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FUZZY LOGIC APPROACH FOR PREDICTING STUDENT ACHIEVEMENT IN SCRATCH TRAINING

Ali ÇETİNKAYA

Konya Technical University, Engineering Faculty, Computer Engineering Department, Konya, TÜRKİYE
ali.cetinkaya@gmail.com

Highlights

- Predictions were made about students' programming skills using fuzzy logic.
- It was investigated whether students' interest in learning algorithms and coding would increase by creating games with the visual programming tool.

***Corresponding Author**: Ali ÇETİNKAYA, ali.cetinkaya@gmail.com

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ABSTRACT: 21st-century skills such as critical thinking, problem-solving, and analytical thinking gained importance to survive in today's world. There is growing research mostly focus on the prediction of students in higher education using machine learning and statistical models. However, predicting primary and middle school student's performance also becomes important especially in learning computer programming. In this study, it was primarily proposed to a fuzzy logic system to predict student performance during the experiment then compare fuzzy logic prediction results to the experts' results. Secondly, to test the theory that students' interest in learning algorithms and coding can be increased using the creation of games in a visual programming tool for beginners. The fuzzy logic inference system has been employed to predict middle school student's performance in the programming experiment which has been carried out using the Scratch environment with the participation of three different middle school students in Turkey. The success rate of three different middle school group success rates is estimated regarding task completion times, and the regression results with respect to the groups are %80, %97, %84.

Keywords: *Predicting Student Achievement, Scratch Training, Fuzzy Logic*

1. INTRODUCTION

Today, as advanced technologies emerge especially in computer-related technologies, it is imperative for students to gain 21st-century skills such as critical thinking, problem-solving, and analytical thinking. In order to acquire these skills, computer, and coding, which is also a part of everyday life, education has become crucial. Therefore, coding ability should be given to every student as a basic educational right of this century [1].

The young generation is so fluent with the Internet and other digital technologies that they can be called "digital natives" [2]. As seen, being a digital native requires not just browsing or interacting via social media but demands the skill to imagine, design, and invent using new media. To do so, it requires to learn some form of coding [3]. Visual programming techniques are becoming increasingly important when teaching programming concepts. Visual programming applications provide an environment that makes programming easy and fun [4]. The main applications of these applications are Scratch [3] and Alice [4].

Using Scratch-like visual block programming languages gives students more opportunity to concentrate on the semantics of programming languages instead of syntax issues. In addition to that, primary school pupils have not achieved a suitable level of conceptual thinking necessary to code up until now, which makes learning coding harder [5]. Learning coding with the help of a visual coding language tool could supply a concrete understanding to conceptual thinking. [4], and could hence be used as a mechanism for a suitable mindset shift [6] to "real" coding. Coding in Scratch environment switches the coding framework from solving math problems creating stories, games etc. which is more fun to do [5].

Students with under the average math skills could grasp programming and problem-solving easier if given suitable tools and the employing of less complicated visual environments before shifting to integrated development environments (IDEs) which are commonly used in the software industry and

***Corresponding Author**: Ali ÇETİNKAYA, ali.cetinkaya@gmail.com

are seen as more complicated [7].

In recent years, machine learning techniques, fuzzy logic and artificial intelligence methods have been frequently used in estimating the performance of the students. L.A. Zadeh introduced the fuzzy logic theory in 1965 [8]. Fuzzy logic allows for the inclusion of vague human assessments in computing problems. A lot of work has been done about fuzzy logic so far. Fuzzy logic can be used in the development of intelligent systems for decision making, prediction, identification, pattern recognition, optimization, and control [9].

It is important for educators to recognize students' performance during training time. Therefore, this paper presents a fuzzy model approach to predicting student performance during Scratch programming training. In the proposed method, the completion of the tasks and mathematics grades were taken into consideration to test students' achievement of completing the given Scratch tasks. the high correlation coefficient between the real values and Fuzzy values indicates that the system works successfully. The proposed method can be used automatically to measure students' performance without expert supervision.

This paper is organized as follows. Section 2 presents the related work. Section 3 describes the material and methods employed in this paper. Section 4 presents our proposed method. Finally, Section 5 presents our conclusions.

2. RELATED WORK

There was huge excitement to educate children on how to code when personal computers were presented to the public. Most schools trained millions of pupils to code in Logo or Basic [3]. Seymour Papert's 1980 book Mindstorms [10] presented Logo as a keystone for rethinking approaches to education and learning. Recently, fresh efforts have been put forward to introduce programming to the younger generation, especially primary and middle school children using visual programming environments such as: Scratch [10] and Alice [4].

