Fuzzy Based Model for Students Debar Policy in Indian Engineering Institutes

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Abstract
All around the world, a critical aspect of the higher education system is the evaluation of students through periodic examinations. To exemplify, many higher education centers in India allow students to undertake rigorous semester-based examinations i.e., End-Semester (or End-Term) examination, provided they meet the criteria of class attendance up to a certain percentage. However, below the mandatory percentage, the students are considered debarred from the examination. There are several instances been observed, especially since the Covid-19 cases arrived in India, where students have missed their classes due to genuinely unfavorable causes. In such cases, debarring students due to insufficient classroom attendance is unfair and this can affect students' careers in adverse ways. To work in this direction, this paper analyses a computational model that takes into account multiple parameters reflecting students' performance to determine whether they should be allowed to undertake the End-Term examination or not. The proposed model implements the machine learning-based K-means clustering and Fuzzy Modelling techniques, as an inclusive approach for strategic examination of debarred policy in engineering institutes. It is observed that in comparison to other existing models, quite fewer students are declared as debarred using the proposed model. To the best of the authors' knowledge, no such system exists to date.

Keywords: Machine Learning, K-Means, Fuzzy Logic, Class Attendance, Engineering Institute, Examination Debar Policy, Performance Evaluation

1. Introduction

In a higher education system, the teaching-learning process has undergone a drastic shift lately, especially since Covid-19 (Jain et al., 2021a) cases are observed not only in developed countries but also in developing countries such as India. The offline mode of teaching is mapped to online teaching using modernized tools and techniques of the learning process (Furlong et al., 2003; Fredricks et al., 2004). However, still few facets of educational practices are not yet garnered the attention of policymakers. One of these practices is the determination of examination debar criteria for students enrolled in undergraduate education.

In undergraduate or other higher education courses in India, examinations and their related procedures are considered a very important component for evaluating the students' overall performance. The semester-based evaluations, prominently End-Semester (or End Term) examinations are a way of validating the students' learning as well as their preparation for futuristic learning in their selected careers. However, most of the higher educational institutions in India allow only those students to appear for the end-term examinations who have attended their classes regularly during the entire semester. This is measured by the criteria of the number of classes attended by the student over a total number of classes being conducted by the institute/university, as in equation (1).

$$Student\ Attendence\ (\%) = \frac{No.of\ classes\ attended\ by\ student}{No.of\ classes\ conducted\ by\ institute} * 100 \qquad (1)$$

This is quintessential since classroom participation is deemed important for students' learning and preparation for their examinations (Borland & Howsen, 1998; Moore et al., 2003; Veerasamy et al., 2018). The evaluation includes written examinations which in general, are permitted to be attempted by the students who have regularly attended their classes. A threshold of attendance percentage is decided by the institute or university and those students who do not possess the required threshold attendance are considered debarred from appearing in the examinations. The sole class attendance-based criterion for eligibility to appear for the examination is lopsided and unfair whenever students are involved in varied learning activities during the semester such as assignments, projects, reports, viva-voice, and so on. In addition, disparity in students' family, economic and cultural backgrounds also affect their regularity of attendance in classes. The debarring of students from appearing for the end-term examination that too due to inadequate class attendance leads to serious consequences upon students, ranging from loss of academic progress, dissatisfaction among students, loss of interest towards career, and personal side-effects (Avasthi et al., 2022) such as loss of self-confidence, self-esteem, mental stress, anxiety, etc.

To handle the examination-based debar problem, a computational model is proposed, taking care of an all-rounded evaluation of students learning. The proposed model works upon multiple parameters that are postulated with respect to students learning during the entire term or semester, not merely confined to classroom attendance. The multi-parameters include eight factors that highlight students' performance through varied aspects, for example, performance in previous examinations, regular involvement in subject-related activities, capability to prepare for examination independently, and performance in creative or intellect-based activities. Based on these parameters, an initial set of different fuzzy rules are framed. Fuzzy logic (Pandey & Jain, 2020) is chosen for solving the problem due to the inclination of domain experts for inferring the rules as well as due to the linguistic nature of the factors. By evaluating students in eight dimensions, a better-informed decision is made for the considered problem. However, the complexity in framing the fuzzy rules and their implementation over a larger set of students is quite tedious to execute. In addition, unlabeled data cannot be classified directly using the machine learning (Jain et al., 2018) approaches. Therefore, the K-Means clustering algorithm (Jain et al., 2021b) is applied over the initial drawn fuzzy rules. The clustering is performed by assigning weights to eight attributes. Once the clusters are obtained, a refined set of fuzzy rules are framed based on the observations from the formulated clusters. Thereafter, the resultant generation of seven fuzzy rules is applied to solve the examination debar problem. Thus, the model provides an inclusive view of students' performance before imposing a decision to debar them from appearing in the end-term examinations. The research objectives of the proposed work are highlighted as follows:

- To propose a computational model that takes into account multiple parameters reflecting students' performance to determine whether they should be allowed to undertake the End-Term examination or not.
- To include a comprehensive set of domain-related eight parameters that encompass the students' overall performance and execute the debar decision in a better way.
- To apply clustering algorithm while assigning weights and to implement fuzzy modeling, in order to capture the linguistic nature of attributes and to prevent inaccuracies during quantification of attribute values.
- To develop a simple yet effective model while working with a small set of fuzzy rules to capture the domain knowledge.

The remaining paper is arranged as follows: Section 2 enlists the work done in the related domain. Section 3 puts forth the design of the proposed model. Section 4 explains the implementation results. Section 5 finally concludes the paper.

2. Related Work

The importance of efficient educational practices in higher education institutes is reflected by numerous studies mentioned below. These studies are carried out to emphasize students' facets such as their behavior, diversity in their habits, customizing study material according to their needs, and evaluating their performance. So that the examination debar policy can then be laid and implemented in a better way at the higher educational systems at different levels.

Yadav et al. (2014) have pointed out several cognitive factors that influence students' academic performance and hence, are not to be gauged by arithmetic techniques. Andrietti & Velasco (2015) have undertaken a study at a public university in Spain to evaluate the role of study time including self-study and class attendance of students on academic performance. Their study has suggested that attendance has a lesser effect on academic performance than study time. Barlybayev et al. (2016) have proposed a qualitative method for the evaluation of student performance using Fuzzy Logic instead of traditional methods. Pani & Kishore (2016) have mentioned that high-performer students are lesser affected by absenteeism than low-performers students. They have conducted their study on the students in the British university campus in the Middle East. Odokuma & Obagbuwa (2017) have applied Fuzzy methods on the grounds that they can correctly capture the judgment of teachers through the Fuzzy Mamdani Inference system. Their system is developed to identify the students who have dropped out of higher educational institutions. This Fuzzy system classifies the students who are not performing well so that corrective measures are to be taken in this regard. Krouska et al. (2019) have underlined the benefits of customizing educational practices and evaluation methods based on students' requirements. Moores et al. (2019) have reviewed studies that have investigated the determinants of attendance for a better understanding of improving attendance rates in higher education institutions. Fuzzy logic systems for students' evaluations have also been proposed by researchers (Gokmen et al., 2010; Petrudi et al., 2013; Yousif & Shaout, 2018; Othman et al., 2019). Apart from evaluations, another important aspect of higher education practices is the classroom attendance evaluation since it generally determines if students are eligible to appear in examinations. Researchers (Bennett & Yalams, 2013; Lukkarinen et al., 2016) have outlined the benefits of classroom attendance for students and have attempted to identify the common reasons for low-class attendance of students. Several studies have demonstrated that more classroom attendance has yielded improved performance of students. In addition, it has also been observed that students who are allowed to take the exams without attending classes regularly, often have some compelling reasons for not attending classes, or are able to prepare for the course on their own.

In a few instances, such as Baker et al. (2001) have observed that one of the main reasons for absenteeism in classes is due to improperly framed policies on absenteeism. Rodgers (2001) has stated that class attendance is not found to influence the students' performance. Massingham & Herrington (2006) have discussed the reasons for the non-attendance of classes. Their study has shown that many students are having compelling reasons for non-attendance. Singh et al. (2016) have designed a mobile app for a higher education institute. In their app, they have used two parameters namely- attendance and marks in the previous subject, in order to decide whether students should be debarred from the examination or not. Their approach is very harmful to the students, failing a course can imply failing subjects in a cascade without even having taken them. Jain & Jaggi (2020) have implemented the Fuzzy Logic-based attendance evaluation system. Their system considers attributes- student attendance in the current course, performance based on continual assessment in the current course, overall performance and assessment by faculty for deciding whether the students are to be debarred from the examinations, or allowed to take the examinations, or be given any kind of reconsideration. Chen et al. (2021) have worked with a mobile phone-based lightweight attendance system. They have recorded attendance by scanning QR codes for first-year college students. Their attendance control is done within one minute, so it is easy to cheat to save this requirement.

