Good (633/275)
6. (Repeated_Courses = 0) and (2^{nd}_Year_Average >= 2.61) and (2^{nd}_Year_Average<= 2.89) and (Credit_Semester_4 = 15) −⟶ Student_Rate = Good (469/118)
7. (2^{nd}_Year_Average >= 3.08) and (Repeated_Courses = 0) and (1^{st}_Year_Average <=3.24) −⟶ Student_Rate = Very_Good (446/120)
8. (1^{st}_Year_Average <= 3.06) and (2^{nd}_Year_Average >= 3.01) and (Fees = 0) −⟶Student_Rate = Very_Good (464/159)
9. (2^{nd}_Year_Average >= 2.56) and (Credit_Semester_1 = 12) and (Repeated_Courses =0) −⟶ Student_Rate = Good (321/105)

Based on the (A - B) values, the rule with the highest value is the first rule with 4725 (A - B) value. This rule is interpreted as: If the student's second-year average is equal to or greater than 3.16 and they have not repeated any courses, then their student rate is classified as "Very Good." This rule has the highest number of instances correctly classified compared to the instances misclassified. It suggests that students who achieve high second-year averages and do not have any repeated courses are more likely to have a very good student rate. From the interpretations of the above nine rules, several insights can be deduced:

1- The second-year average is an important factor: Several rules include conditions related to the second-year average. Higher second-year averages, such as 3.16 or above, are associated with a higher likelihood of achieving a very good or excellent student rate.

2- Avoiding repeated courses improves student rate: Rules that include the condition of no repeated courses indicate that students who manage to avoid repeating courses tend to have higher student rates, such as very good or good.

3- High school performance matters: The rule that includes a condition on high school averages indicates that students with higher high school averages, particularly above 91.5, are more likely to have a good student rate.

Overall, these insights suggest that factors such as academic performance, course repetition, financial circumstances, and credit semester distribution play important roles in determining students' performance rates. The second year's average is a powerful indicator of excellent ratings, whereas, the first- and second-year averages, if the student repeated courses, and the fees, are the best features for identifying the students. Besides, for the good students, the second-year average, if the student repeated courses, fees, high school average, Credit_Semester_4, and Credit_Semester_1, are indicators for this category of students.

The following list presents the generated rules for *Grant_SRC*_0, which represents students who received no grant during their study period. The Admit_Type = (1) means in competition and evenly with others, and "Fees" indicates if the student has registration fees.

1. (2^{nd}_Year_Average >= 2.51) and (Repeated_Courses = 0) −⟶ Student_Rate = Good (3837/1122)
2. (2^{nd}_Year_Average >= 3.17) and (Admit_Type = 1) −⟶ Student_Rate = Very_Good (1680/167)
3. (2^{nd}_Year_Average >= 3.25) −⟶ Student_Rate = Very_Good (1384/210)
4. 4. (2^{nd}_Year_Average >= 3.04) and (Repeated_Courses = 0) −⟶ Student_Rate = Very_Good (1330/390)
5. (2^{nd}_Year_Average >= 3.71) −⟶ Student_Rate = Excellent (803/126)
6. (2^{nd}_Year_Average >= 2.59) and (Fees = 0) −⟶ Student_Rate = Good (870/318)

7. (High_School_Avg >= 91.5) and (2^{nd}_Year_Average >= 2.68) −→ Student_Rate = Good (145/48)
8. (2^{nd}_Year_Average >= 2.38) and (Repeated_Courses = 0) and (Credit_Semester_5 = 18)−→ Student_Rate = Good (154/70)
9. (1^{st}_Year_Average <= 3.18) and (Credit_Semester_4 = 15) and (2^{nd}_Year_Average >= 3) −→ Student_Rate = Very_Good (99/40)

From the interpretations of the nine rules for the *Grant_SRC*_0, several insights can be deduced:

1- Second-year average is a crucial factor: Many rules consider the second-year average as a significant determinant of student rate. Higher second-year averages, such as 3.17 or above, are associated with a higher likelihood of achieving a very good or excellent student rate. Even a second-year average of 2.51 or higher is associated with a good student's rate.