Predicting students' performance gets a lot of attention with the help of dizzying advancements in machine learning, fuzzy logic and statistical methods. Fuzzy logic techniques have been used in prediction in recent years. Yildiz et al. developed three types of fuzzy (classical fuzzy, gene-fuzzy, expert fuzzy) models to predict the student's year-end performance using the first eight weeks' data as a result the gene-fuzzy and the expert fuzzy models performed better than the classical fuzzy model [11]. Ingoley et al. proposed the multiple node fuzzy logic method, which takes into consideration the ambiguity of students' question paper beside certainty rate, complexity, and importance during the evaluation process, to provide more clear and objective results to all students [12]. Jamsandekar et al. proposed the fuzzy inference technique to evaluate student performance using grades as input data to the system and the proposed approach is further compared with traditional methods for evaluating the difference [13]. Yildiz et al. introduced a new approach using the fuzzy decision support system to evaluate student performance in laboratory applications and the results showed the proposed model performed better than the classical systems in terms of the reliability and the actuality of educational assessment [14]. Jyothi et al. proposed a fuzzy expert system for assessing teachers' overall performance in terms of an optimization evolution model for evaluating teachers' academic performance based on teaching activities [15]. In [16], the authors developed an intelligent tutoring system using Bayesian networks and fuzzy logic to assist students in educational settings and improve their academic performance. The system adhered to the conventional architecture of intelligent tutoring systems and used a fuzzy logic system to evaluate student performance in a particular topic by considering two factors: the pre-test grade and the topic test grade. They used three fuzzy sets for each input variable to characterise the students' grades as poor, good or excellent, and two fuzzy sets to describe the output (low and high). Doz et al., introduced a novel assessment model using fuzzy logic, combining teacher-assigned grades with results from the Italian National Assessment of Mathematical Knowledge (INVALSI). Applied to over 90,000 students across different grades, the fuzzy logic model yielded lower scores compared to traditional grading. However, its consistent results across educational levels suggest its suitability for diverse contexts [17]. Jan et al., utilized fuzzy logic-based artificial intelligence for monitoring student academic performance in engineering education. The study introduces stress as an additional factor and employs both Mamdani and Sugeno inferencing methods. Results show promise, highlighting the potential for automated intelligent systems to contribute to achieving quality education goals [18]. Dhokare et al., proposed a fuzzy logic-based model to address the complexities in evaluating students' performance during the COVID-19 pandemic, considering the evolving teaching methods and the need for a comprehensive assessment approach [19]. In recent years, the combination of artificial intelligence and fuzzy logic has become popular in student performance prediction [20-23].

The classification technique is also one of the important areas in the prediction of teachers or pupil’s performance. Agaoglu employs classification techniques, which are decision tree algorithms, support vector machines, artificial neural network, and discriminant analysis to determine a teacher's accomplishment instead of a student’s accomplishment [24]. Lye et al. tried to predict pre-university pupils’ math performance using several types of neural network models (the Back-propagation Neural Network, Classification and Regression Tree, and Generalized Regression Neural Network) which achieved moderate success in prediction rate [25].

It has become crucial for educators to teach younger age students programming skills and realize students’ skills and accomplishments during training time. This study focuses on students’ performance prediction using fuzzy logic approach.

3. MATERIAL AND METHODS

3.1. Fuzzy Logic

L.A. Zadeh introduced fuzzy logic theory in 1965 [8]. Fuzzy logic is used when conventional logic does not work properly. What makes fuzzy logic powerful is the concept of the linguistic variable whose values are not numbers but words or sentences in a natural or artificial language [26].

A fuzzy logic system (FLS) can be described as the nonlinear mapping of an input data set to a scalar output data [10]. An FLS is based on four essential sections: fuzzifier, rules, an inference engine, and defuzzifier (Fig. 1).

The fuzzifier maps crisp numbers into fuzzy sets. The defuzzifier maps output sets into crisp numbers.

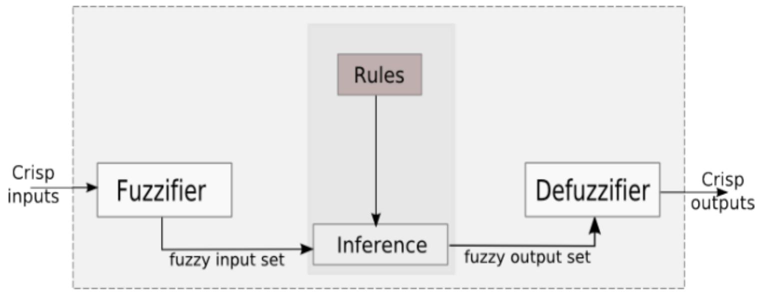

Fig. 1. A Fuzzy Logic System.

Fuzzy inference system (FIS) is the heart of FLS which consists of rules and inference. Two FISs are popular. First one is Mamdani FIS was introduced by Ebrahim Mamdani [27] and second is Takagi–Sugeno–Kang (TSK-FIS) was proposed in 1985 [28]. The main difference between Mamdani FIS and TSK-FIS is that the TSK-FIS output membership functions are either linear or constant [29]. The membership functions (MFs) are the key concept in fuzzy logic. MFs can be defined on input and output data sets. As shown in Fig. 2 several types of MFs can be used.

