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ASSESSMENT OF STUDENT LEARNING USING COMPUTATIONAL INTELLIGENCE

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ABSTRACT

Student performance and academic achievement are the most important aspects of a student's education. The educational system relies heavily on assessments of student achievement. This grading procedure must be helpful to the student. Inspired by the effective use of K-means, fuzzy C-means (FCM), and subtractive clustering (SC) approaches, this paper offers a research of academic performance assessment utilizing soft computing techniques. Optimization problems like modeling pupils' academic achievement are notoriously challenging. Fuzzy logic was used in conjunction with the models to analyze the pupils' performance.

KEYWORDS: K-means, academics, student, fuzzy logic, techniques.

INTRODUCTION

Management in the field of education deals with the business side of schools and learning. For an education administrator to effectively evaluate and oversee classroom operations, they must be schooled in the use of relevant tools and methods. Because it requires managing people to effectively administrate and facilitate educational activities, it is possible at all stages of education (elementary, secondary, and higher). For the last decade, educators have struggled to determine the best strategies for helping pupils acquire and retain information. These days, both conventional classroom instruction and online courses are used. Students and instructors can communicate and work together more effectively thanks to this technology. There are several areas in which AI-based solutions have been used in classrooms. Evaluating, grading, and improving the education of students, especially at the higher levels of personalized learning and academic growth, is facilitated. Because of technological advancements, several useful educational apps and websites have been created. The field of educational administration has made extensive use of soft computing (SC) and artificial intelligence (AI) methods.

This hole should be patched up using a hybrid of fuzzy logic and fuzzy clustering methods. There is now an inquiry of their level of influence. Throughout their academic career, a student's academic performance and grades will be crucial. When a teacher is aware of a student's strengths and shortcomings, they are better able to provide the timely counseling necessary for the student to get excellent marks and improve performance. We may employ various prediction approaches or comprehensive diagnostic/formative examinations of each kid to determine these characteristics. This may be done taking into account a variety of elements.

There are three pillars upon which academic success rests: 1) intelligence two) the potential to learn 3. the unique characteristics of each pupil. If a model can predict a student's performance early on by taking these into account, and if a student is found to be weak, the teacher can provide them with guidelines to help them improve their performance going forward; this can have important applications in the admissions process, in placement activities, in employee performance evaluation, and so on. (2). There is a significant role for

evaluating student achievement in which students must provide justification for their efforts. As a result, there is a wide selection of soft computing algorithms from which to choose when gauging effectiveness.

There are two distinct ways to assess students' performance in school: (1) using a rule-based system, and (2) operating outside of any predetermined set of guidelines. Neural Networks (NN), Fuzzy Inference Systems (FIS), Neuro Fuzzy Systems (NFS), Genetic Algorithms (GA), Decision Trees (DT), Linear Discriminators (LD), K Nearest Neighbors (KNN), Support Vector Machines (SVM), Naive Bayes (NB), and Ensembles are just some of the soft computing techniques we've covered here. Parameters like confusion matrix, Root Mean Squared Error value (RMSE), Training time, Accuracy, and so on may be used to compare and contrast the classifiers' respective performances. All these methods take into account a wide range of factors when determining a student's final grade, including the student's prior performance, the student's socioeconomic status, the student's family's background, the student's geographical location, and the student's cumulative grade point average over the course of multiple.

LITERATURE AND REVIEW

YixiaZhou et al (2021) Embedding AI developers should aim to come up with as novel a solution as they can. One of the most important technologies for cyber-physical systems like robots and autonomous vehicles is artificial intelligence (AI), which has enabled the rise of the Internet of Things (IoT). The phrase "embedded AI" refers to a wide range of techniques that make use of deep learning and software platforms to enhance the working life of the employee. Science and technology are being pushed forward because they are essential to the long-term success of society and the economy. The field of artificial intelligence (AI) has recently emerged as a crucial area of research in the development of human science and technology. Consistent AI development isn't only benefiting humans, but; it's also creating novel opportunities across a range of potential future services. The goals of this endeavor may be specified using data already collected as part of the project. A company may use the knowledge contained in the processed records to make decisions that are both timely and adequate. This new sort of student information management system uses fingerprint scanning to identify and track individual students. For the sake of data confidentiality, we propose a new way of data encryption.

