IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

LEARNING STYLE FORECASTING SYSTEM WITH FUZZY LOGIC

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Abstract:

By recommending suitable e-contents from e-learning servers based on an analysis of the learners' preferred learning modes, the quality of e-learners can be raised.. Because psychological balance is variable in nature, and e-learners differ based on their learning patterns, environment, time, and mood, the learning styles had to be carefully predicted. Furthermore, the knowledge about the learners used for learning style prediction is inherently uncertain. This research suggests using survey guidelines to manage the uncertainty in learning style predictions and finds the Felder-Silverman learning style model as a good model for learning style prediction, particularly in web contexts. Fuzzy logic using a Gaussian membership function has been tried in evaluations with students learning the C programming language, and it has been found that the proposed model greatly increased prediction accuracy.

1.INTRODUCTION:

In order to save time, effort, and money, e-learning refers to the dissemination of information and knowledge to everyone, anytime, and anywhere. The main goals of e-learning include flexibility, individualized learning, knowledge acquisition, an intelligent tutoring system, and ongoing evaluation of students' e-learning progress. The learning objects, their delivery, related information retrieval, knowledge management, performance evaluation, and the impact of learners' learning styles, which differ from one learner to another, are additional aspects that affect whether the e-learning framework is successful or unsuccessful. Butler (1986) defined learning style as the unique way that each individual learns. Many methods and tools, including as surveys, interviews, and the sharing of profile data, have been developed in the past to anticipate the learning styles of students in a variety of settings. Several methods of identification might work well in a conventional classroom context. Yet with e-learning, face- to-face contacts are completely eliminated, body language is understood, progress is constantly tracked, motivation is strong, and self-efficacy is boosted. The two key components that determine learning styles are static and dynamic factors, which are distinguished based on a number of characteristics as shown in Table 1. The models for learning theory and learning style are associated based on the dimensions listed in Table 1. Thus, it is necessary to use specialized approaches to determine each learner's unique learning preferences and to suggest appropriate e-content to those learners who are learning in web settings from the e-learning servers. Some of the key elements for determining learners' learning styles are shown in Table

1.Static and dynamic factors are the two main elements. These variables were selected in accordance with the empirical research described in the relevant literature. The learning models that assume learners' learning patterns are static and never alter are known as static factors. The dynamic factors, in contrast, are those in which the learners' cognitive and psychological characteristics cause their preferred learning styles and preferences to fluctuate over time.

2.A SUMMARY OF VARIOUS EDUCATIONAL SYSTEMS

E-learning or web-based learning is a new revolution in online education. There are many different educational systems accessible, including e-learning, intelligent tutoring, adaptive learning, and learning systems with learning style prediction. An overview of the current educational systems is given in Table 2, along with pertinent descriptions. In order to increase the accuracy of forecasting learners based on their learning preferences in e-learning, the main goal of this work is to address the ambiguity that existed in the earlier models.

This is accomplished by employing fuzzy membership functions to divide the learners in (Sanders & Bergasa-Suso's,2010) model's unknown category into four groups: active, medium active, medium reflective, and reflective. The suggested model has a lot of benefits. Secondly, it has the capacity to anticipate learners' preferred learning styles using data from both their original profiles and online activity. Second, fuzzy membership functions are utilized in the suggested model. As a result, it is possible to analyze the students accurately according to their learning preferences. Third, by dividing the students into two of the four categories— active, medium active, medium reflective, and reflective—it can effectively analyze the students' learning styles.

3.OVERVIEW OF LEARNING STYLES

By examining the behavior of the students taking part in an online course, it is possible to identify how having a thorough awareness of one's own learning style can result in significant personal empowerment and confidence. The use of online browsing activity is one method for detecting this type of learner behavior in e-learning.

Type of factor	Learning theory	Underlying principleof learning theory
Static	Model for experimental theory	Learning solely through experiences
	Model of behavioral theory	learning based solely on individual behaviour.research of how people react to novel situations
	Model of cognitive theory	Using the environment's emotions to inform learning
	Model of psychological theory	Similar to behavioral theory, it focuses on how people learn based on their environment and the actions they take as a result.
	Model of the meta-learningtheory	Learn new information based on perception, enquiry, and learning in a setting that is safe and encouraging.
Dynamic	Personality model	Openness, Consciousness, Extraversion, Agreeableness, and Neuroticism (OCEAN) model-based learning
	Model for intelligence theory	Using intelligence quotient as a basis for learning
	Model of the neuropsychological theory	Using innate interests and biological changes brought on by external variables to learn

Table 1. Factors influencing learning style prediction

Educational system	Description
Traditional offline learning system	In a classroom setting, teachers and students interacted face-to-face to understand the course topics.
E-learning system	With electronic gadgets, students are taught their course materials.
intelligent system for learning	Artificial intelligence methods include software agents, page rankings, and machine learning algorithms improve learning activities.
System of adaptive learning	Instructional materials can be changed to suit the tastes of the students.
Exclusive e-learning performance evaluation	always keeping track of how well students are performing in online courses
Blended education	Learning Learning and content management are combined in a way that combines traditional classroom instruction and online learning.