It has been inferred from the above studies that not many significant attempts have been made to develop an efficient or flexible attendance evaluation system in the context of the Indian higher education institutes. Compared with the above research, this paper presents a significant extension of the existing work (Jain & Jaggi, 2020). The proposed model is specifically aimed at closer scrutiny of students with lower attendance to check if they have met other related criteria or not. For the sake of the same, eight parameters are considered to make the model more robust. Fuzzy logic is integrated with K-means clustering to obtain satisfactory results in domain-based expert knowledge and is marked by subjectivity.

3. Proposed Computational Model

The classroom attendance of students is computed as a percentage of classes the students have attended for their courses. The higher educational institutes or universities usually employ this as the sole criterion for deciding whether students are allowed to appear for the end-term examination or not. However, in several instances, absenteeism of students from their classes is due to valid reasons, for example, medical emergency, placements/other employment-related activities, preparation for competitive examinations, participation in various competitions, involvement in research projects, and so on. These students are capable to perform well in their examinations, provided they are allowed to appear for the exams by their institute/university.

In this section, a computational model for examination debar policy is proposed that evaluates multiple parameters related to students, before determining whether they are to be debarred from their examination. The proposed model is improvised over other existing approaches – Model 1 (Kassarnig et al., 2017) and Model 2 (Jain & Jaggi, 2020) since it undertakes a well-informed decision and thus, yields better results.

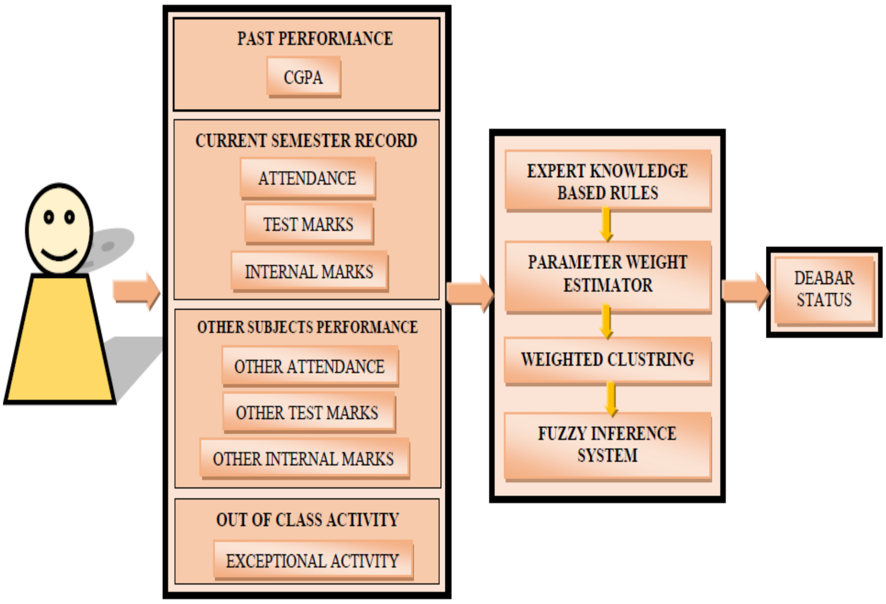

Fig. 1. Proposed computational model for examination debar policy.

Fig. 1 illustrates the proposed model that evaluates students based upon 8 attributes within 4 defined categories. The first category is related to the past performance of students and extracts their Cumulative Grade Point Average (CGPA) as an important value. The second category of attributes is related to the performance of students within the ongoing subjects under consideration. This category includes values for students' attendance in the subject, marks in the exams held (such as test 1, and test 2) during the term for the subject, and the teacher's assessment marks based on class projects, assignments, etc. The third category of attributes is related to the performance of students in other subjects in the current term. The fourth and last category of attributes is related to the evaluation of whether the students have undertaken any creative or exceptional activity in the semester which is out of a specific subject's realm. All the above categories and their related parameters constitute input variables, and there is a sole output variable, i.e., *"is_debarred"* for the proposed system. All of them are explained in detail as stated below.

3.1 System Variables

There are two types of system variables under consideration, i.e., Input variables and Output variable. Each one of them is discussed here one by one.

Input Variables. The input variables are divided into 4 categories (Category I-IV), where each category has its own set of variables to work with, totaling 8 parameters. Each one of them is detailed here. It is noted that the value of each input variable is normalized on a scale of 0 to 1.

