Role of Fuzzy Model System for Predicting and categorizing Learners Performance

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Abstract

Education System is the backbone of country which builds the elements which contribute in development of nation. By focusing on education system, its need of changing approach towards traditional result analysis. Proposed study enlighten on predicting and categorizing learners performance using soft-computing approach. In this paper fuzzy inference system model is used as a soft-computing. Traditional result analysis produces the results only on the basis of obtained marks which is not sufficient in today's generation. Proposed study focuses on other factors which impact on overall result of students.

Keywords: Fuzzy Inference System; Bloom Taxonomy; Soft computing

. Introduction

The study of results in the educational system has become increasingly significant in classifying pupils according to their grades and learning capacities, as well as in directly or indirectly affecting human existence. Teachers usually face issues with performance evaluation following a training program or educational process. The traditional method of analyzing results focuses simply on the marks that students have received, averages them, and then groups the students based on that information. This typical technique falls short of highlighting students' "critical thinking ability." Numerous other elements, such as course topic, material difficulty level, time, mood, conduct, and teaching approach, can also have an impact on students' outcomes. The conventional way of averaging might not shed light on comprehension, assessment, production, etc.

Fuzzy logic was initially conceptualized by Zadeh in 1964, and Mamdani created the first fuzzy logic controller in 1974. Fuzzy logic is used to forecast outcomes when data is ambiguous or inaccurate. It is trustworthy and based on rules. Strong decision-making is aided by the ability to forecast outcomes and learners' capacity for learning through the use of the FIS soft computing tool.

The proposed study aims to use FAM (Fuzzy Averaging Method) to address the shortcomings of the CAM (Conventional Averaging Method) of score for grading. It also aids in forecasting children for various learning groups based on how well they perform at various Bloom's taxonomy levels. A variety of taxonomy levels were used in the design of the question paper. The resultant score that shows the various question levels

2. Literature review

The educational system makes use of fuzzy logic theory as well. Fuzzy logic is being applied to a growing number of different student performance tasks. In 1995, a study was conducted on student performance utilizing soft computing approaches. Additionally, a fuzzy logic-based approach for evaluating student performance in network analysis courses was proposed by Deshmukh et al. [1, 2]. Biswas recently published on the use of fuzzy sets for student paper evaluation by matching answer scripts, which might become laborious when there are a lot of data. With the use of expanded fuzzy grade sheets and degree of satisfaction, more generalized intelligent expert systems were put into place [3, 4]. In order to forecast a cricket player's international ranking, a model for evaluating player performance was provided [5]. The impact of each parameter on performance is also covered. A customized student performance was shown alongside the back propagation algorithm and traditional statistical method [6]. Since every student is different, fuzzy systems allow for the evaluation of both student performance and learning progress [7]. To simulate and assess the attainment of learning objectives in information system courses, fuzzy rules have been devised [8]. In order to reduce complexity and ambiguity in the evaluation process, it was suggested to adopt the fuzzy set technique [9]. The suitability of fuzzy logic for the resolution of fair assessment has been examined. It is used to grade poster competition entries using fuzzy logic in addition to traditional numerical grading. It was found that the fuzzy grading approach is superior to the classic method it models in several ways. Using various input values for student attendance, efficient instruction, and other facilities, the fuzzy inference system has been employed to acquire student performance [12].

As per the literature review, researchers are driven to create a fuzzy expert system that can forecast distinct learners based on their learning levels and make decisions for improved performance and advancement.

3. Research Experiment

Dataset:

The aptitude test data set is used in this instance. The purpose of the test is to assess final-year students' knowledge of numerical analysis and logical thinking, which are prerequisites for employment in multinational corporations. In order to provide relevant study, the course is held before the exam. The concepts of mathematical formulas, hints, reasoning, etc., must be taught to learners. Each of the 50 questions on the question paper, which is designed for 50 marks, is worth one mark. The Bloom's Taxonomy was used in the design of the paper to cover all question level in almost equal proportion. There is an hour allotted for this test. The student receives the link ten minutes ahead of schedule, and the test is taken online. Following the exam, information such as their name, roll number, date, and completed questions is gathered. The scored mark for every level is transformed to an out of 100 for computation purposes, as table II illustrates. A total of 86 students are enrolled in this test. We determine each learner's overall test score. The chart (chart I) displays the average proportion of students answering each level of questions. Remember level (RM), Understanding level (UN), Analyzing level (AN), Apply level (AP), Evaluation level (EV), and Creative level (CR) are the many learning levels.