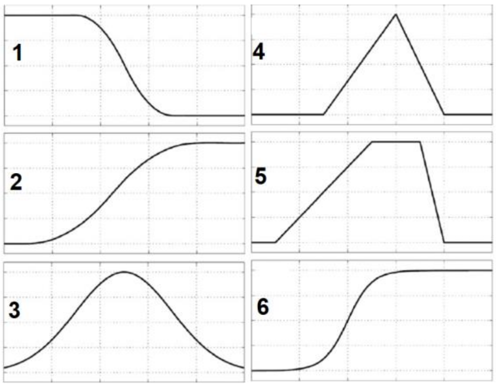

Fig. 2. Membership functions [29]: 1- z-shape, 2-s-shape, 3-gaussian, 4-triangular, 5- trapezoidal, 6-sigmoid.

3.2 Scratch

Scratch is a graphical programming language environment which developed by the Lifelong Kindergarten research group at the MIT Media Lab [30]. The Scratch environment which allows users to create interactive stories, games etc. easily is more than a visual block programming tool. It is open source and free and also an active learning community which so far has over 29 million registered users and almost 30 million projects shared [30]. Because of this easy to use graphical block style, any child who knows how to read or write, or who is just beginning to learn, can easily learn and use Scratch. The classical programming environment mostly uses text-based commands. However, The Scratch-like visual programming environments are founded on blocks which are a component of the language. Instead of test-based commands blocks are used to define a function, a variable, a control structure etc. during programming. A view of the comparison between Scratch and traditional programming language in Fig. 3. Scratch and similar visual programming applications are thought to improve the user's computer thinking skills [31].

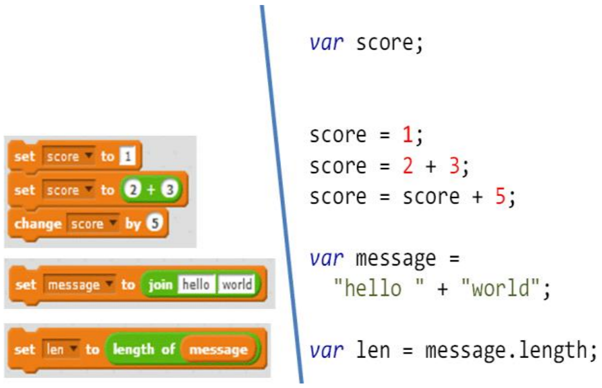

Fig. 3. Scratch vs. text based programming language

3.3 Participants

This experiment had been conducted in the 2016-2017 academic year with three groups of a randomly selected total of 61 sixth grade students of three different middle schools in the city of Konya, Turkey as shown in Table 1.

The students from each group received 3-hour Scratch training which was offered by Konya Science Center instructors. The students were asked to complete the tasks from simple to complex during the training session.

The students who were primarily trained for Scratch activities and who did not have a lot of computer training, in general, were preferred. Thus, it has been tested that a student who has never used a computer can easily learn to code with Scratch.

Table 1. Group characteristics

Group 1	Group 2	Group 3
17 students	22 students	22 students
12 male, 5 female	11 male, 11 female	13 male, 9 female
Public School	Public School (village)	Private School

To determine students programming level, the survey which consists of demographic backgrounds and math grades questions was hand out to all pupils before beginning to introduce the Scratch environment. During the training, firstly presented basic information about Scratch environment then students were given three different tasks, which is shown in Table 2, were from simple to the complex. Each student's the completion times of given task, which can be seen in Table 3, were noted by the instructor.

Table 2. Tasks

Tasks	Description
Task 1	To implement sound effect on the Scratch's main character
Task 2	To implement small fish which is chased by a shark
Task 3	To implement a prince and a princess who walk to each other and say "hello".

3.4 Method

In this study, A Mamdani-type FIS [27] and Scratch environment [30] have been used for building for the proposed model.

The Mamdani type FIS model given in Fig. 4, has been developed to predict participants' success during the Scratch training sessions. The fuzzification with four linguistic variables (i.e., very slow, slow, average, fast) is applied to each of the input and output attributes.

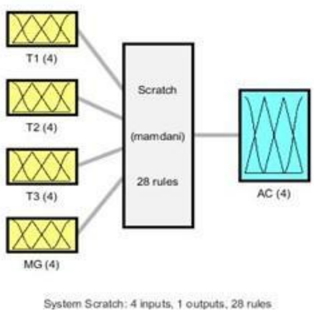

Fig. 4. The proposed model of Mamdani-type FIS

Four input and one output parameters (Table 3) were used to determine the students' success in the Scratch training. The membership functions that will result in the best performance were selected (Figs. 6-10).

Table 3. Input and Output Parameters

Parameter	Input/Output	Description
T1	Input	The first task completion time
T2	Input	The second task completion time
T3	Input	The third task completion time
MG	Input	Mathematics grade
SR	Output	Success Rate

The fuzzy inference diagram shows all pieces of the fuzzy inference process (Fig. 5).

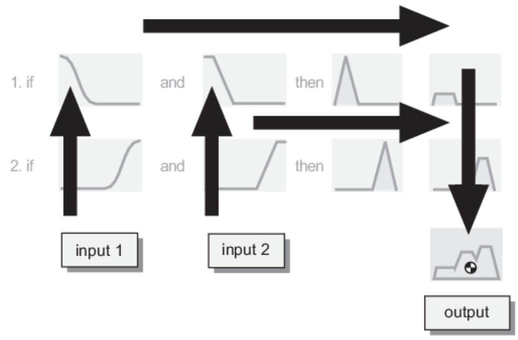

Fig. 5. Fuzzy Inference Diagram [29].