Category I. The variable of this category represents the past performance of students. This category includes the variable name *"preMarks"* which is discussed here.

1. preMarks: This attribute reflects the students' performance in general, till-date. It is included in decision making since it is useful to identify otherwise good students who have attended fewer classes in the current subject, maybe due to some valid reasons in the present time.

Category II. The variables of this category represent the performance of students in the ongoing subjects under consideration. This category includes the variable names *"subjAttendence"*, *"subjTestMarks"*, and *"subjInternalMarks"* that are discussed here.

2. subjAttendance: This attribute stands for the percentage of classes of the current course attended by the students and is specified in percentage.
3. subjTestMarks: This attribute corresponds to the performance of students in an examination that is held during the term for the course whose attendance is being evaluated.
4. subjInternalMarks: This attribute inculcates the subject teacher's evaluation of subject-related activities undertaken by the students. This includes project development, timely assignment submission, etc.

Category III. The variables of this category represent the performance of students in other subjects. This category includes the variable names *"otherAttendance"*, *"otherMarks"*, and *"otherInternalMarks"* that are discussed here.

5. otherAttendance: This attribute is used to gauge the attendance of students in other courses they are offered during the current term. The comparative better attendance records in most other courses indicate that there is some problem faced by the students while attending the classes of a particular subject.
6. otherMarks: This attribute is used to obtain a view of how the students have fared in the examinations of subjects other than the one being considered.
7. otherInternalMarks: This attribute is used to remove any biased or unfairness in evaluation. This parameter captures the average evaluation of students by other subjects' teachers.

Category IV. The variable of this category takes care of the performance of students in creative or intellect-based activities. This category includes the variable name *"exceptionalActivity"* which is discussed here.

8. exceptionalActivity: This attribute gives credit for any innovative or creative work that is done by the students in the current term. Such activity has taken up most of the time from students' curriculum and so is essential to consider.

Output Variable. There is one output variable, *"is_debarred"* that denotes the decision whether students are debarred or not from the end-term examination in the institute.

3.2 The Computational Model

The proposed computational model is explained here in four consecutive steps, Step 1-4 respectively. As is explained in the above section, the model undertakes eight input parameters *("preMarks", "subjAttendance", "subjTestMarks", "subjInternalMarks", "otherAttendance", "otherMarks", "otherInternalMarks", "exceptionalActivity")* and generates an output whether students should be debarred from their end-term examination or not.

Step 1. In this step, all the stated 8 attributes are considered together to comprehensively represent the students' performance and to conclude the fair and informed decision on whether students are allowed to appear for the final end-term examination or not. To do so, knowledge from experts is gathered from the faculties of higher educational institutes, based upon which fuzzy rules are generated. These fuzzy sets of rules are in terms of if-conditions such that they are sufficient to establish the relationship between input variables and output attributes. The nature of if-conditions is linguistic, so their quantification leads to certain inaccuracies in the model. Hence, fuzzy modeling is deemed appropriate to represent the proposed system. However, fuzzy rules that are framed on the basis of the choice of attributes are too large in number. For example, considering 3 classes for each attribute can have 38 rules, which faces severe challenges while framing the exact rules for any domain expert as well as during implementation. Moreover, the input variables have some weighted impact on the output. So, it is important to assign weights to these variables and accumulate them, in order to reduce the total number of variables to be processed by the system. Here, the weight of each attribute denotes its importance in fuzzy decision-making.

Consider the attribute of *"subjAttendance"*, if students have good attendance in their subject, irrespective of the value of other attributes, they should be allowed to appear in the examination. Hence, the attribute weight equals the sum of weights of all other attributes, and so is assigned to this attribute. In addition, the weight of *"exceptionalActivity"* is the same as the sum of weights of the three attributes that represent other subjects *("otherAttendance", "otherMarks", "otherInternalMarks")*. Hence, assigned the weight of 1 unit to each of these three attributes, and a weight of 3 units to *"exceptionalActivity"*. Also, equal importance is given to the attributes- *"preMarks", "subjTestMarks", "subjInternalMarks"*, and *"exceptionalActivity"*, hence, the same weight is assigned to each of these attributes, i.e., the weight of 3 units each.

