Early Multi-criteria Detection of Students at Risk of Failure

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***Abstract* – In this paper, we present a new fuzzy methodology for early students' failure detection. High school background, subjects studied in the university and activities in learning management systems were determined to be the factors influencing students' performance. After selection of the impact factors of students' assessment, we convert linguistic evaluations into fuzzy numbers and employ multi-criteria methods for educational data processing. In two practical examples, the aggregate students' scores were calculated by using fuzzy multi-criteria algorithms. The obtained students' ranking helps instructors during the semester to detect students who will drop out the course and to plan additional learning activities for these students. In the future, we plan on analysing students' data from different university's courses and majors and mining several academic years in order to create a reliable assessment index for early prediction of students' failure.**

***Keywords* – Academic failure, learning analytics, MADM, fuzzy EDAS, students' failure prediction, students' ranking.**

1. Introduction

New information technologies transform all aspects of human activity - industry, agriculture, healthcare, transport.

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This rapid change creates a need for new professional competencies, and it requires quick changes in the education system as well. Thus, the paradigm of digital education is born. The term "digital education" means teaching, learning, communicating, and assessing by using digital devices.

Nowadays blended learning is widely adopted. It combines traditional teaching methods with a dynamic e-learning environment, such as Moodle. The good online communication skills and global networking experience of generation z make it easy to redirect the learning process to the new digital environment. Modern electronic educational platforms enable students to acquire knowledge in an accessible and convenient way as well as to develop their creativity, analytical thinking, and collaborative abilities. E-learning is already personalized, offers content according to the student's profile, and it is a prerequisite for adequate and successful realization in life and in the modern labor market.

The deployment of e-learning platforms generates a huge amount of data that needs to be stored and analyzed. The aim is this data to be used to improve the learning process, support quality control and increase the efficiency of training. One of the most serious problems in higher education institutions in Bulgaria is the high students' failure rate.

This study proposes to implement fuzzy multi-attribute evaluation methods to detect educational deficiencies. The main contribution of the paper is the development of a methodology that evaluates student performance based on fuzzy multi-criteria analysis. The use of linguistic variables makes it possible to convert qualitative factors into quantitative data in students' performance evaluation. Early diagnosis of the problem is of great practical importance as it will not only save cost and time for universities, but will also prevent some social and economic repercussions for university students.

The rest of this paper is organized in the following way: the study starts with a literature review of students' failure evaluation methods. Section III introduces the new fuzzy multi-criteria methodology for students' evaluation. The proposed methodology is applied to real datasets for students' performance in section IV. Finally, the last section concludes the paper and presents the limitations and future research plans.

2. Literature Review

The recent research on processing of educational data can be categorized as three basic approaches – via statistical techniques, machine-learning methods and fuzzy sets.

Ilieva et al. [1] apply the first approach. They teach their students in two different manners – according to the "learning by doing" principle and in the traditional manner. The statistical analysis of the exam data shows that the first group of students assimilates the learning content better (the difference in the average score is statistically significant).

Elepo and Balogun [2] use kappa statistics to examine the performance of students measured by their Grade Point Average (GPA) and Cumulative Grade Point Average (CGPA) in both their first and final year. Many researchers use combinations of data mining algorithms (neural networks, classification and regression methods) to forecast the low performance of students ([3], [4], [5], [6], [7]).

Bai and Chen [8] present a method to automatically construct the grade membership functions of different types of grades (lenient-type, strict-type grades and normal-type grades) and apply fuzzy rules for students' evaluation. Based on the constructed grade membership functions, the system performs fuzzy reasoning to infer the scores of students.

To improve the classical statistics of the teaching assessment Ingoley and Bakal [9] implement fuzzy logic to solve the problem of evaluating student learning achievement. Depending on complexity, importance and difficulty faced by students, final marks are adjusted to generate students' ranks in a fair and transparent way.

Kosheleva and Villaverde [10] employ different fuzzy approaches to improve the holistic education process from forming a curriculum to deciding in which order to present the material to students' grading.