2- Repeated courses negatively impact student rate: Rules that include the condition of no repeated courses indicate that avoiding course repetitions is beneficial for student rates. Students who do not repeat any courses tend to have higher chances of achieving very good or good student rates.

3- Admit type can influence student rate: The rule that includes the condition of an admit type equal to 1 suggests that students admitted in competition and evenly with others are more likely to have a very good student rate.

4- High school performance matters: Rules that include the condition of a high school average above 91.5 indicate that students with higher high school averages have a higher likelihood of achieving a good student rate.

In general, when considering the excellent rating, the second-year average emerges as the most significant feature for identifying for identifying students in this category. In comparison, the first and second-year averages, admission type, repeated courses, and Credit_Semester_4 are the most elucidating features for the very good student rating. And for the good rating, the second-year average, repeated courses, high school average, and Credit_Semester_5 were the best-indicating features.

The following list presents the generated rules for *Grant_SRC*_3, which refers to students who received the High Royal Honorable grant. At Faculty_Code as 9 means the faculty of engineering. Likewise, the second-year average was the best feature for identifying students with excellent ratings. Regarding the "Very-Good" average, the second and first- year averages, repeated courses, and Credit_Semester_2 were the best features. Besides, for the students of a satisfactory rating, the best indicator features were the first and second-year averages, repeated courses, fees, and Credit_Semester_4.

1. (2^{nd}_Year_Average >= 3.21) −→ Student_Rate = Very_Good (610/66)
2. (2^{nd}_Year_Average <= 2.45) and (1^{st}_Year_Average <= 2.9) −→ Student_Rate = Satisfactory (551/80)
3. (2^{nd}_Year_Average <= 2.41) and (1^{st}_Year_Average <= 2.33) −→ Student_Rate = Satisfactory (486/32)
4. (2^{nd}_Year_Average >= 3.07) and (1^{st}_Year_Average <= 3.19) and (Repeated_Courses= 0) −→ Student_Rate = Very_Good (107/17)
5. (2^{nd}_Year_Average >= 3.75) −→ Student_Rate = Excellent (98/11)
6. (2^{nd}_Year_Average <= 2.5) and (Repeated_Courses = 1) −→ Student_Rate = Satisfactory (107/28)
7. (2^{nd}_Year_Average >= 3.02) and (1^{st}_Year_Average <= = 3.18) and (Credit_Semester_2= 15) −→ Student_Rate = Very_Good (93/15)
8. 8. (2^{nd}_Year_Average <= 2.69) and (Repeated_Courses = 1) and (Faculty_Code = 9)−→ Student_Rate = Satisfactory (58/20)
9. (2^{nd}_Year_Average <= 2.65) and (Fees = 1) and (Credit_Semester_4 = 12) −→ Student_Rate= Satisfactory (41/10)

For the grant source *Grant_SRC*_181, the following list presents the generated rules. Grant source 181 indicates students who received the Ministry of Education honoring the children of teachers, which, the Study_Level is the year of study and the Certificate_Amman indicates if the nationality on the high school certificate is Jordan. From the list, we can see that also the second-year average was the best pointer for excellent students. For the students with a good rating, the first- and second-year averages, high school average, and the study's plan year were the best illustrating features. Moreover, for the satisfactory rating, the second-year average, if the certificate was from Jordan and the level of study best explained this category of students.

1. (2^{nd}_Year_Average <= 2.87) −→ Student_Rate = Good (400/77)
2. (2^{nd}_Year_Average >= 3.74) −→ Student_Rate = Excellent (169/14)
3. (2^{nd}_Year_Average <= 2.47) and (Study_Level = 4) −→ Student_Rate = Satisfactory (161/18)
4. (2^{nd}_Year_Average <= 3.11) and (1^{st}_Year_Average >= 3.18) −→ Student_Rate = Good (93/30)
5. (2^{nd}_Year_Average <= 2.55) and (Certificate_Amman >= 1) −→ Student_Rate = Satisfactory (69/25)

6. (2^{nd}_Year_Average <= 2.95) −→ Student_Rate = Good (71/29)
7. (2^{nd}_Year_Average >= 3.68) −→ Student_Rate = Excellent (66/25)
8. (2^{nd}_Year_Average <= 2.99) and (Plan_Year = 2010) and (High_School_Avg <=93.3) −→ Student_Rate = Good (47/11)