Table I: Average percentage of students in each level.

Level	Percentage
Remember	72.09302
Understand	58.43023
Apply.	56.10465
Analyze	61.49871
Evaluation	54.65116
Creative.	54.52196

The average mark obtained using the fuzzy and traditional methods is compared (the FIS output system has a range of 0 to 10). The table displays the sample data from 12 students (Table II).

TABLE II: Sample of Student Data set

RM	UN	AP	AN	EN	CR	Conventional Method	fuzzy method
mark	mark	mark	mark	mark	mark	mark	average result out of 10
13	25	0	11	25	22	16	1.47
50	25	25	11	38	11	26	2.97
13	25	50	33	13	11	24	2.88
50	75	38	44	13	11	38	3.46
63	50	50	67	25	11	44	5
25	38	13	33	25	22	26	2.94
25	13	38	22	13	33	24	2.94
13	63	38	11	25	44	32	4
88	88	63	89	88	100	86	8
38	13	50	44	0	11	26	2
100	100	88	100	100	100	98	9.36
88	88	88	100	100	100	94	9.36

Table II shows a good agreement between the average mark generated by the conventional technique and the mark calculated using the fuzzy method.

Methodology: The suggested work creates a set of guidelines based on the quality of a learner's aptitude test result to determine which learner group they fall into.

The following is the design of the fuzzy expert system in the proposed work:

1.1 Crisp Value (Data)

The exam is administered using the level of thinking specified by Bloom's taxonomy. The learner's result is the achieved score, which is then examined using FIS. The precise values of the input parameters for this experiment are the values that were achieved (the results) for each level. There are six levels of taxonomy, which correspond to the six input variables used in this experiment. The level- and criteria-specific questions and marks are displayed in Table III.

TABLE III: Level (Criteria) Wise Total Questions and Total Marks in Test

Sr. no.	Level	No. of questions	Total Marks
1	Remember	8	80
2	Understand	8	80
3	Analyse	8	80
4	Apply	9	90
5	Evaluate	9	90
6	Create	8	80

1.2 Fuzzification (Fuzzy input value)

Membership functions (MF) are fundamental components of fuzzy set theory. This fuzziness of a fuzzy set is determined by its MF. They can have a variety of shapes, including triangular, trapezoidal, and Gaussian. Triangular or trapezoidal MF is built with straight lines and has the advantage of simplicity. Because of their simple formulas and computing efficiency, triangular and trapezoidal MFs have been widely employed, particularly in real-time implementations. The sole requirement for MF is that it ranges between 0 and 1.

1.3 Linguistic Values:

The suggested work fuzzifies six input variables (parameters) using linguistic values that are equivalent to spoken human language, such as Poor, Average, Good, and Very good. Using the Trapezoidal membership function, each input parameter is defined by lower limit 'a', lower support limit 't2', upper support limit 'c', and upper limit 't4', with t1<b<c<t4. The following table (TABLE III) provides the lower and upper limits for the trapezoidal membership function. This provides the score for each category of linguistic variables. Students who score 0 to 49 fall into the poor category, those who score 50 to 69.9 fall into the average category, those who score 70 to 79.9 fall into the good category, and those who score more than 80 fall into the very good category, as stated in the table (TABLE IV). For selection in MNCs, the minimum passing score is 50%, hence the range for the poor category is up to 50.

TABLE IV: Upper and Lower limits for each Linguistic Variable in Trapezoidal function.

Category	Lower Limit (a)	Lower Support (b)	Upper Support (c)	Upper Limit (t4)
Poor	0	10	30	50
Average	40	50	60	70
Good	65	70	80	85
Very Good	80	90	100	110

The degree of association of respective linguistic variables is represented in following equation (1).

$$trapezoid(x;a,b,c,d) = \left\{ \begin{array}{cc} 0, & x \le a \\ \dfrac{x-a}{b-c}, & a \le x \le b. \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{array} \right\} \qquad ----(1)$$

The process of fuzzification of six input variables is shown below based on the given score and varying restrictions for the trapezoidal function. For example, to calculate membership value of achieved score x, if x = **40** marks scored in Remember (RM) level, which falls in the poor group, membership value can be computed as

$$\mu_{poor}(x) = \frac{d-x}{d-c}$$

$$\mu_{poor}(x) = \frac{50-40}{50-30}$$

$$\mu_{poor}(x) = \mathbf{0.5}$$

This is the membership value for a poor score value 40.