Borissova and Keremedchiev [11] assess and rank students via extended multi-attribute decision-making model based on Simple Multi-Attribute Ranking Technique (e-SMART) with two sets of weight coefficients – for criteria importance and for instructors' grades.

Hussain et al. [12] apply four classification methods, the J48, PART, Random Forest and Bayes Network Classifiers to predict final semester results of the colleges' students' dataset. Via a priory algorithm, they find the association rule mining among all the attributes and display the best rules.

The studies described above provide valuable information on the assessment of the students, but also reveal some shortcomings:

1) Often, criteria systems include only assessment of students' performance and the assessment should be a function of many other factors, such as internal and external course data;
2) Most papers do not address sufficiently the problem of evaluation indicators' reduction;
3) If the grade depends on qualitative factors, their conversion into quantitative data is often subjective and should be preferably made using linguistic variables.

In order to overcome the mentioned shortcomings, the next section offers a new assessment methodology for students' failure. This methodology is broadly applicable and easy to implement.

3. A New Multiple Criteria Students' Evaluation Methodology

The new fuzzy methodology consists of four stages, as presented in Figure 1.

Stage 1. Establishment of a multi-criteria system for students' evaluation – this procedure establishes a multi-criteria index system for students' evaluation. The system includes various assessment measures:

- High-school data;
- Data about this academic course – the grades, received in the traditional way and e-platform data like time spent in the e-course, downloading of materials and submission of homework;
- Data about courses studied previously at the university.

Stage 2. Data pre-processing – this is the stage where the redundant criteria are determined, using statistical instruments for dimensionality reduction, such as correlation analysis, discriminant analysis and factor analysis.

Next, the weight coefficients are being calculated via statistical methods (such as variation, mean squared error and entropy method) or via multi-criteria methods (such as Analytic Hierarchy Process (AHP), Best Worst Method (BWM), Decision-making Trial and Evaluation Laboratory (DEMATEL) and Measuring Attractiveness by a Categorical-Based Evaluation Technique (MACBETH)).

In variation method, high variability of assessment's indicator means that this indicator can clearly distinguish the status of the evaluated students. In mean squared method, if the normalized score of an attribute has a higher mean squared error, then this attribute has a greater influence over the evaluation result and a greater weight should be assigned to it.