Marzia Khan et al (2018) More studies on how to best administer schools and universities have been conducted throughout the previous two decades. Because of this shift, many institutions of higher learning around the globe, including in less developed nations like Pakistan, now offer Master of Education Management and MBA education management degrees. Applications of AI and SC methods for tackling practical issues are cropping up in many areas. This article presents a literature overview, examines current and potential future uses of soft computing approaches in educational administration, and proposes areas for further study in this field.

XueHong Yin (2021) The concept of "data mining" is quite modern. Data mining is a technique used to extract useful information from databases in order to help in making educated business choices. This study applies data mining techniques to the college student information management system, mines data from student evaluations, designs assessment modules with the help of those techniques, and uncovers the elements that influence student growth and the interconnections between them. The framework relies on predictive knowledge evaluation and individualization of pedagogical choices. After laying out the landscape of genetic algorithms and fuzzy genetic algorithms, a better genetic fuzzy clustering method is given. The efficiency of the technique suggested in this research is shown by comparison with both classic clustering algorithms and the enhanced genetic fuzzy clustering algorithm. A basic student information management system is planned and built-in response to the demands of the student information management system, which offers a platform and data source for the subsequent application of a clustering algorithm for performance analysis. Finally, testing findings demonstrate that this technique may better assess student scores and aid relevant instructors and departments in making judgments by grouping the scores using a clustering algorithm based on fuzzy genetic algorithm.

Faizal Khan et al (2021) The SLS is a method for measuring the extent to which a student has studied and internalised material. Thanks to technological developments, SLS is now a viable option for a larger range of students, from complete beginners to seasoned experts, to expand their knowledge and expertise. Learning architectures have recently used artificial soft computing technologies to provide a more favourable atmosphere for instruction. We want to improve education by exploring soft computing

applications in this essay. We also discuss the structural similarities and differences between E-learning and m-learning and the different soft computing solutions. This study develops an AI-based model for learning methods, and it explores the potential of soft computing to offer users with access to data and to assist them in being prepared for learning difficulties by means of specialised software. This article's findings suggest that soft computing might be leveraged to develop novel strategies for effective administration of pedagogical techniques.

Ijaz Khan et al (2021) Instructors have significant challenges while trying to keep track of their students' academic progress in a given course. Once the children who are not making enough progress are recognized, the teacher may take steps to provide them with further help. Today's educational institutions acquire vast amounts of data on their students from a variety of sources, but they're always on the lookout for new ways to put that information to work to boost their profile and the quality of their instruction. This study assesses how well machine learning algorithms can track students' academic progress and flag those who are at danger of failing the course to their teacher. The teacher can quickly and easily arrange the appropriate safety measures since the prediction model has been reshaped into a more comprehensible form. Using several machine learning methods, we created a suite of prediction models. Due to its success, the decision tree model has been turned into a structure that is simple to explain. The research's end product is a collection of preventative measures to provide extra help to the difficult students and a set of supporting measures to keep an eye on students' progress from the very beginning of the course.

METHODOLOGY

This article discusses the use of K-means, fuzzy C-means (FCM), and subtractive clustering (SC), all of which produce homogenous clusters (or classes) of students for the purpose of automated development of membership function in evaluating students' academic achievement. This is a concise statement of the clustering problem: Create a system for categorizing things based on their shared characteristics, given a collection of data (X) that is itself finite. For traditional cluster analysis to work, these categories must divide X in a way that strongly associated data resides inside blocks of the partition and weakly associated data resides across blocks. However, in real-world applications, this condition is excessively stringent, making a lighter requirement preferable. Fuzzy clustering is a new kind of issue that arises when the need for a crisp partition of X is replaced with the less stringent need for a fuzzy partition or a fuzzy pseudo partition on X. The number of fuzzy classes in a partition is denoted by the letter C, hence fuzzy C partitions are another common name for fuzzy pseudo partitions. It's not easy for people to find ways to classify or organize data. This is why various soft computing approaches have been presented as a means to address challenging optimization issues like assessing a student's academic achievement. Commonly referred to as data clustering approaches, these five are outlined below along with an analysis of their root-mean-square-error (RMSE) results.