The fuzzy rule system, which is designed based on how the experts describe the attributes of the variables of the system, may vary from one expert to another. It is possible to write down a lot of "if-then" fuzzy rules. This study considers 28 if-then rules and some of the rules used in the model are as shown in Table 4.

Table 4. Subset of the if-then rules

	Input								Output
IF	T1	And	T2	And	T3	And	MG	Then	SR
	Fast		Fast		Fast		High		Successful
	Average		Average		Average		High		Average Successful
	Slow		Slow		Slow		High		Low Successful
	Very Slow		Very Slow		Very Slow		High		Unsuccessful
	Fast		Very Slow		Very Slow		High		Unsuccessful
	Fast		Slow		Slow		High		Low Successful
	Fast		Average		Average		Very Low		Average Successful
	Fast		Average		Average		Low		Average Successful
	Fast		Average		Average		Average		Successful
	Fast		Average		Average		High		Average Successful

3.5 Fuzzification of Inputs

Input 1. The Input 1 is represented in the FIS as "T1: The first task completion time" (Fig. 6) and fuzzified with fast [0-33 second], average [0-66 second], slow [33-100 second], very slow [66+ second]. The triangular, s-shape and z-shape MF's were considered for the analysis (Fig. 6).

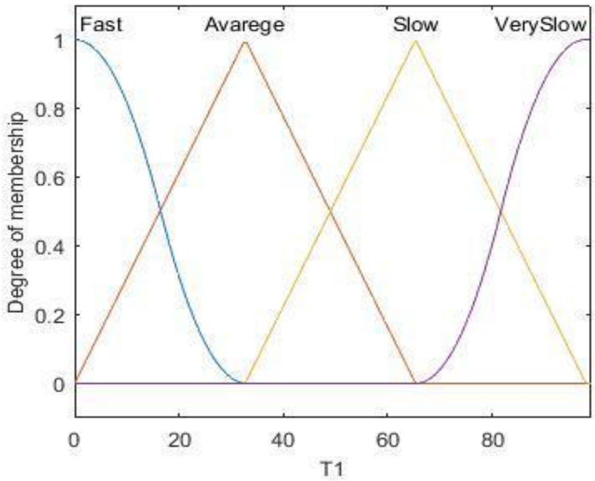

Fig. 6. MF's for Input T1

Input 2. The Input 2 is represented in the FIS as "T2: The second task completion time" (Fig. 7) and fuzzified with fast [0-150 second], average [0-300 second], slow [150-450 second], very slow [300+ second]. The triangular, s-shape and z-shape MF's were considered for the analysis (Fig. 7).

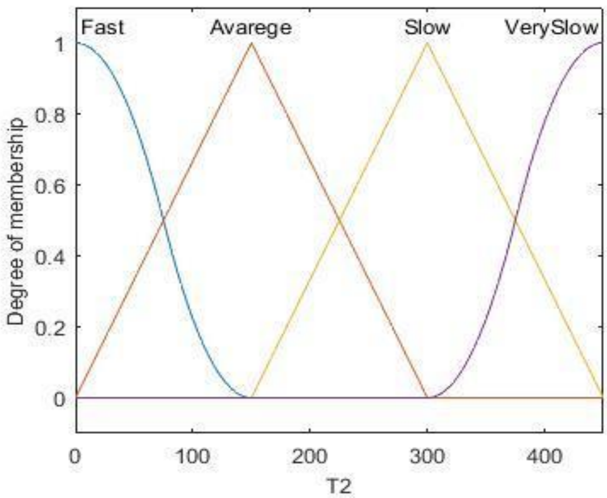

Fig. 7. MF's for Input T2

Input 3. The Input 3 is represented in the FIS as "T3: The third task completion time" (Fig. 8) and fuzzified with fast [0-330 second], average [0-660 second], slow [330-1000 second], very slow [660+ second]. The triangular, s-shape and z-shape MF's were considered for the analysis (Fig. 8).

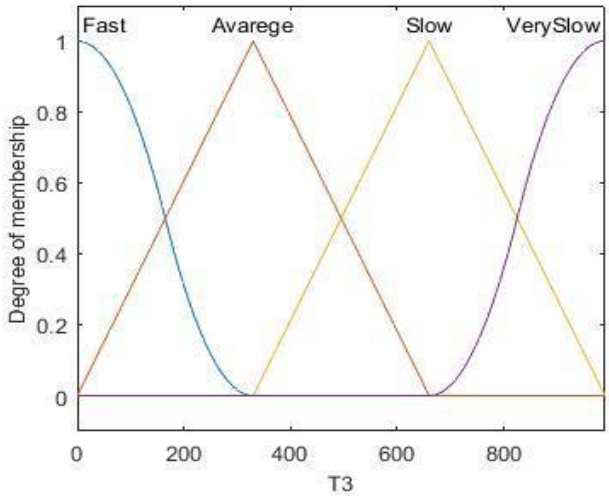

Fig. 8. MF’s for Input T3

Input 4. Mathematics plays a very important role during the high school entrance exam and also in the university entrance exam in Turkey. If somebody wants to pursue his career in the engineering field, the mathematics’ importance has remained quite constant so far. A number of studies by [32], [33], [34] confirmed that mathematical knowledge is a strong predictor of success in programming.