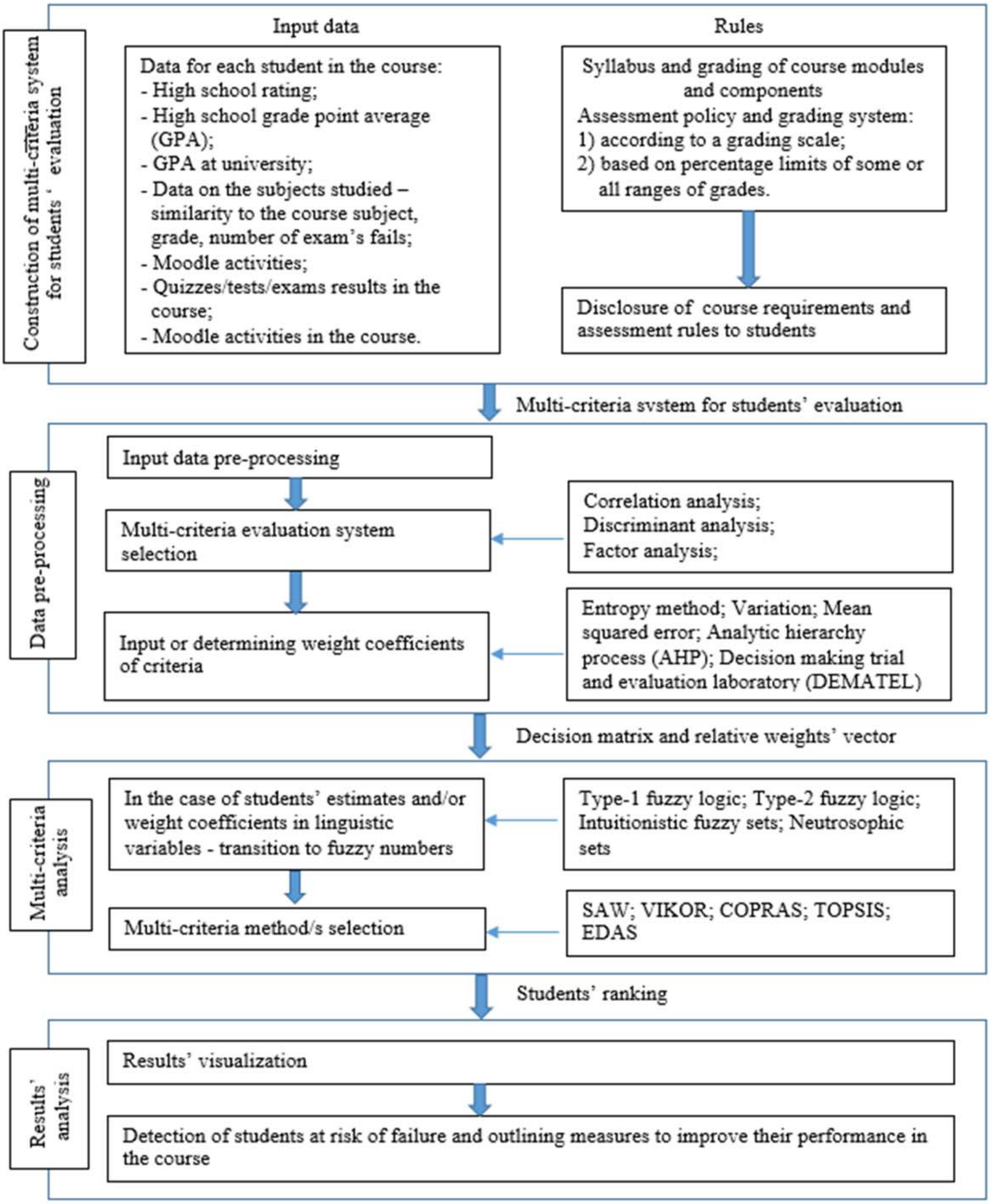

Figure 1. The fuzzy methodology for early students' failure detection

The entropy method, introduced by Shannon (1948), measures the disorder degree of a system. The substantial difference in the values of evaluated objects on one criterion means that this criterion provides more useful information and the entropy is low, i.e. the weight of this criterion should be high. Hence, the variation, mean squared error and entropy methods are objective means to determine weight coefficients.

Unlike those, the Analytical Hierarchy Process (AHP) is a method of subjective weighting, which combines qualitative and quantitative analysis. The AHP evaluation system has hierarchical structure and after pairwise comparisons, the decision maker acquires the comparison matrix elements and calculates the relative weights. In addition to the AHP method, the pairwise weight comparison methods in the methodology also include the Best Worst Method (BWM), the Decision-making Trial and Evaluation

Laboratory (DEMATEL) and the Measuring Attractiveness by a Categorical-Based Evaluation Technique (MACBETH).

Stage 3. Multi-criteria analysis – if students' grades depend on quantitative factors, then we convert them into non-crisp numbers. They help the instructors overcome the uncertainty and incompleteness of educational data by applying various types of non-crisp evaluations via classical fuzzy, intuitionistic or neutrosophic numbers.

In Zadeh's fuzzy set theory (1965) one element may belong (or not) to the fuzzy set with a degree in the interval [0, 1] instead of belonging completely (value 1) or not belonging (value 0). At the end of 20^{th} and the beginning of 21^{st} century varieties of the classical fuzzy numbers (type-1 fuzzy numbers) appeared, such as type-2 fuzzy numbers (Zadeh in 1975), intuitionistic fuzzy numbers (Atanassov in 1983), neutrosophic numbers (Smarandache in 1998). The advantages of the fuzzy approach are as follows:

- It is applicable even on a small number of observations, while the alternative probabilistic approach is suitable only for a large quantity of homogenous objects;
- It renders subjectivism in the assessments of the decision makers, as according to Zadeh's theory, the membership function can be subjective.

The next step in this stage determines the current ranking of the students via fuzzy multi-attribute decision making algorithms (such as Simple Additive Weighting (SAW), multi-criteria optimization and compromise solution (VIKOR), COmplex PRoportional ASsessment (COPRAS), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Evaluation based on Distance from Average Solution (EDAS)).