DATA ANALYSIS

K-means, FCM, and SC are some of the suggested approaches that may be used to place new students into groups with similar demographics up to a certain maximum, and then analyze the impact of these placements on students' academic outcomes. The training and testing datasets in these techniques are composed of scores from the first, second, and third semesters taken by a total of sixty students. Thirty of these datasets have been used for training, while the remaining thirty have been used for testing (Tables 1 and 2). Table 3 displays the experiment's grading classification as determined by the MATLAB program (used for modeling students' academic performance assessment based on maximum value of marks that relates to the degree of achievement). Each student's raw scores from the first, second, and third semester exams must be adjusted. By dividing each semester's exam grade by the overall grade, we may get a normalized number between zero and one. The normalized score will serve as the evaluative input. The grades and their corresponding levels of success are also shown in Table 3. Table 4 displays the average test results from 15 freshmen using the suggested models.

K-means method

K-means clustering was used in conjunction with MATLAB to classify the datasets shown in Tables 1 and 2 into distinct groups. The pupils have been divided into the five clusters of very high, high, medium, low, and very low. By attempting to minimize an objective function, the K-means clustering approach locates the

centers of clusters. It does a combination of updating the membership matrix and updating the cluster centers until no more improvement in the objective function is seen. Since the method randomly chooses the cluster centers to begin with, the initial cluster centers may have a significant impact on the algorithm's performance. Once the cluster centers have been identified, the assessment data vectors may be placed into the appropriate clusters based on their distance from the centers. The root-mean-squared error (RMSE) is then used to determine the level of error. Table 5 details the outcomes of this strategy, whereas Figure 1 displays the objective function values. It's important to notice that 3 students are in cluster 1, 3 students are in cluster 2, 5 students are in cluster 3, 2 students are in cluster 4, and 1 student is in cluster 5. (Table 5).

Table 1. Student training dataset

Sl no.	Sem-1	Sem-2	Sem-3	Final marks (statistical method)	Observed output	Grade
1	0.05	0.37	0.18	0.200	0.25	E
2	0.10	0.23	10.6	0.163	0.25	E
3	0.15	0.13	0.06	0.113	0.25	E
4	0.40	0.13	0.20	0.243	0.25	E
5	0.25	0.31	0.14	0.233	0.25	E
6	0.15	0.10	0.26	0.170	0.25	E
7	0.10	0.13	0.30	0.177	0.25	E
8	0.10	0.17	0.08	0.117	0.25	E
9	0.25	0.23	0.04	0.173	0.25	E
10	0.05	0.17	0.12	0.113	0.25	E
11	0.12	0.32	0.34	0.260	0.45	D
12	0.25	0.33	0.30	0.293	0.45	D
13	0.30	0.30	0.34	0.313	0.45	D
14	0.40	0.20	0.38	0.327	0.45	D
15	0.50	0.40	0.30	0.400	0.45	D
16	0.65	0.17	0.38	0.400	0.45	D
17	0.50	0.26	0.38	0.380	0.45	D
18	0.55	0.35	0.38	0.427	0.45	D
19	0.50	0.40	0.40	0.433	0.45	D
20	0.45	0.51	0.36	0.440	0.45	D
21	0.40	0.60	0.44	0.480	0.55	C
22	0.35	0.60	0.48	0.477	0.55	C
23	0.32	0.50	0.65	0.490	0.55	C
24	0.55	0.60	0.48	0.543	0.55	C
25	0.30	0.70	0.54	0.513	0.55	C
26	0.45	0.47	0.60	0.507	0.55	C
27	0.40	0.40	0.64	0.480	0.55	C
28	0.35	0.50	0.58	0.477	0.55	C
29	0.35	0.63	0.58	0.520	0.55	C
30	0.25	0.47	0.72	0.480	0.55	C