Figure 1 illustrates the membership function of the input variable Understand (UN).The remaining variables, such as Remember (RM), Analyse (AN), Apply (AP), Evaluate (EV), and Create (CR), have the same graph appearance. Table (TABLE V) displays the range of linguistic variables for the input parameter based on the graph.

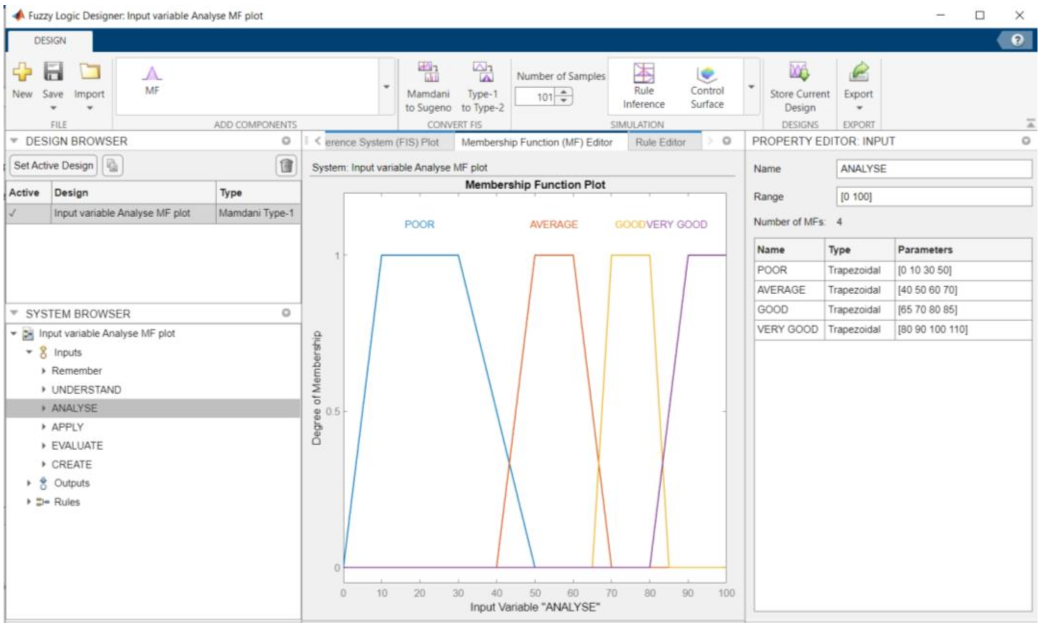

Figure (1) Membership function plot for Input variable Analyse (AN)

TABLE V: Score Range of Linguistic Variables for each Input Parameter.

LEVEL	POOR	AVERAGE	GOOD	VERY GOOD
RM	< 50	10 -65	40 – 95	>=70
UN	< 50	10 -65	40 – 95	>=70
AN	< 50	10 -65	40 – 95	>=70
AP	< 50	10 -65	40 – 95	>=70
EV	< 50	10 -65	40 – 95	>=70
CR	< 50	10 -65	40 – 95	>=70

Development of Fuzzy rules and Inference Mechanism

Fuzzy inference rules are employed during the inference process to connect the input and output membership functions. These rules are versatile and use a "If-Then" statement with the AND, OR, and NOT operators. They are developed based on the importance assigned to specific input parameters using a standard and expert system such as bloom taxonomy in this suggested work. In the proposed work, about 4096 rules are created from six input variables, each of which having four linguistic values. Rules are just various combinations of input variable values and their associated output, such as (4^6= 4096).In this study, we use 54 rules for experimental purposes. Figure (2) depicts interference from input to output in the form of rules.