Table 2. Overview of educational systems.

Also, the learners' knowledge is typically limited and ambiguous. This essay presents the findings of a brief examination of earlier learning style models. The learning style preferences found in the Felder and Silverman learning style model serve as the foundation for the proposed approach. Based on this paradigm, numerous works have already been discovered in the past. In order to better handle uncertainty in their model, (Sanders & Bergasa-Suso,2010) built an earlier model that is precisely the subject of this paper's examination. The learners are categorised into one of the three categories clearly as active, reflective, or "unknown" according to (Sanders & Bergasa-Suso,2010). Their model's unknown category is thought to be uncertain, however our suggested approach uses fuzzy logic to address this problem.

The "unknown" category in the current model has been further classified in the suggested model. All of the target learners can be accurately categorized by the proposed model into one of the four groups of active, medium-active, medium-reflective, or reflective learners. The model employs a Gaussian membership function to achieve this goal, making it possible to classify learners in e-learning settings effectively according to their preferred learning styles.

For a variety of purposes, the conventional Gaussian membership function is employed. The target applications often have a normal distribution, and this function follows one as well. It reduces the likelihood of significant data skewing because it follows a normal distribution.

4.BACKGROUND RELATED WORKS

4.1 study of models for learning styles

Many learning theories, such as experiential, behavioural, cognitive, biological, and psychological qualities, have given rise to a variety of learning style models.The study of the available learning style models is clearly displayed in Table 3 below. There are numerous difficulties in adapting these models to web-based learning, though. of the challenges The difficulties are that all of these models favor gathering comprehensive information about the students before classifying them. In actuality, the majority of the data regarding the students is hazy. So, learning some efficient strategies to derive conclusions even from insufficient data or information must be required. The next problem is that all of these models rely on frequent face-to-face interactions between the teacher and the students, which makes it possible to forecast the learners' learning preferences. Finally, a crucial aspect that is typically ambiguous is taken into account by the current models. It is preferable to employ a rule-based technique, such as neural networks or fuzzy logic, which can successfully manage partial information, inorder to grasp the learners' psychology, which is incomplete.

Learning style models	Learning theory	Limitations
David Kolb model (Cornwell& Manfredo 1994)	Experiential learning theory	Mixed empirical results and low to motivate predictive reliability
Honey and Mumford model (2000)	Behavioral theory	Assumed to acquire preference that are adaptive, either at will or changing circumstances
Gregorc model (Gregorc 1985)	Cognitive theory	Some qualities and ordering abilities are more dominant within certain individuals
Flemming VAK model (Fleming 2001)	Meta-learning theory	Low validity and reliability
Dunn and Dunn model(Dunn 1990; Dunn &Dunn 1989)	Biological & Experimental theory	Criticized for not considering the differences among the individuals
Chris Jackson (Jackson 2002)	Neuro-psychological theory	Contextual differences in the dependent variable
Carl Jung and Myers Briggs type indicator (McCaulley 2000)	Personality theory	Lacks convincing validityData

Howard Gardner multiple Intelligence (Gardner 1999)	Intelligence theory	Detecting additional intelligen- ces is not easy and is not well suited for all types of individuals
Felder-Silverman Index of learning styles (Felder & Silverman 1988)	Psychological theory	Dependencies between two styles exist and hidden dimensions prese in dataset produces a greater impac onthe identification

Table 3. Existing learning style models.

4.2 Use an offline environment to predict learning styles offline

The following category of learning style prediction systems is well suited for many online courses and might successfully use internet education systems. These programs, however, do not take the learner's aptitude into account or offer any sage counsel regarding possible websites. WebCT is the first online educational platform that could offer course materials through the internet but was unable to do so with an intelligent method that took the learner's capacity into account. The next suite of internet educational systems, like LSAS (Yang et al. 2013), CS388 (Carver et al. 1999), and Tangow (Paredes & Rodriguez 2002), could predict the learning styles of the learners effectively, but content adaptation was made based on previous knowledge.