Step 2. In this step, the attributes are aggregated together and normalized to form a single compound attribute, *"compound_attribute"* as is in equation (2).

$$compound\_attribute = (preMarks * 3 + subjTestMarks * 3 + subjInternalMarks * 3 + otherAttendance * 1 + otherMarks * 1 + otherInternalMarks * 1 + exceptionalActivity * 3) / 15 \tag{2}$$

Step 3. In this step, unlabeled students' data is collected from four engineering institutes in India. Here, a clustering-based K-means algorithm is applied to the resultant two attributes, namely- *"subjAttendance"* (Step 1), and *"compound_attribute"* (Step 2) to formulate two clusters. It is observed that the cluster that contains data of high attendance of students, in addition to other data belongs to non-debarred students. However, another cluster represents the debarred students.

Step 4. In this step, the output obtained from the previous step (Step 3) is analyzed to obtain the correlation of *"subjAttendance"*, and *"compound_attribute"* with the output variable *"is_debarred"*. Further, the input variables are now represented via three defined Fuzzy Sets [30] - *"high"*, *"medium"*, and *"low"*. The output variable is represented using two defined Fuzzy Sets: *"yes"* and *"no"*. Here, *"yes"* indicates that the student is debarred, and *"no"* indicates the student is not debarred from the examination. Also, the correlation is represented using the 7 defined Fuzzy Rules over the two input attributes *("subjAttendence" and "compound_attribute")* and one output attribute *("is_debarred")*. Finally, the Mamdani Inferencing method [10] is applied to determine the debar decision of students, and thence, Fuzzy Inference System (FIS) is designed. Table 1 represents the 7 stated Fuzzy rules.

Table 1. Fuzzy rules for students debar decisions.

	Inputs		Output
	subjAttendance	*compound_attribute*	*is_debarred*
Fuzzy Rules	High	-	no
	Medium	high	no
	Medium	medium	no
	Medium	low	yes
	Low	high	no
	Low	medium	yes
	Low	low	yes

4. Implementation and Results

4.1 Dataset

In order to test the performance of the model, data from 1,074 students in the age group of 18-24 years is collected from four engineering institutes in India. It is observed that the data is scattered over the range and is unbiased. The debar criteria do not depend upon the gender of students, therefore it has not been discriminated against. The proposed model is implemented using the Fuzzy Toolbox of OCTAVE (Markowsky & Segee, 2011). Table 2 represents the sample snapshot of the students' dataset which comprises *"sid"* (student unique identification), and 8 input parameters *("preMarks", "subjAttendance", "subjTestMarks", "subjInternalMarks", "otherAttendance", "otherMarks", "otherInternalMarks", "exceptionalActivity")* respectively.

Table 2. Sample student dataset.

sid	*preMarks*	*subjAttendance*	*subjTestMarks*	*subjInternalMarks*	*otherAttendance*	*otherMarks*	*otherInternalMarks*	*exceptionalActivity*
1	0.7	0.22	0.55	0.6	0.15	0.87	0.08	1.0
2	0.2	0.52	0.10	0.4	0.73	0.9	0.64	1.0
3	0.1	0.46	0.13	0.76	0.37	0.97	0.96	0.9
4	0.8	0.46	0.13	0.16	0.46	0.67	0.68	0.9
5	0.9	0.26	0.63	0.32	0.53	0.00	0.44	0.3

4.2 Results and Discussion

The proposed model once simulated, is compared with two different existing models- Model 1 (M#1): Kassarnig et al. (2017), and Model 2 (M#2): Jain & Jaggi (2020).

Table 3 shows excerpts from the data samples with respect to the three models. The comparison is performed for all of the 1,074 students' data.

In Model 1, the decision to debar students is based only on classroom attendance. If their attendance is lesser than a threshold, students are simply debarred. They are not been able to take their examination in this case. In Model 2, the decision to debar students is based upon three parameters but is specific to the subject under consideration. In this method, students are debarred from their examination through *"debar_yes"* or allowed to take their examination through *"debar_no"*, or are given reconsideration through *"conditionalNo"*. The *"conditionalNo"* parameter is to be resolved based on the subject teacher's discretion. In this case, there are chances that the decision may be biased or cause dissatisfaction among students. To overcome these facets, the proposed computational model looks upon eight parameters that encompass the students' overall performance and executes the debar decision in a better way. Further, the final decision is achieved as *"yes"* or *"no"*, thereby, removing any uncertainty in the decision to debar students or not.