Grant source *Grant_SRC*_94 relates to students who have an exemption because they are the children of employees. The following list presents the generated rules, where the Transition_Flag indicates if the student transferred from another college. Regarding the excellent rating, the second-year average and Credit_Semester_6 were the most indicative features. For the very good rating, the first and second-year averages, transition flag, fees, repeated courses, Credit_Semester_7, and Credit_Semester_3 were the best pointing features. Finally for the good rating, the second-year average, repeated courses, Credit_Semester_6, and Credit_Semester_7 were the most explainable features indicating this student category.

1. (2^{nd}_Year_Average >= 3.68) −→ Student_Rate = Excellent (27.0/10.0)
2. (2^{nd}_Year_Average >= 3.44) and (Credit_Semester_6 = 18) −→ Student_Rate = Excellent (9.0/3.0)
3. (2^{nd}_Year_Average >= 3.1) and (Transition_Flag = 0) −→ Student_Rate = Very_Good(154.0/18.0)
4. (2^{nd}_Year_Average >= 3.03) and (Fees = 0) and (Repeated_Courses = 0) −→ Student_Rate= Very_Good (43.0/7.0
5. (2^{nd}_Year_Average >= 3.03) and (Credit_Semester_7 = 18) −→ Student_Rate = Very_Good (12.0/0.0)
6. (2^{nd}_Year_Average >= 2.89) and (1^{st}_Year_Average <= 2.86) −→ Student_Rate = Very_Good (35.0/17.0)
7. (2^{nd}_Year_Average >= 2.89) and (Credit_Semester_3 = 18) −→ Student_Rate = Very_Good (6.0/1.0)
8. (2^{nd}_Year_Average >= 2.54) and (Repeated_Courses = 0) −→ Student_Rate = Good (277.0/57.0)
9. (2^{nd}_Year_Average >= 2.51) and (Credit_Semester_6 = 18) −→ Student_Rate = Good (22.0/4.0)
10. (2^{nd}_Year_Average >= 2.41) and (Credit_Semester_7 = 17) −→ Student_Rate = Good (17.0/2.0)

Furthermore, for the grant source *Grant_SRC*_105, the following list shows the generated rules. This grant source refers to students who received student support fund loans. These rules are the result of the best-obtained model, which is based on the RIDOR algorithm, which the Initial_Admit_Type is competitive or other admit types and sex (1) indicates a male. For the “Very Good” rating, the second-year average, repeated courses, Credit_Semester_4, and sex were the most indicative features. Whereas for the “Good” rating, the first and second-year averages, repeated courses, high school average, Credit_Semester_1, initial admit type, and high school branch were the best features pointing to students of good rating. Furthermore, for the “Satisfactory” rating, the first- and second-year averages and Credit_Semester_1 were the best elucidating features for this class of students.

1. (2^{nd}_Year_Average <= 3.55) and (2^{nd}_Year_Average <= 3.45) −→ Student_Rate =Very_Good (490/0)
2. (2^{nd}_Year_Average > 2.685) and (Repeated_Courses = 0) and (2^{nd}_Year_Average> 2.785) −→ Student_Rate = Good (293/0)
3. (2^{nd}_Year_Average <= 2.905) and (2^{nd}_Year_Average <= 2.695) −→ Student_Rate = Good (160/1)
4. (2^{nd}_Year_Average > 2.755) −→ Student_Rate = Good (130/0)
5. (2^{nd}_Year_Average > 3.125) and (2^{nd}_Year_Average > 3.245) −→ Student_Rate = Very_Good (114/2)
6. (2^{nd}_Year_Average <= 2.905) and (2^{nd}_Year_Average <= 2.655) and (1^{st}_Year_Average <= 2.74) −→ Student_Rate = Satisfactory (109/0)
7. (2^{nd}_Year_Average <= 3.005) and (2^{nd}_Year_Average <= 2.905) and (Credit_Semester_1

= 12) −→ Student_Rate = Satisfactory (40/0)