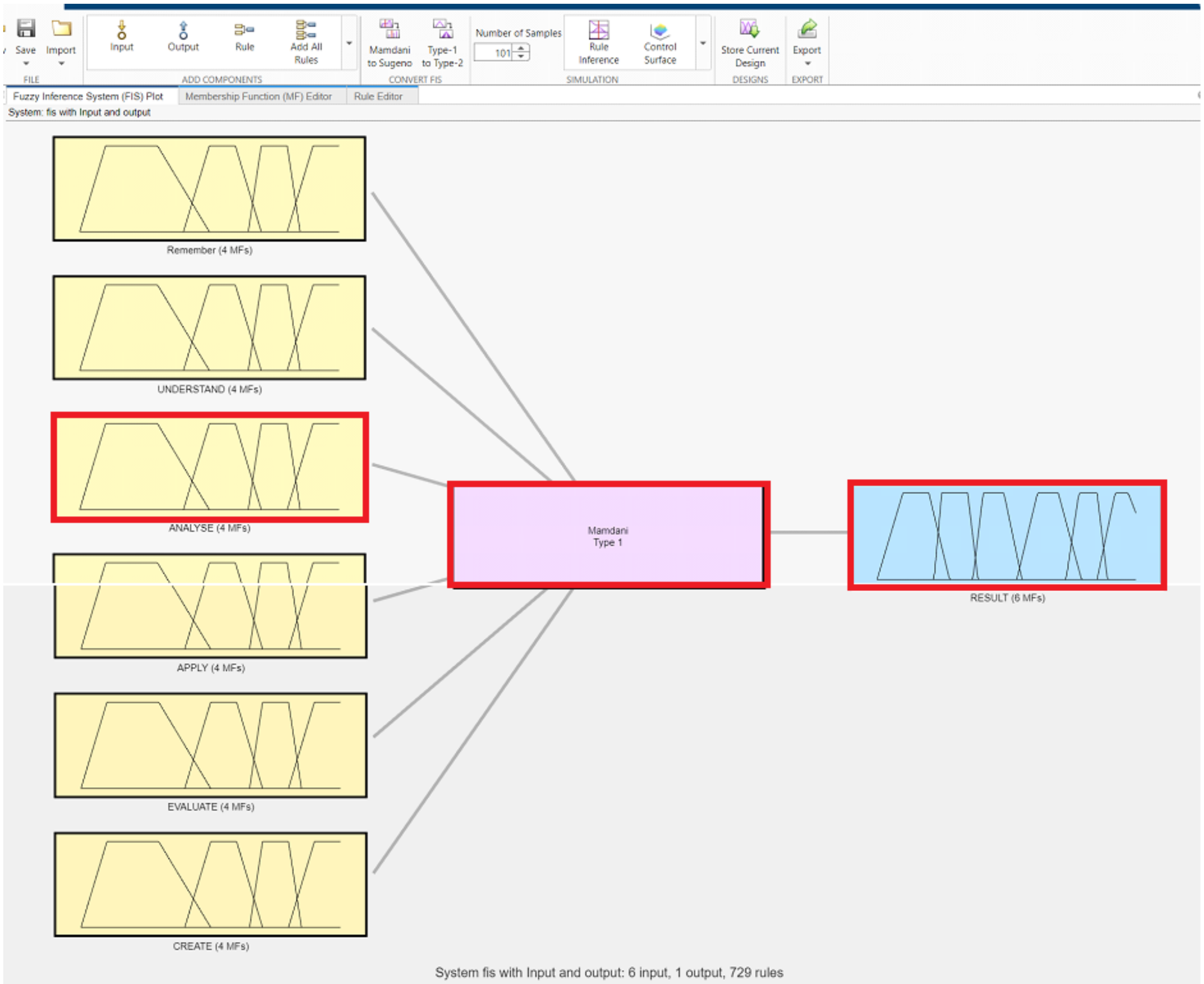

Figure (2) Fuzzy Inference System with input and output

Defuzzification of Fuzzy Output:

Defuzzification is the process of representing a fuzzy set with a crisp number that is fuzzy value to precise value. The defuzzification method to find out final result as follows. There are various ways for defuzzification [13].

Centre of Sums Method (COS)
Centre of gravity (COG) / Centroid of Area (COA) Method
Centre of Area / Bisector of Area Method (BOA)
Weighted Average Method
Maxima Methods

The proposed method uses Centre of gravity (COG) method for defuzzification because this method determines the centre of area of fuzzy set and returns the corresponding crisp value.