The Input 4 is represented in the FIS as “MG: Mathematics grade” (Fig. 9) and fuzzified with very low [0-33 point], low [0-66 point], average [33-100 point], high [66+ point]. The triangular, s-shape and z-shape MF's were considered for the analysis (Fig. 9).

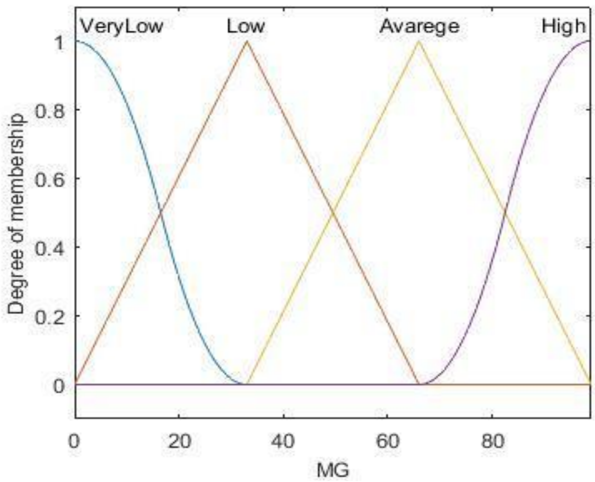

Fig. 9. MF’s for Input MG

Defuzzification of Output. Centroid method was used for defuzzification. The Output is represented in the FIS as “SR: Success Rate” (Fig. 10) and classified with unsuccessful [0-33 point], Lsuccess [0-65 point], Asuccess [33-100 point], successful [65+ point]. MF's considered for the analysis were of triangular, s and z shape.

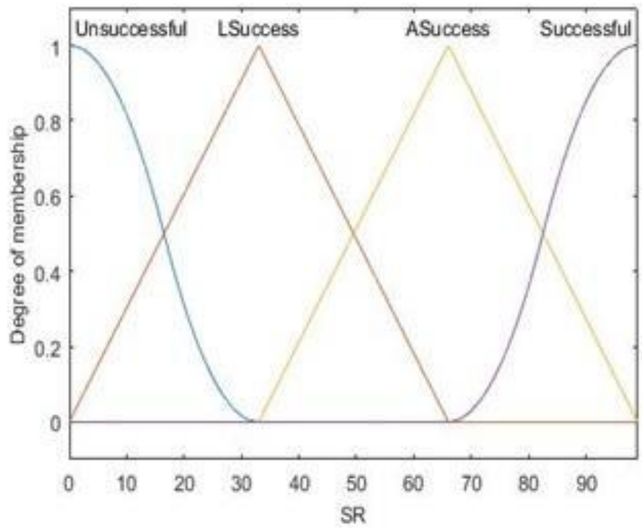

Fig. 10. MF's for Input SR (Success Rate)

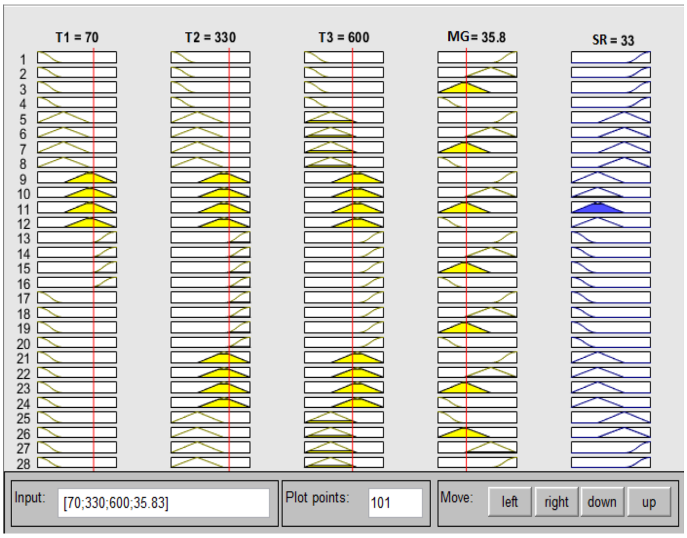

Fig. 11. Output for random input values

Fig. 11 shows the output for randomly selected input values. The inputs values, T1=70, T2=330, T3=600, MG=35.83, the system produced the output value as SR=33 which indicates the success of a student performance in the Scratch programming for the given T1, T2, T3 and MG values. The students are given an estimated success value by taking into consideration the task completion time and their course grades. If the given task's completion time is short and participant's course grade is high, then participant is rated with the highest success rate. If the given task's completion time is long and participant's course grade is low, then participant is rated with the lowest success rate. Then, the connection between the success rate (fuzzy value) and the real value obtained by experimental data was determined by regression analysis.