8. (2^{nd}_Year_Average > 2.635) and (Credit_Semester_1 = 12) and (High_School_Avg <= 96.55) and (Initial_Admit_Type = 1) −→ Student_Rate = Good (32/0)
9. (2^{nd}_Year_Average <= 3.085) and (1^{st}_Year_Average > 3.095) and (High_School_Branch = 2) and (High_School_Avg <= 96.7)−→ Student_Rate = Good (11/0)
10. (2^{nd}_Year_Average > 2.405) and (Credit_Semester_4 = 15) and (Repeated_Courses =0) and (Sex = 2) −→ Student_Rate = Very_Good (8/0)

Generally, the generated rules give more weight to the high school average, the first- and second-year averages, and the accumulative hours in a semester. The generated rules can aid decision-makers when selecting suitable students evenly by considering various factors, including the admit type, the nationality of the certificate holder and gender, as presented above. It is worth mentioning that these rules are based on an optimal performing algorithm. However, in some cases, the other algorithms performed somewhat similarly which means that they might provide reasonable rules to consider as well.

Thus, a complete set of rules should be provided to the granting agency which will be responsible for evaluating the rules with the best approach and for respective situations.

5. Educational and managerial implications

Based on the analysis of the results, as well as the interpretations and insights derived from the generated rules, several educational and managerial implications can be suggested to enhance the decision-making process of granting agencies in higher education.

5.1. Educational implications

- Consider university academic performance: It is important to revise the scholarship allocation strategy in higher education. It is recommended that granting agencies consider students' performance throughout their university journey when awarding scholarships. Instead of solely focusing on the beginning of university studies, scholarships should be distributed over multiple years, with a portion of the scholarships allocated in the second year or later stages. This approach allows for a more accurate assessment of students' capabilities, motivations, and dedication, taking into account their actual performance and progression within the academic environment. By doing so, granting agencies can ensure that scholarships are awarded to deserving students who have demonstrated consistent academic excellence and commitment over time, promoting fairness and maximizing the impact of financial support in higher education. Furthermore, this approach encourages students to maintain high levels of motivation, engagement, and achievement throughout their university experience. By implementing this educational implication, granting agencies can optimize the impact of scholarships, effectively supporting students' educational journey and fostering a culture of continuous improvement and excellence in higher education.

- Considering Socioeconomic Factors: Some rules involve variables related to fees, socioeconomic background, and admission type. This suggests that granting agencies should consider the financial needs and backgrounds of students while making decisions about grant awards. Supporting students from disadvantaged backgrounds can contribute to improving access to higher education.

- Consider multiple criteria: The rules reveal that multiple criteria contribute to determining the student's rate for different grant sources. Granting agencies should consider various factors such as academic performance, credit semesters, repeated courses, admission types, gender, financial need, and other relevant factors to make fair and comprehensive decisions about grant allocation.

- Define clear performance thresholds: The rules frequently involve thresholds for academic performance, such as average grades in specific years or across semesters. This highlights the importance of academic achievement for grant eligibility. Granting agencies should consider rewarding students who meet or exceed these thresholds to encourage continuous academic excellence. These thresholds should be based on empirical data and domain expertise to ensure they align with the desired objectives and outcomes.

- Tailor grant criteria for different sources: Each grant source may have its specific criteria and requirements. Granting agencies should consider the unique characteristics of each source and customize the eligibility criteria accordingly. Understanding the unique characteristics of each grant source and the corresponding rules will enable more effective and fair distribution of resources.

- Monitor and evaluate the effectiveness: Granting agencies should establish a monitoring and evaluation system to assess the effectiveness of the grants provided. By collecting data on the academic performance and outcomes of grant recipients, agencies can analyze the impact of the grants and make data-driven decisions for future allocations.

- Regularly update and refine the rules: As the educational landscape and student profiles evolve, granting agencies should regularly update and refine the rules used or grant allocation. By incorporating new data and insights, agencies can ensure that their decision-making processes remain relevant and effective over time.

- Foster transparency and communication: Granting agencies should maintain transparent and clear communication channels to inform students about the criteria, application process, and outcomes of grant allocation. This fosters trust, allows for feedback, and ensures that students have a clear understanding of the requirements and expectations.