The resultant membership functions are developed by considering union of the output of each rule. It consider maximum area but overlapping area of fuzzy output is counted as one providing more result. It gives answer in more precision which tends to exactness [17]. The centroid defuzzification system is expressed as

$$Z_{COG} = \int_z \frac{\mu_A(x)xdx}{\mu_A(x)dx}$$

The output variable is OUTPUA (F) shows different learners such as F1: Weak Learner (WL), F2: Slow Learner (SL), F3: Average Learner (AVGL), F4: Satisfactory Learner (SATL), F5:Fast Learner (FL), and F6: Extraordinary Learner (EOL). The different Learners are decided by applying different rules on marks scored by student in each level of questions.

If six input variables are expressed as f1,f2, f3, f4, f5 and f6 and membership function of theses six variables are μ(f1), μ(f2),μ(f3),μ(f4),μ(f5) and μ(f6) respectively for rule k = 1, 2, 3, …. r, then the membership function of output variable F is given by equation (2) as [1,2]

$$\mu(F) = Max_k[\min[\mu(f1), \mu(f2), \ldots \mu(f6)]], k = 1, 2, 3, \ldots r \qquad (2)$$

This expression expresses the value of membership function for output variable overall performance for active rules for each input. The AND logical operator is used among the six input. Like linguistic variables for input we have used linguistic variables for output also. Following table (TABLE VI (A)) shows linguistic variables of output (i.e. different learners) and their mark range.

Table VI(A): Different Scores assigned for linguistic variables of output.

INPUT VARIABLES	WEAK LEARNER (WL)	SLOW LEARNER (SL)	AVERAGE LEARNER (AVGL)	SATISFACTORY LEARNER (SATL)	FAST LEARNER (FL)	EXTRA ORDINARY LEARNER (EOL)
REMEMBER	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.9	> = 9.0
UNDERSTAND	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.9	> = 9.0
ANALYSE	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.9	> = 9.0
APPLY	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.4	> = 8.5
EVALUATE	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.4	> = 8.5
CREATE	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.0	> = 8.0

In the above table the ranges for linguistic values are different in each level because applying evaluating and creating levels are high level thinking process in comparison to the previous three levels like Remember, Understand, and Analyse. Bloom's taxonomy level is in increasing order of thinking and complexity hence [2]. Following figure shows trapezoidal membership function plot for output which shows different learners. For example the red coloured part in graph shows satisfactory learners has linguistic values from 5.5 to 7.9. Its membership value is maximum i.e. one for linguistic value 5.8 to 6.2 and changes from 0 to 1for rest of the range.