4. RESULTS AND DISCUSSION

A regression analysis was carried out between experimental and the predicted (fuzzy) values. The R^2 correlation coefficient shows the relationship between real values and fuzzy values. The relationship between values increases as the correlation coefficient approaches +1. As shown in Figs. 12-14, R^2 values for the success rates are 0,8023 for Group 1; 0,9704 for Group 2; 0,8446 for group 3 respectively. The R^2 values indicate that the predicted (fuzzy) value and the real value obtained by experimental data fairly close to each other. This shows the success of the fuzzy logic system.

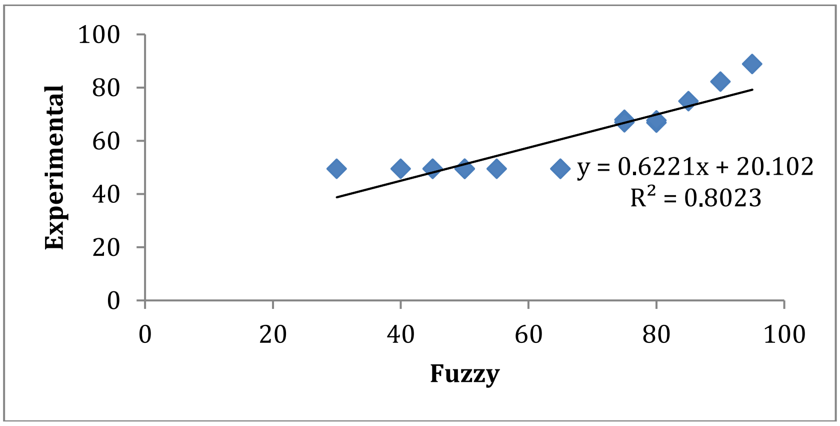

Fig. 12. R^2 value for group 1

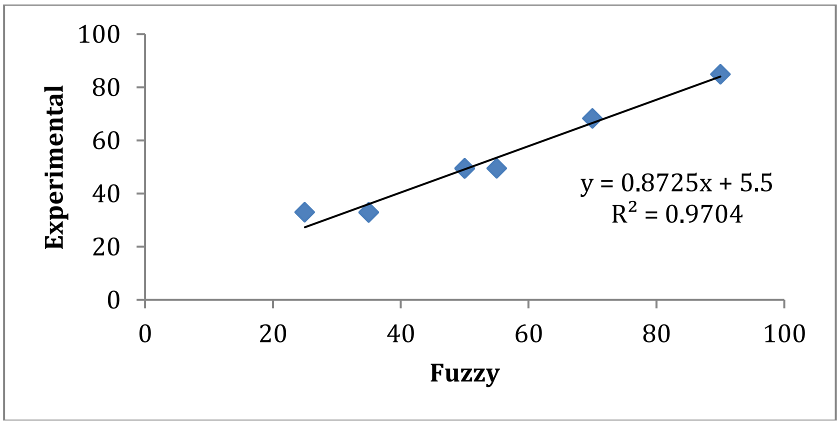

Fig. 13. R^2 value for group 2

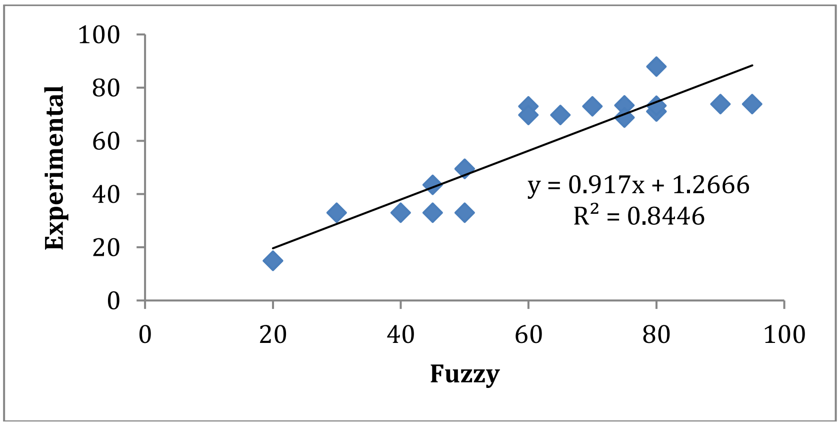

Fig. 14. R^2 value for group 3

Table 5. ANOVA analysis

	Sum of squares	DF	Mean Squares	F	P value
Factor1	10.801	1	10.801	0.041123	0.84028
Errror	11031	42	262.65		
Total	11042	43			

We have performed a one-way ANOVA with a single factor. According to Table 5 below considerations can be said: The F-statistic (0.041) is very small, indicating little difference between the variance explained by Factor1 and the residual (unexplained) variance.

The p-value (0.840) is much greater than the typical significance threshold of 0.05. This means we cannot reject the null hypothesis of no effect with enough confidence. In other words, there is no significant difference in means among the groups. It's important to note that when the p-value is high (above 0.05), it suggests that any observed differences could be due to random chance, and you do not have enough evidence to conclude that the factor has a significant effect.