Fuzzy SAW (f-SAW) is a standard method of multi-criteria analysis that uses fuzzy utility function deriving from the weight coefficients and the estimates from the decision matrix. The main idea of the VIKOR method is to find the alternatives with maximum utility and minimum deficiency. In COPRAS algorithm the impact of the minimizing criteria over the final assessment of the alternative is reduced in cases of a small number of minimizing criteria. TOPSIS calculates the distance between every alternative and the ideal solution (the best result on each criterion). The classical and fuzzy EDAS calculate the Euclidean distance between the average value of the alternatives and the current alternative for each criterion. The selected multi-criteria methods belong to the two basic models for most MCDM methods – additive weighted value function (SAW, COPRAS, VIKOR) and similarity to the best alternative (TOPSIS, EDAS).

Stage 4. Results analysis – this is the point where the instructors decide how to help the students in risk not to fail the course – additional exercises and tasks, face-to-face work (individual and team work) within office hours, step-by-step explanations, more examples, work with software as a modelling tool.

The proposed new methodology is used for assessment and ranking of students' datasets by Borissova and Keremedchiev [11] and Hussein et al. [12]. In the next section, we solve the problems of students' assessment via fuzzy EDAS algorithm [13], [14].

4. Numerical Examples

4.1. Web Programming Course Dataset

To verify the new methodology, we use a dataset for evaluations scores of students from a Web programming course [11]. The input data are based on only one group composed of 21 students (S_1, S_2, …, S_{21}) and 7 assessment criteria (C_1, C_2, …, C_7). The first two criteria address the theoretical knowledge of students from the course and are determined via two test examinations, C_1 and C_2, conducted by the lecturer. The second part of assessment (criteria C_3, C_4, …, C_7) is a result of demonstrated practical skills during the exercises. These criteria are related to different aspects of Web sites development and include the following five attributes: C_3 – Visual design, C_4 – User interface, C_5 – Content strategy, C_6 – Technical implementation, and C_7 – Creativity. The evaluations scores as linguistic variables are shown in Table 1. Collection and pre-processing of the students data (Stage 1 and Stage 2 of the new methodology) have already been done. Three different cases representing different combinations for importance of decision makers (course's instructors) are investigated: Case-1 (equal importance of the theoretical knowledge and practical skills), Case-2 (emphasizes on the theoretical knowledge) and Case-3 (most important are practical skills), corresponding to weight coefficients W_1, W_2, W_3 (Table 1). The next stage is the multi-criteria analysis.

For converting linguistic variables into their corresponding symmetric triangular fuzzy numbers, we apply a correspondence table (Table 2).

EDAS is the preferred multi-criteria method because it calculates distances to the average solution and allows historical data on student performance to serve as a benchmark for each criterion. The final ranking objectively eliminates possible deviations in the dataset of the student assessments.

The students' ranking obtained by using e-SMART (e-SMART columns) [11] and by fuzzy EDAS (f-EDAS columns) for the three different sets of weight

Table 1. Evaluation scores and weight coefficients for a group of students

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
S_1	H	L	MH	M	VH	L	VH
S_2	L	VL	VH	M	L	VL	ML
S_3	M	H	VH	H	MH	H	MH
S_4	VH	ML	L	ML	L	M	VH
S_5	L	VL	H	M	ML	L	M
S_6	M	H	MH	M	M	VH	H
S_7	ML	MH	L	ML	L	M	VL
S_8	ML	M	ML	VL	M	M	L
S_9	H	MH	MH	MH	M	MH	H
S_{10}	VH	ML	ML	M	M	VH	MH
S_{11}	ML	L	L	ML	VL	MH	M
S_{12}	L	VL	VL	L	L	M	M
S_{13}	M	VH	M	M	MH	H	VH
S_{14}	VH	M	MH	ML	M	VH	M
S_{15}	VL	M	ML	L	M	L	ML
S_{16}	H	MH	MH	VH	VL	MH	VH
S_{17}	MH	MH	MH	MH	L	ML	M
S_{18}	VH	M	MH	MH	MH	VL	ML
S_{19}	L	VL	ML	MH	MH	MH	ML
S_{20}	H	L	VL	M	H	VH	M
S_{21}	L	L	VL	M	MH	MH	M
W_1	0.194	0.314	0.036	0.044	0.032	0.040	0.048
W_2	0.242	0.308	0.086	0.095	0.081	0.090	0.099
W_3	0.198	0.252	0.105	0.116	0.099	0.110	0.121