- Consider additional support services: Granting agencies can collaborate with educational institutions to provide additional support services to grant recipients. These services can include academic advising, mentoring programs, career counseling, and financial literacy workshops. Such support can enhance the effectiveness of grants and contribute to the overall success of students.

- Data Privacy and Ethics: As the decision-making process relies on student data, granting agencies should prioritize data privacy and adhere to ethical guidelines. Ensuring data security and anonymization is crucial to safeguard the rights and privacy of individual students while ensuring fairness.

- Collaboration and Research: Collaboration between granting agencies, educational institutions, and researchers can lead to more robust models and evidence-based decision-making. Ongoing research and data analysis can provide valuable insights to improve the efficacy of grant allocation strategies.

5.2. Managerial implications

• Use automated decision support systems: Granting agencies can leverage automated data driven decision support systems to assist in the evaluation and allocation process. By analyzing historical data and using machine learning algorithms, agencies can identify patterns and relationships that can inform their grant allocation strategies. Regularly updating and refining the rules based on new data will lead to more accurate and effective decision making.

• Implement a centralized data management system: A centralized data management system can integrate and organize data from various sources, facilitating data-driven decision-making. Granting agencies should invest in robust data infrastructure to ensure data quality, security, and accessibility. This enables effective analysis of historical data and the identification of trends and patterns.

• Continuous Improvement: Regularly refining the decision-making models and rules through feedback and evaluation can lead to continuous improvement in the allocation of grants. As new data becomes available and circumstances change, the rules should be reviewed, refined, and validated to ensure their relevance and accuracy. Incorporating machine learning techniques that adapt to changing student dynamics and needs may further enhance decision-making accuracy.

• Conduct sensitivity analysis and scenario planning: Granting agencies can perform sensitivity analysis and scenario planning to assess the impact of potential changes in the rules or criteria. By simulating different scenarios, agencies can understand how modifications to the rules may affect grant allocation outcomes and make informed decisions accordingly.

• Establish performance metrics and benchmarks: Granting agencies should define performance metrics and benchmarks to evaluate the effectiveness and efficiency of the grant allocation process. By monitoring key indicators such as student success rates, graduation rates, and return on investment, agencies can assess the impact of their decisions and identify areas for improvement.

• Foster collaboration and knowledge sharing: Granting agencies can foster collaboration and knowledge sharing among different stakeholders, including educational institutions, researchers, and policymakers. This collaboration can provide valuable insights and expertise to enhance the decision-making process and improve the overall effectiveness of grant allocation.

• Use of explainable AI: To ensure transparency and accountability, granting agencies should use explainable AI models. These models provide interpretable insights, making it easier for managers and stakeholders to understand the factors influencing grant allocation decisions and gain confidence in the process.

• Flexibility and adaptability: The educational landscape is continuously evolving, and student profiles may change over time. Granting agencies should remain flexible and adaptable in their decision-making processes, regularly updating their rules to respond to new challenges and opportunities.

• Ethical considerations: Granting agencies must consider ethical aspects when using AI algorithms for decision making. They should ensure that the models do not inadvertently lead to biased or discriminatory outcomes. Regular audits and reviews of the models can help identify and address any potential biases.

6. Conclusions and future works

This paper presented and used a data mining and rule-based approach to interpret the most influencing factors affecting granting organizations. These factors are important when scholarship organizations and agencies select which students to award a study grant. The paper closely studied undergraduates from the University of Jordan, where the data was drawn from its databases. The data was used to train and model three rule induction and data mining algorithms. The result of the three algorithms indicates a high correlation of different features: the first two-year average, the high school average, the cumulative number of courses across the study semesters, the study admits type and the initial admission, the repeated courses, and the fees. However, we recommend that a granting agency give more weight to the high school average, the first- and second-year averages, and the accumulative hours taken by the student. These generated rules can be utilized as a decision support system for granting organizations in Jordan. Regarding future work, this study can be extended further and enhanced by collecting more data from different local universities in the region. This will be a precious addition to enrich and generalize the study's outcomes. Furthermore, additional exploration is required to investigate the influence of having a scholarship on students' motivation.

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