Table 2. Student testing dataset

Sl no.	Sem-1	Sem-2	Sem-3	Final marks (statistical method)	Observed output	Grade
1	0.05	0.34	0.16	0.183	0.25	E
2	0.02	0.45	0.46	0.310	0.45	D
3	0.23	0.45	0.19	0.290	0.45	D
4	0.34	0.43	0.46	0.410	0.45	D
5	0.05	0.23	0.11	0.130	0.25	E
6	0.17	0.96	0.48	0.537	0.55	C
7	0.61	0.98	0.94	0.843	1.00	A
8	0.29	0.97	0.57	0.610	0.75	B
9	0.74	0.90	0.93	0.857	1.00	A
10	0.52	0.34	0.69	0.517	0.55	C
11	0.33	0.39	0.37	0.363	0.45	D
12	0.06	0.21	0.22	0.163	0.25	E
13	0.15	0.74	0.35	0.413	0.45	D
14	0.48	0.76	0.50	0.580	0.75	B
15	0.81	0.89	0.97	0.890	1.00	A
16	0.79	0.92	0.98	0.890	1.00	A
17	0.28	0.66	0.87	0.603	0.75	B
18	0.23	0.84	0.23	0.433	0.45	D
19	0.08	0.39	0.14	0.203	0.25	E
20	0.19	0.33	0.64	0.387	0.45	D
21	0.58	0.64	0.98	0.733	0.75	B
22	0.39	0.25	0.65	0.430	0.45	D
23	0.43	0.39	0.65	0.490	0.55	C
24	0.52	0.94	0.66	0.707	0.75	B
25	0.68	0.79	0.94	0.800	1.00	A
26	0.48	0.77	0.51	0.587	0.75	B
27	0.01	0.43	0.13	0.190	0.25	E
28	0.21	0.31	0.81	0.443	0.45	D
29	0.45	0.75	0.53	0.577	0.75	B
30	0.65	0.97	0.79	0.803	1.00	A

Table 3. Marks and their associated original grade and level of achievement

SI. no.	Marks	Grade	Level of achievement
1	0.76–1.00	A	Cluster-1 (very high)
2	0.56–0.75	B	Cluster-2 (high)
3	0.46–0.55	C	Cluster-3 (average)
4	0.26–0.45	D	Cluster-4 (low)
5	0.00–0.25	E	Cluster-5 (very low)

Table 4. Dataset of students' score in sem-1, sem-2 and sem-3

SI. no.	Sem-1	Sem-2	Sem-3	Final marks (Statistical method)	Grade
1	0.100	0.233	0.200	0.178	E
2	0.500	0.167	0.120	0.112	E
3	0.150	0.133	0.180	0.154	E
4	0.450	0.267	0.400	0.372	D
5	0.350	0.333	0.300	0.328	D
6	0.350	0.500	0.380	0.410	D
7	0.450	0.433	0.540	0.474	C
8	0.500	0.400	0.500	0.467	C
9	0.450	0.500	0.580	0.510	C
10	0.500	0.700	0.620	0.607	B
11	0.650	0.700	0.740	0.697	B
12	0.850	0.600	0.760	0.737	B
13	0.950	0.767	0.860	0.859	A
14	0.850	0.833	0.960	0.881	A
15	0.900	0.900	0.980	0.927	A

Table 5. Students' academic performance results using K-means method

SI. no.	Sem-1	Sem-2	Sem-3	Grade based on K-means
1	0.100	0.233	0.200	D
2	0.500	0.167	0.120	E
3	0.150	0.133	0.180	D
4	0.450	0.267	0.400	C
5	0.350	0.333	0.300	C
6	0.350	0.500	0.380	C
7	0.450	0.433	0.540	C
8	0.500	0.400	0.500	C
9	0.450	0.500	0.580	C
10	0.500	0.700	0.620	B
11	0.650	0.700	0.740	B
12	0.850	0.600	0.760	B
13	0.950	0.767	0.860	A
14	0.850	0.833	0.960	A
15	0.900	0.900	0.980	A