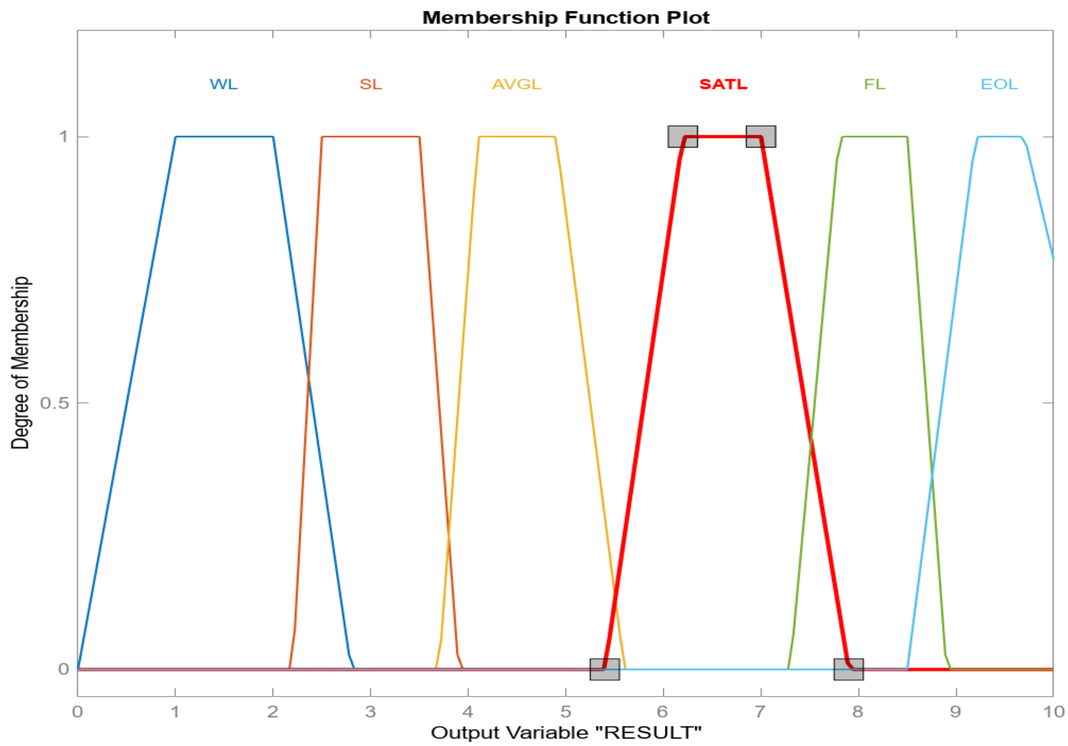

Figure (3) Membership function plot for Output as Output1

4. Result and Discussion

In the suggested method, we investigated rule-based classifiers such as fuzzy, which provide classification accuracy of 100 percent. The crisp values of the fuzzification result are contrasted to a classical or traditional averaging approach. Figure 2 illustrates the application of the Mamdani fuzzy system with input variables RM, UN, AP, AN, and EV. The output variables for learner performance in linguistic variables are as follows: Poor (< 50), Average (50 - 69.9), Good (70 - 79.9), and Very Good (above 80), as shown in Table VII.

TABLE VII : Crisp value of Final score

Final Score of (Linguistic variables)	**Poor**	**Average**	**Good**	**Very Good**
Crisp value	< 50	50 – 69.9	70 – 79.9	>=80

The following table (TABLE VIII) shows the crisp values for output for different learner categories. As output has six linguistic values, which are nothing more than six sorts of learner categories, their crisp value ranges vary as well. If the crisp value is less than 3, the learners are classified as Weak Learners (WL); if the crisp value is between 3.0 and 3.9, the learners are Slow Learners (SL); Average Learners (AVGL) have a range of 3.0 to 6.0; Satisfactory Learners (SATL) have a range of 5.5 to 7.9; fast Learners (FL) have a range of 7.5 to 8.9; and Extraordinary Learners (EOL) have a range of more than

TABLE VIII: Crisp value of Different Learners.

Output	Weak Learner	Slow Learner	Average Learner	Satisfactory Learner	Fast Learner	Extra ordinary Learner
Crisp Value	< 3	3.0 – 3.9	3.0 - 6.0	5.5 – 7.9	7.5 – 8.9	> = 9.0

Rules of the proposed fuzzy expert system for the evaluation of overall student's performance is shown in figure (4). It also shows crisp value of output for respective crisp value of input parameter.