Table 6. Each groups' task completion time (Min., Max., Avg., Std. Deviation)

	Group 1	**Group 2**	**Group 3**
Minimum duration	Task 1: 5 sec	Task 1: 5 sec	Task 1: 5 sec
	Task 2: 5 sec	Task 2: 60 sec	Task 2: 30 sec
	Task 3: 60 sec	Task 3: 90 sec	Task 3: 120 sec
Maximum duration	Task 1: 120 sec	Task 1: 90 sec	Task 1: 21 sec
	Task 2: 30 sec	Task 2: 410 sec	Task 2: 350 sec
	Task 3:1260 sec	Task 3: 990 sec	Task 3: 750 sec
Average duration	Task 1: 35,94 sec	Task 1: 57,36 sec	Task 1: 12,31 sec
	Task 2: 13,76 sec	Task 2: 222,27sec	Task 2: 115,68 sec
	Task 3: 377,64 sec	Task 3: 319.10 sec	Task 3: 332,72 sec
Standard deviation	Task 1: 43,12 sec	Task 1: 27,61 sec	Task 1: 5,40 sec
	Task 2: 6,74 sec	Task 2: 137,41 sec	Task 2: 116,23 sec
	Task 3: 401,80 sec	Task 3: 307,41 sec	Task 3: 235,95 sec

According to Table 6 below considerations can be said:

Evaluation of success according to the groups (schools): Given the average of the completion times of the assigned tasks of the groups, Group 2 can be considered to be more successful than the other groups. However, in Group 2, 10 students did not complete task 3. While the number of students who could not complete task 3 in Group 1 was 8, in Group 3, there were no failed students. Overall, it is possible to be considered that the students in Group 3 are more successful comparing to Group 2 and Group 1.

Evaluation of success according to the gender: Group 1: Among 17 students, 2 males and 1 female student seem to be over the average in terms of completion of the tasks. Group 2: 4 out of 22 students are over the average in terms of completion time of the task. No male students can be found over average. Group 3: Among 22 students, 8 males and 5 female students are above the average in terms of completion of the task. Since the standard deviations are low for all groups, we can say that the values for that task are close to the mean and suggest consistency.

According to the results, students in private schools were more successful than those who were in public schools. The private students' parent's education level, school facilities and financial opportunities have played an important role in their programming skills.

3. CONCLUSIONS

In this study, the programming experiment has been carried out using the Scratch environment. It was primarily proposed to a fuzzy logic system to predict student performance during the experiment then compare fuzzy logic prediction results to the experts' results. Secondly, to test the theory that students' interest in learning algorithms and coding can be increased using the creation of games in a visual programming tool for beginners.

During Scratch training, the students were tasked with three different gaming challenge. Instead of figuring out programming syntax, the Scratch environment allowed Pupils concentrate their attention on tackling problems. The tasks completion time and mathematics grades of students has been used as input the Mamdani type fuzzy logic system and the success rate has been calculated.

While students were performing the given Scratch tasks there were no signs of boredom or distraction. On the contrary, it was observed that they try to complete the given tasks as if they were playing a game and without conscious effort, they were improving their analytical and problem-solving skills. In addition, it was observed that students who were coming from the village school and did not use computers before were able to use computers easily while trying to accomplish the given Scratch tasks.

With fuzzy logic, the success rate can be estimated for different task completion times. It is also possible to predict how long a student must perform a task in order to be successful.

In later studies, different factors can be used as inputs to measure the success of students in learning to code with Scratch environment.

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Declaration of Competing Interest

The authors declared that they have no conflict of interest.

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Data Availability

Data available on request from the author.

REFERENCES

[1] J. H. Maloney, K. Peppler, Y. Kafai, M. Resnick, and N. Rusk, "Programming by choice: urban youth learning programming with scratch," in Proceedings of the 39th SIGCSE technical symposium on Computer science education, 2008, pp. 367-371.

[2] M. Prensky, "Digital natives, digital immigrants part 2: Do they really think differently?," On the horizon, vol. 9, no. 6, pp. 1-6, 2001.

[3] M. Resnick et al., "Scratch: programming for all," Communications of the ACM, vol. 52, no. 11, pp. 60-67, 2009.

[4] W. Dann and S. Cooper, "Education Alice 3: concrete to abstract," Communications of the ACM, vol. 52, no. 8, pp. 27-29, 2009.

[5] M. Mladenović, D. Krpan, and S. Mladenović, "Learning programming from Scratch," in International Conference on New Horizons in Education INTE, 2017.

[6] W. Dann, D. Cosgrove, D. Slater, D. Culyba, and S. Cooper, "Mediated transfer: Alice 3 to java," in Proceedings of the 43rd ACM technical symposium on Computer Science Education, 2012, pp. 141-146.

[7] A. K. Whitfield, S. Blakeway, G. E. Herterich, and C. Beaumont, "Programming, disciplines and methods adopted at Liverpool Hope University," Innovation in Teaching and Learning in Information and Computer Sciences, vol. 6, no. 4, pp. 145-168, 2007.

[8] L. A. Zadeh, "Fuzzy sets," Information and control, vol. 8, no. 3, pp. 338-353, 1965.