Source: Based on (Borissova and Keremedchiev, 2019) [11]

Table 2. Linguistic variables and their corresponding triangular fuzzy numbers

Linguistic term	**Triangular FN**
Very low (VL)	(0, 0, 0.17)
Low (L)	(0, 0.17, 0.33)
Medium Low (ML)	(0, 0.17, 0.33)
Medium (M)	(0.33, 0.5, 0.67)
Medium High (MH)	(0.5, 0.67, 0.83)
High (H)	(0.67, 0.83, 1)
Very High (VH)	(0.83, 1, 1)

coefficients are shown in Table 3. The results obtained with f-EDAS (last three columns in Table 3) are very similar to those obtained by Borissova and Keremedchiev [11]. The degree of proximity was determined by using Spearman's rank correlation coefficient – 0.968 (Case-1), 0.973 (Case-2), and 0.953 (Case-3). In all three cases Spearman's coefficient values indicate a high degree of closeness. As the grading scale in Bulgaria is 5-graded, let at risk of dropping out are the last 20% from students' ranking. The following students are at risk:

Table 3. Students ranking by e-SMART and fuzzy EDAS

Students	Ranking					
	e-SMART (Case-1)	e-SMART (Case-2)	e-SMART (Case-3)	f-EDAS (Case-1)	f-EDAS (Case-2)	f-EDAS (Case-3)
S_1	10	9	10	10	9	9
S_2	20	20	20	20	19	19
S_3	4	3	4	2	2	1
S_4	11	11	11	13	12	12
S_5	19	19	19	19	18	17
S_6	5	5	5	3	5	5
S_7	13	13	13	11	13	13
S_8	14	14	14	14	14	15
S_9	3	4	3	5	4	4
S_{10}	8	8	8	9	10	10
S_{11}	16	17	16	18	20	20
S_{12}	21	21	21	21	21	21
S_{13}	2	2	1	1	1	2
S_{14}	6	6	6	6	6	6
S_{15}	18	18	15	15	16	18
S_{16}	1	1	2	4	3	3
S_{17}	7	7	7	7	8	8
S_{18}	9	10	9	8	7	7
S_{19}	15	15	17	17	17	16
S_{20}	12	12	12	12	11	11
S_{21}	17	16	18	16	15	14
			Spearman coefficient:	0.968	0.973	0.953

For Case-1: e-SMART: $S_{15} \prec S_5 \prec S_2 \prec S_{12}$
f-EDAS: $S_{11} \prec S_5 \prec S_2 \prec S_{12}$
For Case-2: e-SMART: $S_{15} \prec S_5 \prec S_2 \prec S_{12}$
f-EDAS: $S_5 \prec S_2 \prec S_{11} \prec S_{12}$
For Case-3: e-SMART: $S_{21} \prec S_5 \prec S_2 \prec S_{12}$
f-EDAS: $S_{15} \prec S_2 \prec S_{11} \prec S_{12}$

If we assume that high risk students are the weakest students from at least one of the three cases, then according to e-SMART, the risk group includes students S_2, S_5, S_{12}, S_{15} and S_{21}, and according to f-EDAS the risk group comprises the following students: S_2, S_5, S_{11}, S_{12} and S_{15}. There is a discrepancy concerning student S_{21}, who is one of the drop-out students in e-SMART solution, but is ranked 16, 15 and 14 in f-EDAS result. The second difference is with student S_{11}, who is ranked 16, 17 and 16 according to e-SMART method, but appears in drop-out list according to f-EDAS method.