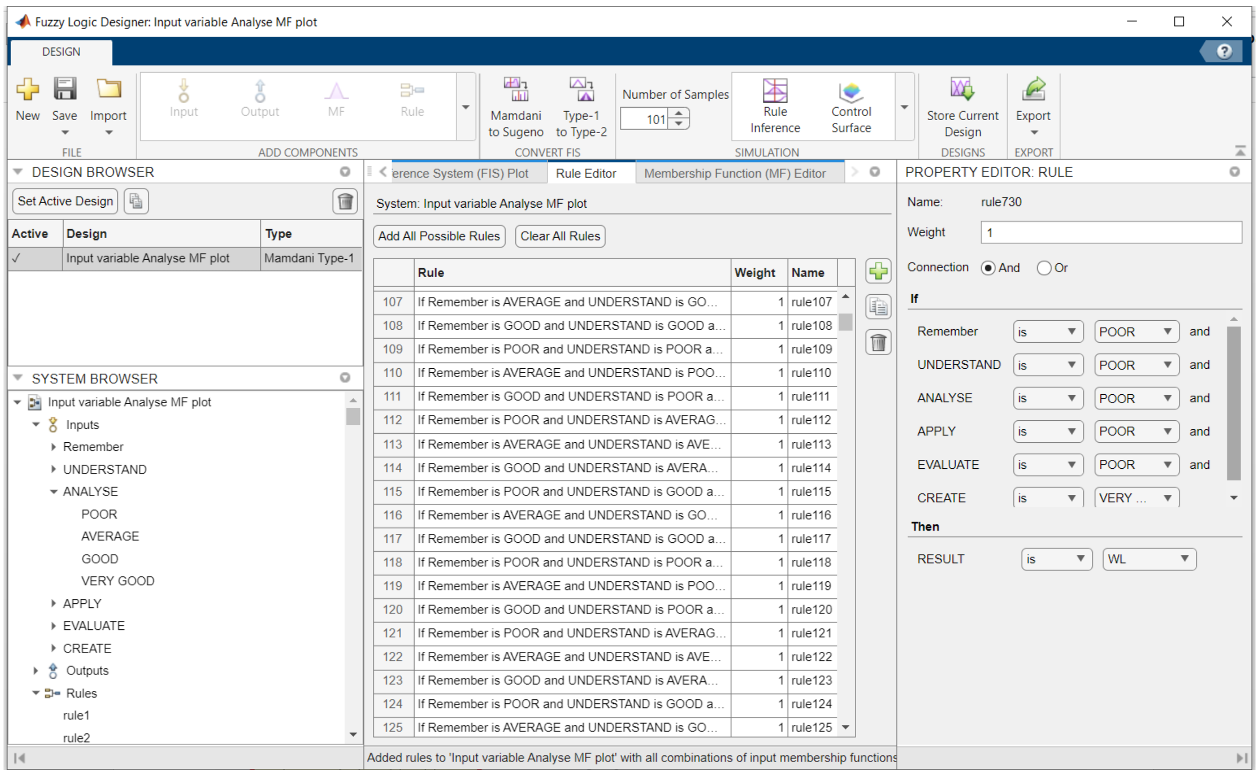

Figure (4) Rules of Fuzzy Inference system

Table (I) in the data set section displays the average proportion of students who solved questions and received marks at each level. According to the table, the scored percentage of Remember level questions is higher and are solved properly by 72.09%, which is the most among all levels. The average percentage of comprehension is too low, at 58.43%, in comparison to the degree of remembering, and hence their analysis and application are both ordinary. The average proportion of questions solved at the evaluation and creation level is equally low, as are the levels above it, such as comprehending, applying, and analysing. The table (Table II) in data sets contains only sample data from a population (total data) of 151 instances. In the table, we calculate each student's average marks using both the conventional and fuzzy averaging methods. Both classifiers can be used to assess student performance based on the classification and time needed to categorize. The fuzzy technique achieves 100% classification accuracy, and the results are compared to the conventional method, which is nearly identical in most cases but differs in others. Though both methods produce similar results, if the data is extensive, the rules are more numerous and the training period is longer, resulting in greater complexity; in such cases, the fuzzy method is more pleasant and trustworthy for performance evaluation.

Conclusion

When the Fuzzy method findings were compared to the conventional technique of averaging using the null hypothesis and t-test method, it was discovered that the fuzzy averaging approach provides about 100% classification accuracy. It was also discovered that fuzzy methods outperform standard methods when the criteria are more complex. For big amounts of data, the rules and training periods are longer, resulting in increased complexity. In such instances, the fuzzy technique is better suitable for performance evaluation. According to the Blooms Taxonomy, the proposed research task learner's capability is classed as RM, UN, AN, AP, EV, and CR.

It is also obvious that students' remembering abilities are good, but there is a need to improve their understanding, analysis, and application abilities in order to achieve higher levels of evaluation and creativity. Upgrading this level is one of the goals for both students and teachers. Using FIS, it is possible to identify in-between phases, which aids in the transition from lower to upper phases and reduces the gap between learners. In a teaching-learning system, evaluation of learners is a vital phase that provides teachers with the right direction to inspire, promote, and upgrade their students. The conventional technique evaluates learners based on the marks they receive, whereas the proposed FIS method analyzes learners based on their learning capability and performance at various levels.