[9] H. Singh et al., "Real-life applications of fuzzy logic," Advances in Fuzzy Systems, vol. 2013, pp. 3-3, 2013.

[10] S. A. Papert, Mindstorms: Children, computers, and powerful ideas. Basic books, 2020.

[11] O. Yildiz, A. Bal, and S. Gulsecen, "Improved fuzzy modelling to predict the academic performance of distance education students," International Review of Research in Open and Distributed Learning, vol. 14, no. 5, pp. 144-165, 2013.
[12] S. Ingoley and J. Bakal, "Use of fuzzy logic in evaluating students' learning achievement," International Journal on Advanced Computer Engineering and Communication Technology (IJACECT), vol. 1, no. 2, pp. 47-54, 2012.
[13] S. S. Jamsandekar and R. Mudholkar, "Performance evaluation by fuzzy inference technique," International Journal of Soft Computing and Engineering, vol. 3, no. 2, pp. 158-164, 2013.
[14] Z. Yıldız and A. F. Baba, "Evaluation of student performance in laboratory applications using fuzzy decision support system model," in 2014 IEEE Global Engineering Education Conference (EDUCON), 2014: IEEE, pp. 1023-1027.
[15] G. Jyothi, C. Parvathi, P. Srinivas, and S. Althaf, "Fuzzy expert model for evaluation of faculty performance in Technical educational Institutions," International Journal of Engineering Research and Applications, vol. 4, no. 5, pp. 41-50, 2014.
[16] M. Eryılmaz and A. Adabashi, "Development of an intelligent tutoring system using bayesian networks and fuzzy logic for a higher student academic performance," Applied Sciences, vol. 10, no. 19, p. 6638, 2020.
[17] D. Doz, D. Felda, and M. Cotič, "Combining Students' Grades and Achievements on the National Assessment of Knowledge: A Fuzzy Logic Approach," Axioms, vol. 11, no. 8, p. 359, 2022.
[18] N. U. Jan, S. Naqvi, and Q. Ali, "Using Fuzzy Logic for Monitoring Students Academic Performance in Higher Education," Engineering Proceedings, vol. 46, no. 1, p. 21, 2023.
[19] M. Dhokare, S. Teje, S. Jambukar, and V. Wangikar, "Evaluation of academic performance of students using fuzzy logic," in 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), 2021: IEEE, pp. 1-5.
[20] J. A. Rojas, H. E. Espitia, and L. A. Bejarano, "Design and optimization of a fuzzy logic system for academic performance prediction," Symmetry, vol. 13, no. 1, p. 133, 2021.
[21] M. Abou Naaj, R. Mehdi, E. A. Mohamed, and M. Nachouki, "Analysis of the Factors Affecting Student Performance Using a Neuro-Fuzzy Approach," Education Sciences, vol. 13, no. 3, p. 313, 2023.
[22] R. Mehdi and M. Nachouki, "A neuro-fuzzy model for predicting and analyzing student graduation performance in computing programs," Education and Information Technologies, vol. 28, no. 3, pp. 2455-2484, 2023.
[23] R. Parkavi and P. Karthikeyan, "Predicting academic performance of learners with the three domains of learning data using neuro-fuzzy model and machine learning algorithms," Journal of Engineering Research, 2023.
[24] M. Agaoglu, "Predicting instructor performance using data mining techniques in higher education," IEEE Access, vol. 4, pp. 2379-2387, 2016.
[25] C.-T. Lye, L.-N. Ng, M. D. Hassan, W.-W. Goh, C.-Y. Law, and N. Ismail, "Predicting Pre-university student's Mathematics achievement," Procedia-Social and Behavioral Sciences, vol. 8, pp. 299-306, 2010.
[26] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning—I," Information sciences, vol. 8, no. 3, pp. 199-249, 1975.
[27] E. H. Mamdani and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," International journal of man-machine studies, vol. 7, no. 1, pp. 1-13, 1975.
[28] M. Sugeno, Industrial applications of fuzzy control. Elsevier Science Inc., 1985.
[29] J. R. Jang, MATLAB: Fuzzy logic toolbox user's guide: Version 1. Math Works, 1997.
[30] J. Yuan and R. T. Bowen, "Lifelong Kindergarten: Cultivating Creativity Through Projects, Passion, Peers, and Play," Interdisciplinary Journal of Problem-Based Learning, vol. 12, no. 2, p. 6, 2018.

[31] K. Brennan and M. Resnick, "New frameworks for studying and assessing the development of computational thinking," in Proceedings of the 2012 annual meeting of the American educational research association, Vancouver, Canada, 2012, vol. 1, p. 25.

[32] P. Byrne and G. Lyons, "The effect of student attributes on success in programming," in Proceedings of the 6th annual conference on Innovation and technology in computer science education, 2001, pp. 49-52.

[33] G. White and M. Sivitanides, "An empirical investigation of the relationship between success in mathematics and visual programming courses," Journal of information systems education, vol. 14, no. 4, p. 409, 2003.

[34] J. Bennedsen and M. E. Caspersen, "An investigation of potential success factors for an introductory model-driven programming course," in Proceedings of the first international workshop on Computing education research, 2005, pp. 155-163.