Table 3. Excerpts from data samples with respect to comparative models.

sid	*preMarks*	*subjAttendance*	*subjTestMarks*	*subjInternalMarks*	*otherAttendance*	*otherMarks*	*otherInternalMarks*	*exceptionalActivity*	Model Type		
									M#1	M#2	Proposed
1	0.7	0.22	0.55	0.6	0.15	0.87	0.08	1.0	yes	yes	no
2	0.2	0.52	0.10	0.4	0.73	0.9	0.64	1.0	yes	yes	no
3	0.1	0.46	0.13	0.76	0.37	0.97	0.96	0.9	yes	yes	no
4	0.8	0.46	0.13	0.16	0.46	0.67	0.68	0.9	yes	yes	no
5	0.9	0.26	0.63	0.32	0.53	0.00	0.44	0.3	yes	conditionalNo	yes
---	---	---	---	---	---	---	---	---	---	---	---
1070	0.2	0.55	0.30	0.36	0.28	0.7	0.88	0.1	yes	conditionalNo	yes
1071	0.2	0.49	0.95	0.08	0.39	0.95	0.24	0.1	yes	conditionalNo	yes
1072	1.0	0.54	0.28	0.12	0.68	0.47	0.56	1.00	yes	conditionalNo	no
1073	1.0	0.45	0.23	0.28	0.81	1.00	0.76	0.9	yes	conditionalNo	no
1074	0.4	0.52	0.80	0.4	0.76	1.00	0.96	1.00	yes	conditionalNo	no

Table 4 depicts the detailed description of the three models using different Cases, Cases 1-7 as discussed here.

Case 1. It is observed that out of 1,074 students, a total of 239 students are clearly not debarred using all three models.
Case 2. Out of the remaining 835 students (Case 1) who are declared as debarred using Model 1, a total of 246 students are declared to be in the same category by both- Model 2 and the proposed model.
Case 3. Out of the remaining 589 students (Case 1) who are declared as debarred using Model 1, a total of 80 students are declared to be in the same category by Model 2, however, are categorized as no debar by the proposed model.
Case 4. Out of the remaining 509 students (Case 3) who are declared as debarred using Model 1, a total of 138 students are declared to be in the *"conditionalNo"* based upon the teacher's discretion by Model 2, however, are categorized as debarred by the proposed model.

Case 5. Out of the remaining 371 students (Case 4) who are declared as debarred using Model 1, a total of 256 students are declared to be in the *"conditionalNo"* based upon the teacher's discretion by Model 2, however, are categorized as no debar by the proposed model.
Case 6. Out of the remaining 115 students (Case 5) who are declared as debarred using Model 1, neither students are declared to be debarred by Model 2 nor by the proposed model.
Case 7. Out of the remaining 115 students (Case 6) who are declared as debarred using Model 1, all the 115 are categorized as no debar by Model 2 and the proposed model both.

Table 4. Case-wise comparison among models.

<table>
<tr><th rowspan="2">Cases</th><th colspan="2">Existing Models</th><th rowspan="2">Proposed Model</th><th rowspan="2">Count of Students</th></tr>
<tr><th>Model 1</th><th>Model 2</th></tr>
<tr><td>Case 1</td><td>no</td><td>no</td><td>no</td><td>239</td></tr>
<tr><td>Case 2</td><td rowspan="6">yes</td><td rowspan="2">yes</td><td>yes</td><td>246</td></tr>
<tr><td>Case 3</td><td>no</td><td>80</td></tr>
<tr><td>Case 4</td><td rowspan="2">conditionalNo</td><td>yes</td><td>138</td></tr>
<tr><td>Case 5</td><td>no</td><td>256</td></tr>
<tr><td>Case 6</td><td rowspan="2">no</td><td>yes</td><td>0</td></tr>
<tr><td>Case 7</td><td>no</td><td>115</td></tr>
</table>

There are points to ponder from both Table 3 and Table 4 that are discussed here.

1. The example *"sid"* 1 to 4 (Table 3) corresponds to Case 3 (Table 4). Here, though the students are not doing well in the current subject, the performance in exceptional activities such as competitive programming, etc. are considered very good. Hence, these students are not debarred in the proposed model.
2. The example *"sid"* 5, 1070 to 1071 (Table 3) corresponds to Case 4 (Table 4). Here, these students are not performing well in the current subject, other subjects, and exceptional activities. Hence, they are declared as debarred in the proposed model.
3. The example *"sid"* 1072 to 1074 (Table 3) corresponds to Case 5 (Table 4). Here, though the students are not doing well in the current subject but are performing well in other subjects. There are 256 such students who are in the totally safe zone while considering their performance in other subjects as well and assessing their capability accordingly. Hence, these students are not debarred in the proposed model.