4.2. Dataset From Three Colleges

The dataset contains 131 instances and 22 attributes, collected from three colleges [12][1]. In order to compare our results with those, obtained by Hussein et al., we assume that the same eleven attributes had been selected in the Pre-processing stage (Table 4).

[1] https://archive.ics.uci.edu/ml/datasets/Student+Academics+Performance (accessed October 21, 2019)

Table 4. Colleges' students' dataset description

No.	Attribute	Description	Values	Weight
1	TNP	Class X Percentage	(Best, Very Good, Good, Pass, Fail) If percentage >=80 then Best If percentage >= 60 but less than 80 then Very Good If percentage >= 45 but less than 60 then Good If Percentage >= 30 but less than 45 then Pass	0.154
2	TWP	Class XII Percentage	(Best, Very Good, Good, Pass, Fail) Same as TNP	0.154
3	IAP	Internal Assessment Percentage	(Best, Very Good, Good, Pass, Fail) Same as TNP	0.215
4	ARR	Whether the student has back or arrear papers	(Yes, No)	0.092
5	AS	Admission Category	(Free, Paid)	0.092
6	FMI	Family Monthly Income (in INR)	(Very High, High, Above Medium, Medium, Low) If FMI >= 30000 then Very High If FMI >= 20000 but less than 30000 then High If FMI >= 10000 but less than 20000 then Above Medium If FMI >= 5000 but less than 10000 then Medium If FMI is less than 5000 then Low	0.015
7	FO	Father Occupation	(Service, Business, Retired, Farmer, Others)	0.015
8	NF	Number of Friends	(Large, Average, Small) If NF > 12 then Large If NF >= 6 but less than 12 then Average If NF < 6 then Small	0.015
9	SH	Study Hours	(Good, Average, Poor) >= 6 hours Good >= 4 hours Average < 2 hours Poor	0.123
10	ME	Medium	(Eng,Asm,Hin,Ben)	0.031
11	ATD	Class Attendance Percentage	(Good, Average, Poor) If percentage >= 80 then Good If percentage >= 60 but less than 80 then Average If Percentage < 60 then poor	0.092

Source: Based on (Hussain et al., 2018) [12]

Their weight coefficients were defined via AHP, whereas the obtained values are shown in column Weight of Table 4. The attribute ESP (End Semester Percentage) is a dependent variable. The students had successfully passed their previous examinations (the values of attributes TNP, TWP and IAP differ from Fail). With the exam being completed successfully (all values in the ESP box in the dataset are greater or equal to Pass), we assume that the students with predicted values of the dependent variable equal to Pass are the ones at risk from dropping out.

We hereby apply f-SAW and f-EDAS for students' ranking, whereas the number of the ranks is five, matching the grades Best, Very good, Good, Pass and Fail. Since this is essentially a prediction problem, we construct confusion matrices in order to evaluate the effectiveness of obtained solutions (Table 5 and Table 6).

Table 5. Confusion matrix of f-SAW classification

f-SAW	Actual: no Pass	Actual: Pass	Total:
Predicted: no Pass	TP (86)	FP (12)	98
Predicted: Pass	FN (18)	TN (15)	33
Total:	104	27	131

Table 6. Confusion matrix of f-EDAS classification

f-EDAS	Actual: no Pass	Actual: Pass	Total:
Predicted: no Pass	TP (80)	FP (18)	98
Predicted: Pass	FN (24)	TN (9)	33
Total:	104	27	131

The accuracy,

$$Accuracy = (TP+TN) / (TP+TN+FN+FP),$$

of our f-SAW and f-EDAS decisions are calculated as follows:

$$Accuracy_{f\text{-}SAW} = (86 + 15) / 131 = 77.10\%$$

and

$$Accuracy_{f\text{-}EDAS} = (80 + 9) / 131 = 67.94\%.$$

The f-SAW solution is better than the solutions of Hussain et al., obtained with PART (74.33%), J48 (73%) and BayesNet (65.33%), being yielding precedence only to the RandomForest (99%). The f-EDAS solution is better than the BayesNet one, but defers to PART, J48 and RandomForest. The reason behind the poorer result is due to the fact that we do not have aggregate data, but only 131 records sample, which makes it difficult to determine the average values in a precise way.