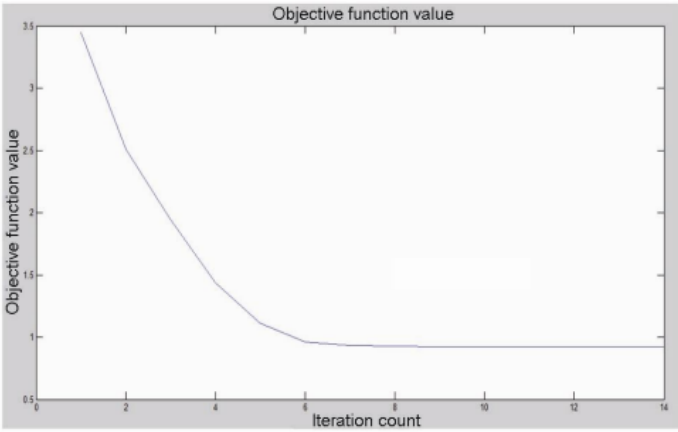

Figure 1. Objective function values of the K-means method.

a student's aggregate grade. The FCM and SC clustering algorithms may be able to help with this kind of situation.

FCM method

Using FCM clustering with weighting exponent m = 2, the initial data sets (Tables 1 and 2) are partitioned into many distinct groups. The FCM method's clustering number was set initially to 5, signifying the availability of five rules. It has 15 cases with three sem-1, sem-2, and sem-3 conditional features and five clusters-1 through 5 classification results (Table 6). For example, the FCM approach indicates that the first student's performance index is 0.354. (Table 6). Similarly, 0.45 is the given value for the fifth performance index. A graph of the objective function values is shown in Figure 2. Based on how the objective function changed over time, the FCM approach seems to be superior than the K-means technique. Based on the following five principles, the FCM approach delivered quicker convergence and greater accuracy when assessing students' academic achievement.

Table 6. Students' academic performance results using FCM method

Sl no	Sem-1	Sem-2	Sem-3	Output	Grade
1	0.100	0.233	0.200	0.354	D
2	0.500	0.167	0.120	0.358	D
3	0.150	0.133	0.180	0.357	D
4	0.450	0.267	0.400	0.457	C
5	0.350	0.333	0.300	0.449	D
6	0.350	0.500	0.380	0.500	C
7	0.450	0.433	0.540	0.555	B
8	0.500	0.400	0.500	0.517	C
9	0.450	0.500	0.580	0.608	B
10	0.500	0.700	0.620	0.687	B
11	0.650	0.700	0.740	0.765	A
12	0.850	0.600	0.760	0.788	A
13	0.950	0.767	0.860	0.877	A
14	0.850	0.833	0.960	0.866	A
15	0.900	0.900	0.980	0.871	A

Cluster 1 represents academic success if (a) semesters 1, 2, and 3 fall into that category. Cluster 2 represents academic achievement if (b) sem-1, sem-2, and sem-3 are all in cluster 2. (c) If semesters 1, 2, and 3 all fall into group 3, then grades are also in group 3. (d) If semesters one, two, and three all fall into cluster four, then there is where you'll find academic performance. Cluster 5 represents academic achievement if (e) semesters 1, 2, and 3 fall within that category. According to the first criterion, the FCM approach relies on inputs that strongly relate to the cluster-1 membership function, such as sem-1, sem-2, and sem-3, and student performance. The rule is important because it provides a concise mapping between cluster-1 in the input space and cluster-1 in the output space. The second set of rules does the same thing for cluster 2 in the input space, transforming it into cluster 2 in the target space. If a datapoint with strong membership to the first cluster (i.e., one that is geographically near to the first cluster) is used as input to FCM, then rule 1 will be prioritized above rule 2. If the input strongly belongs to the second cluster, then rule 2 will be used more often than the other four rules. The FCM approach uses the output membership functions to construct the output based on the rule outputs. The FCM approach produces five clusters, one of which is student performance, which is represented by five linear membership functions. However, the coefficients of the linear membership functions are not obtained directly from the cluster centers. Instead, the Tskagi-Sugeno (T-S) fuzzy model uses the least-squares estimation approach to infer them from the data.