Figures, Fig. 2(a)-2(c) show the pictorial representation of students for debar decision over Model 1, Model 2, and proposed models. In these figures, red color dots indicate debarred students, blue color dots indicate not debarred students, and green color dots indicate conditionally debarred students respectively.

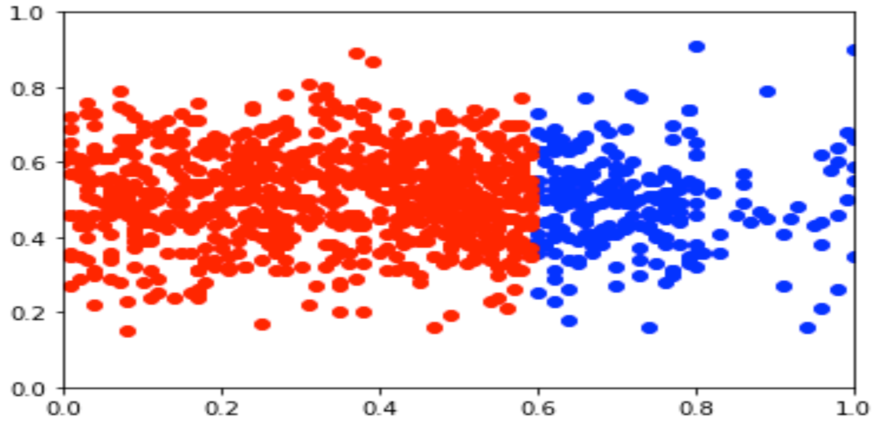

Fig. 2(a). Plot of Model 1.

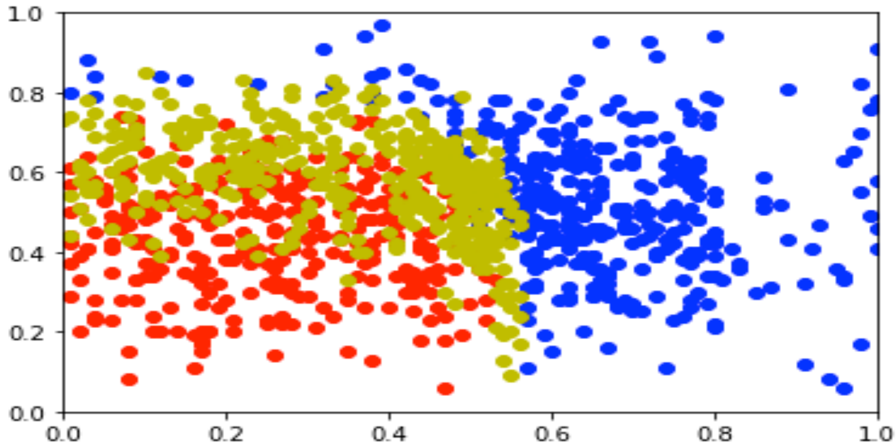

Fig. 2(b). Plot of Model 2.

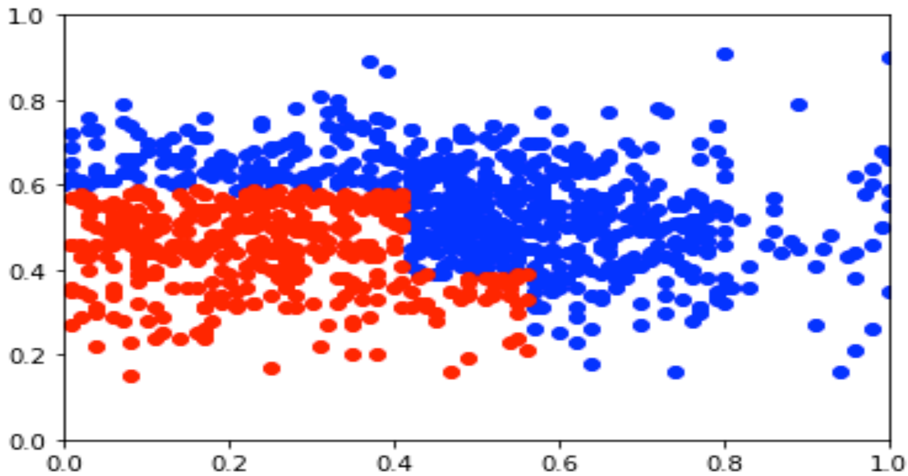

Fig. 2(c). Plot of Proposed Model.