The experimental results show that the proposed method achieves 97.36% accuracy, which is highly significant. Furthermore, we accept the null hypothesis, which states that the conventional result is identical to the mean fuzzy system result at the 95% confidence level. As a result, the computer-based Fuzzy expert system is a superior approach than the traditional method in terms of time, and it meets the needs of today's educational system.

References

1. Deshmukh VB, S. R. Mangalwede and Rao, D. H. , 2017,"Student performance evaluation model based on scoring rubric tool for network analysis subject using fuzzy logic.", International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT), IEEE 2017, pp. 1-5.
2. V. B. Deshmukh, S. R. Mangalwede and Rao, D. H., 2018 "Student performance evaluation model based on Bloom's Taxonomy using fuzzy logic." In International Conference on Electrical, Electronics, Communication, Computer, Mechanical and Computing (EECCMC). IEEE, 2018.
3. Biswas, 1995,"An application of fuzzy sets in students' evaluation", Fuzzy sets and systems,1995, pp.187-194.
4. Shyi-Ming Chen, Chia-Hoang Lee, 1999, "New methods for students' evaluation using fuzzy sets", Fuzzy sets and Systems 1999, pp.209-218.
5. Singh, G., Bhatia, N., and Singh, S.,2011, "Fuzzy Logic Based Cricket Player Performance Evaluator". IJCA Special Issue on "Artificial Intelligence Techniques - Novel Approaches & Practical Applications" 2011, pp. 11-16.
6. Nidhi Arora, Jatinder Kumar R. Saini., 2013, "A Fuzzy Probabilistic Neural Network for Student's Academic Performance Prediction", International Journal of Innovative Research in Science, Engineering and Technology, 2013, Vol. 2. 4425-4432.
7. Z.Jeremic,J.Jovonovic,D.Gasevic, 2012, "Studentmodelling and assessment in intelligent tutoring software patterns", Expert systems with Applications, Elsevier, 2012 pp.210-212 .
8. Faouzi Bouslama, Azzedine Lansari, Akram Al-Rawi., 2006, "Fuzzy Rules In Assessing Student Learning Outcomes", American Society for Engineering Education.
9. Eduardo André Mossin, Rodrigo Palucci Pantoni and Dennis Brandão (2010), "Students' Evaluation based on Fuzzy Sets Theory, Fuzzy Systems", Ahmad Taher Azar (Ed.), ISBN: 978-953-7619-92-3, InTech, DOI: 10.5772/7225. Available from: http://www.intechopen.com/books/fuzzy-systems/students-evaluation-based-on-fuzzy-sets-theory
10. McLoone, Séamus C. s.l. : ISSC 2012,"On Using Fuzzy Logic for Grading Highly Subjective Assessment Material – a Case Study", NUI May- June 28-29, 2012.
11. Shruti S Jamsandekar, R.R Mudholkar. 2013, "Performance Evaluation by Fuzzy Inference Technique",

International Journal of Soft Computing and Engineering (IJSCE), pp. 158-164.

12. Upadhya, Mamatha S. 2012, "Fuzzy Logic Based Evaluation of Performance of Students in Colleges", Journal of Computer Applications (JCA), pp. 6-9.
13. Sameena Naaz, Afshar Alam and Ranjit Biswas, "Effect of different defuzzification methods in a fuzzy based load balancing application" IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 5, No 1, September 2011, pp 261-267.
14. Malatesh Akkur, D.H. Rao. 2018,"Fuzzy Logic: A Tool for Evaluation of Students' Performance", International Journal of Scientific & Engineering Research Vol. 9, Issue 10, pp. 1339-1343.
15. Rajiv Bhatt, Darshana Bhatt., 2011, "Fuzzy Logic based Student Performance Evaluation Model for Practical Component of Engineering Institution Subjects", International Journal of Technology and Engineering Education, 2011, Vol. 8.
16. Maria Samarakou, Andreas Papadakis, PantelisPrentakis, Dimitrios Karolidis, Spyros Athineos, "A Fuzzy Model for Enhanced Student Evaluation",the International Journal of Learning, Vol. 16.
17. KeshengWang, "Computational Intelligence in Agile Manufacturing Engineering" Department of Production and Quality Engineering, Norwegian University of Science and Technology, N-7491 Trondheim, Norway https://doi.org/10.1016/B978-008043567-1/50016-4

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