Table 7. RMSE of training and testing datasets

Training and testing RMSE	SC
Training	0.039
Testing	0.107

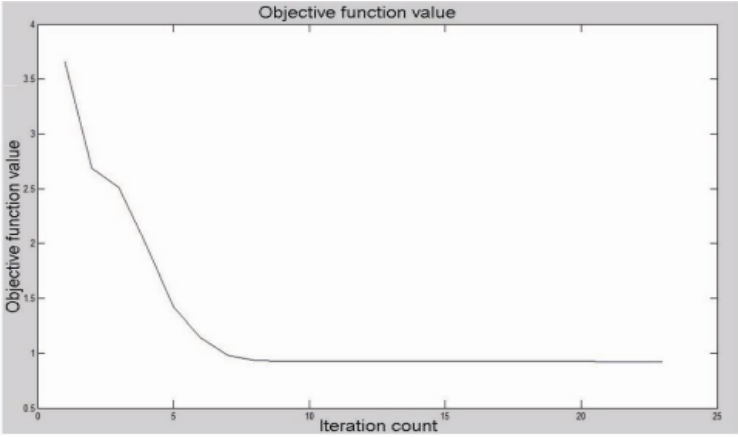

Figure 2. Objective function values of FCM.

Subtractive clustering method

Sixty instances, three conditional characteristics (sem-1, sem-2, and sem-3), and five classification results (clusters-1 through clusters-5) are used to organize the initial data in the SC technique (Tables 1 and 2). In order to keep things simple, only five linguistic labels are employed to indicate student accomplishments, much like the categorization results. There is no doubt that the SC provides superior fuzzification. An important point to keep in mind is that the normal distribution of crisp marks is used to derive the stated concept of fuzzy sets. The RMSE for the SC methodology's training and testing datasets is shown in Table 7. Table 8 shows the results of a SC based on the T-S fuzzy model applied to the students' academic achievement.

Table 8. Students' academic performance results using SC method

Sl. no.	Sem-1	Sem-2	Sem-3	Output	Grade
1	0.100	0.233	0.200	0.276	D
2	0.500	0.167	0.120	0.219	E
3	0.150	0.133	0.180	0.253	D
4	0.450	0.267	0.400	0.479	C
5	0.350	0.333	0.300	0.415	D
6	0.350	0.500	0.380	0.503	C
7	0.450	0.433	0.540	0.550	C
8	0.500	0.400	0.500	0.544	C
9	0.450	0.500	0.580	0.553	B
10	0.500	0.700	0.620	0.767	A
11	0.650	0.700	0.740	0.768	A
12	0.850	0.600	0.760	0.817	A
13	0.950	0.767	0.860	0.943	A
14	0.850	0.833	0.960	1.080	A
15	0.900	0.900	0.980	1.070	A

Table 9. Students' academic performance based on FCM and SC-FCM methods

				FCM		SC-FCM	
Sl no.	Sem-1	Sem-2	Sem-3	Output	Grade	Output	Grade
1	0.100	0.233	0.200	0.516	C	0.354	D*
2	0.500	0.167	0.120	0.518	C	0.469	C
3	0.150	0.133	0.180	0.517	C	0.357	D*
4	0.450	0.267	0.400	0.510	C	0.457	C
5	0.350	0.333	0.300	0.516	C	0.449	D*
6	0.350	0.500	0.380	0.524	C	0.500	C
7	0.450	0.433	0.540	0.571	B	0.556	B
8	0.500	0.400	0.500	0.511	C	0.517	C
9	0.450	0.500	0.580	0.613	B	0.609	B
10	0.500	0.700	0.620	0.688	B	0.686	B
11	0.650	0.700	0.740	0.720	B	0.765	A*
12	0.850	0.600	0.760	0.729	B	0.783	A*
13	0.950	0.767	0.860	0.710	B	0.876	A*
14	0.850	0.833	0.960	0.725	B	0.865	A*
15	0.900	0.900	0.980	0.720	B	0.870	A*

CONCLUSION

Modeling academic performance assessment using FCM, and SC-FMC clustering approaches, this study gives a qualitative methodology for comparing the predictive capacity of clustering algorithm and the Euclidean distance. It's a helpful standard against which students' growth in the field of instructional modeling may be measured. In addition, it helps academic planners make better decisions over time, as seen by improved performance in the next semester. The assessment of student performance is crucial due to the analytical power afforded by the application of appropriate criteria for analyzing student outcomes. Due to the constraints of the university library's lack of access to a number of pay-wall based research papers, this research report relied only on Google scholar to search for relevant literature. Several SC methods have already been put to use in the field of education administration, namely in the areas of student enrollment prediction, teacher assessment, and grade point average projection.

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