Table 5 shows the detailed result analysis of the proposed work with respect to the total number of students, debarred number of students, and percentage of debarred students.

In each of the three comparative models, a total of 1,074 students are taken care of. Among them, in Model 1, 835 students are considered debarred (77.75%). While in Model 2, there are 720 students to be considered debarred (67.04%). Among them, 326 students are debarred and the rest of 394 students have *"conditionalNo"* which is conditionally debarred based upon the subject teacher's discretion. However, in the proposed model only 384 students are considered debarred (35.75%). This clearly indicates that the proposed model allows more students to appear during their end-term examinations for higher studies. In other words, a lesser number of students are debarred using the proposed model in comparison with the rest of the models.

Table 5. Result analysis.

Count of Students	Type of Models		
	Model 1	Model 2	Proposed
Total	1074	1074	1074
Debarred	835	720	**384**
Debarred %	77.75%	67.04%	**35.75%**

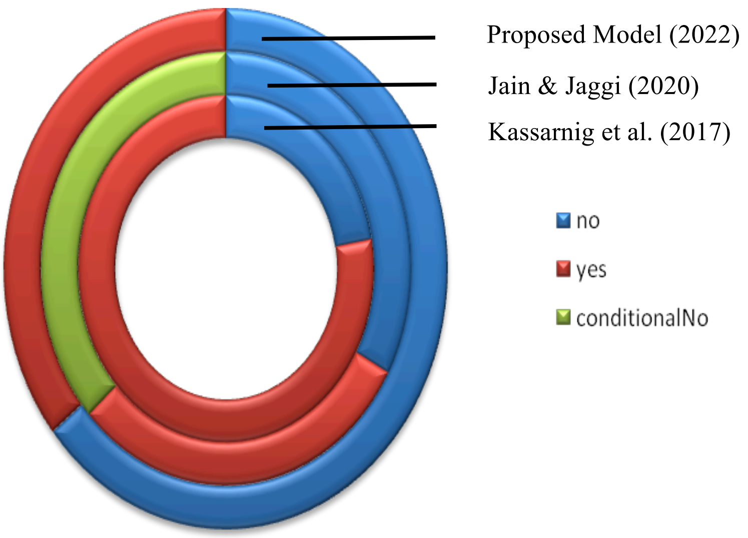

Fig. 3. Comparative analysis of models.

Fig. 3 shows the resultant outcome of all three models- Model 1 (Kassarnig et al., 2017), Model 2 (Jain & Jaggi, 2020), and the Proposed Model. The proposed model is capable of including the performance of university students in each possible direction through various activities: in-classroom, out-of-classroom, innovations, and so on. The final decision that is made by the system is found to be a refinement of the two other existing models.

5. Conclusion

Examinations are a way of validating the learning of students, especially when these students are marching for their career paths. In engineering institutes, especially in India, disallowing them from appearing to take their End-Term examinations that too due to their classroom attendance is below the desired threshold, gives rise to dissatisfaction among such students. These practices are quite unfair to the debarred students, as they may be good in their performance. This paper works with a computational model that takes into account multiple 8 parameters under 4 categories to reflect the performance of students and to assess their eligibility for appearing in the examinations. The proposed model applies machine learning-based K-Means clustering and Fuzzy modeling to solve the stated problem, currently in the context of Indian higher education institutes, and the results are compared with 2 other existing systems over a total of 1,074 students. In Model 1, there are 835 students as debarred (77.75%). In Model 2, there are 720 students as debarred (67.04%) i.e., 326 students are debarred, and the rest 394 students are conditionally debarred based upon teacher discretion. In comparison to these models, the proposed model undertakes only 384 students as debarred (35.75%) i.e., allows more students to appear during their end-term examinations for higher studies. In other words, a lesser number of students are debarred using the proposed model in comparison with the rest of the models. This decision is based upon domain expert knowledge that believes in giving chance to students who have not attended their classes regularly due to some valid reasons but have shown good performance in other assessable parameters. The proposed model successfully addresses diversity in students' requirements and allows them to undertake their academic performance for fair assessment through end-term examinations.

In the future, more insight parameters can be incorporated, a deep learning approach can be applied (Al-Amoudi et al., 2022) and the dataset can be extended for other countries and other fields of study.

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