The advantage of the fuzzy multi-criteria methods is that spreadsheet software is sufficient for their implementation and their algorithmic complexity is lower than that of machine learning methods, such as RandomForest.

Depending on the specifics of the course, instructors can decide how they can help students at risk overcome their lagging behind.

5. Conclusion

This paper offers a new fuzzy methodology to predict university students who are in potential risk to drop out from a given course. The new methodology combines statistical, multi-criteria and fuzzy approaches to process educational data and improve the grading of students' assignments and exams. Factors such as e-learning system's quality, instructors' skills and experience and available students' educational data could prevent students' failure at an early stage. The new methodology integrates all stages of the students' evaluation process, combining diverse data from a variety of online and offline sources.

The validity of this new methodology is verified via two datasets – the first dataset covers data on 21 students and 7 criteria, and the second one – on 131 students and 11 criteria. The accuracy of obtained results is similar to that achieved in previous studies.

The methodology could also be used in courses', lecturers' and universities' assessment and ranking via big data. The proposed methodology fosters the creation of an innovative learning environment and is the next step in digitalization of education.

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References

[1]. Ilieva, G., Yankova, T., & Klisarova, S. (2015, September). Cloud business intelligence: contemporary learning opportunities in MIS training. In *CEUR Workshop Proceedings of the 2015 Balkan Conference in Informatics* (Vol. 1427, pp. 25-32).

[2]. Elepo, T. A. & Balogun, O. S. (2016). Statistical analysis on students' performance. *Covenant Journal of Informatics and Communication Technology 4*(1), 56-65.

[3]. Lykourentzou, I., Giannoukos, I., Nikolopoulos, V., Mpardis, G. & Loumos, V. (2009). Dropout prediction in e-learning courses through the combination of machine learning techniques. *Computers & Education*, *53*(3), 950-965.

[4]. Márquez-Vera, C., Morales, C. R. & Soto, S. V. (2013). Predicting school failure and dropout by using data mining techniques. *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje*, *8*(1), 7-14.

[5]. Costa, E. B., Fonseca, B., Santana, M. A., de Araújo, F. F. & Rego, J. (2017). Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses. *Computers in Human Behavior*, *73*, 247-256.

[6]. Baars, G. J. A., Stijnen, T. & Splinter, T. A. W. (2017). A model to predict student failure in the first year of the undergraduate medical curriculum. *Health Professions Education*, *3*(1), 5-14.

[7]. Gray, C. C. & Perkins, D. (2019). Utilizing early engagement and machine learning to predict student outcomes. *Computers & Education*, *131*, 22-32.

[8]. Bai, S. M. & Chen, S. M. (2007). Automatically constructing grade membership functions of fuzzy rules for students' evaluation. *Expert Systems with Applications*, *35*(3), 1408-1414.

[9]. Ingoley, S. & Bakal J. W. (2012). Use of fuzzy logic in evaluating students' learning achievement. *International Journal on Advanced Computer Engineering and Communication Technology*, *1*(2), 47-54.

[10]. Kosheleva, O. & Villaverde, K. (2018). *How interval and fuzzy techniques can improve teaching. Processing educational data: from traditional statistical techniques to an appropriate combination of probabilistic, interval, and fuzzy approaches*. Springer.

[11]. Borissova, D. & Keremedchiev, D. (2019). Assessing and ranking students by multi-attribute decision making model based on SMART. *Cybernetics and Information Technologies*, *19*(3), 45-56.

[12]. Hussain, S., Dahan, N. A., Ba-Alwi, F. M. & Ribata, N. (2018). Educational data mining and analysis of students' academic performance using WEKA. *Indonesian Journal of Electrical Engineering and Computer Science*, *9*(2), 447-459.

[13]. Keshavarz Ghorabaee, M., Zavadskas, E. K., Olfat, L. & Turskis, Z. (2015). Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). *Informatica*, *26*(3), 435-451.

[14]. Ilieva, G., Yankova, T. & Klisarova-Belcheva, S. (2018). Decision analysis with classic and fuzzy EDAS modifications. *Computational and Applied Mathematics*, *37*(5), 5650-5680.