4.3 Uses the online environment to anticipate the learning styles of students

The system created by (Bergasa-Suso et al.,2005) is known as AHA, and it was a collection of tools that got around the problems with the systems discussed in Section 2.2. The teachings from Bergasa-Suso et al. are the name of this bundle of resources. He put forth a model that used Felder and Silverman's preferences for learning styles as a foundation to group students into one of four categories: active/reflective, sensing/intuitive, visual/verbal, and sequential/global. As a result, iLessons makes a significant contribution to e-learning by classifying learners for the first dimension as either active or reflective. Since students prefer to focus on a particular dimension the majority of the time, this model is satisfied. This circumstance won't always be the case, though. This issue was eventually resolved by the model developed by Sanders and Bergasa-Suso (2010) that was known as a new intelligent system to classify the learners into any one of the four dimensions listed in Felder and Silverman's learning style model and had a decent user interface. For the first dimension (active/reflective), the learners were divided into three groups based on this system: active, reflective, or unknown.In contrast to prior work by Bergasa-Suso et al., the accuracy of classifying the learners in (Sanders & Bergasa-Suso's,2010) work has increased to 81%. Yet, by addressing the learners' unknown category, this model can still be improved. Fuzzy rules can be included for effective classification of learners studying through web environments to address this type of ambiguity in the inference obtained in the unknown category.

4.4 Analyzing similar works

According to the investigation, there were several online educational programs that could accurately predict learning preferences using data from offline surveys or online activities. Despite the valuable insights provided by numerous academics into the prediction of learners' learning styles using online usage data, it would be more beneficial to apply machine learning algorithms for effective classification. None of the current, recent models for accurate prediction address issues depending on the level of activity or reflection of the learners. As a result, it's essential to implement a rule-based technique, such as fuzzy logic or neural networks, for successful classification of learners' learning through web environments. It is determined that rule-based approaches are more suitable because the other conventional strategies do not adequately handle the problem of uncertainty. The model presented in this research uses fuzzy membership functions to classify learners in the unknown category of the previous models into active, medium active, medium reflective, and reflective categories of learners. These functions aid in determining the degree of activeness or reflectiveness (Lu et al 2007).

4.5 Felder-Silverman learning style model overview

Technology-enhanced learning frequently makes use of this learning style model. In a web-based learning environment, this model of learning preferences is typically preferred. The model's four dimensions of learning style preferences, which take into account the technological characteristics of e-learning learners, are particularly helpful. The following arethe four criteria used to group learners:

(i) Active vs. Reflective: Active learners are engaged with themselves and the world around them, and their user activity across web environments is very quick. Reflective learners take their time to consider concepts, and their user activity across web environments is quite slow.

(ii) Sensing/Intuitive: Sensing learners attempt to acquire the fundamental truths, whereas intuitive learners favor finding connections between the ideas.

(iii) Visual/Verbal: Whereas verbal learners typically prefer to learn through textual representations, visual learners prefer to learn through images, flowcharts, and cartoons.

(iv) Sequential/Global: While global learners learn at their own speed, sequential learners acquire knowledge incrementally.

Since students who learn in e-learning environments typically fall into one of the two groups indicated, the suggested model focuses on the first dimension of active/reflective.

5.LEARNING STYLE PREDICTION METHOD BASED ON FUZZY LOGIC

This research proposes a new fuzzy logic-based learning style identification method. The proposed approach is based on the learning style model developed by Felder and Silverman, which is grounded on psychology theory. The concept is evaluated with students using e-learning environments to learn the C programming language. The suggested fuzzy- logic-based learning style prediction model's architecture is depicted in Figure 1. The suggested system takes as inputs the learner's web interface data and preferred Preferences Silverman learning styles.

5.1 The proposed prediction system's inputs

The suggested model makes use of MediaWiki e-learning servers to allow for the posting of e-learning materials in a variety of formats. An e-learning server in our model had textual, audio, and visual course materials for the C programming language. The student might access any kind of content that is available on the MediaWiki E-Learning server after properly authenticating themselves. Our suggested model was assessed and tested for detecting the first dimension of Felder and Silverman's learning style preferences since the target learners tend to favor the textual format of the course contents. For the aim of identifying their learning styles, the learners are asked to submit their original profile information throughout the authentication process. The properties of the earlier learning style models that are employed in different application domains are shown in Table 4. Hence, utilizing their own profile information and their online web usage activities, the learners are appropriately categorised based on their learning styles. A rule base that is completely filled with input and output fuzzy rules has been created to make it easier to evaluate the experimental results. The learning type prediction used meticulous observation and recording of the students' activities. Regarding the parameters listed in Table 4, these activities were noted for study. The learners were categorized into four categories based on the evaluation: active, medium active, medium reflective, and reflective.

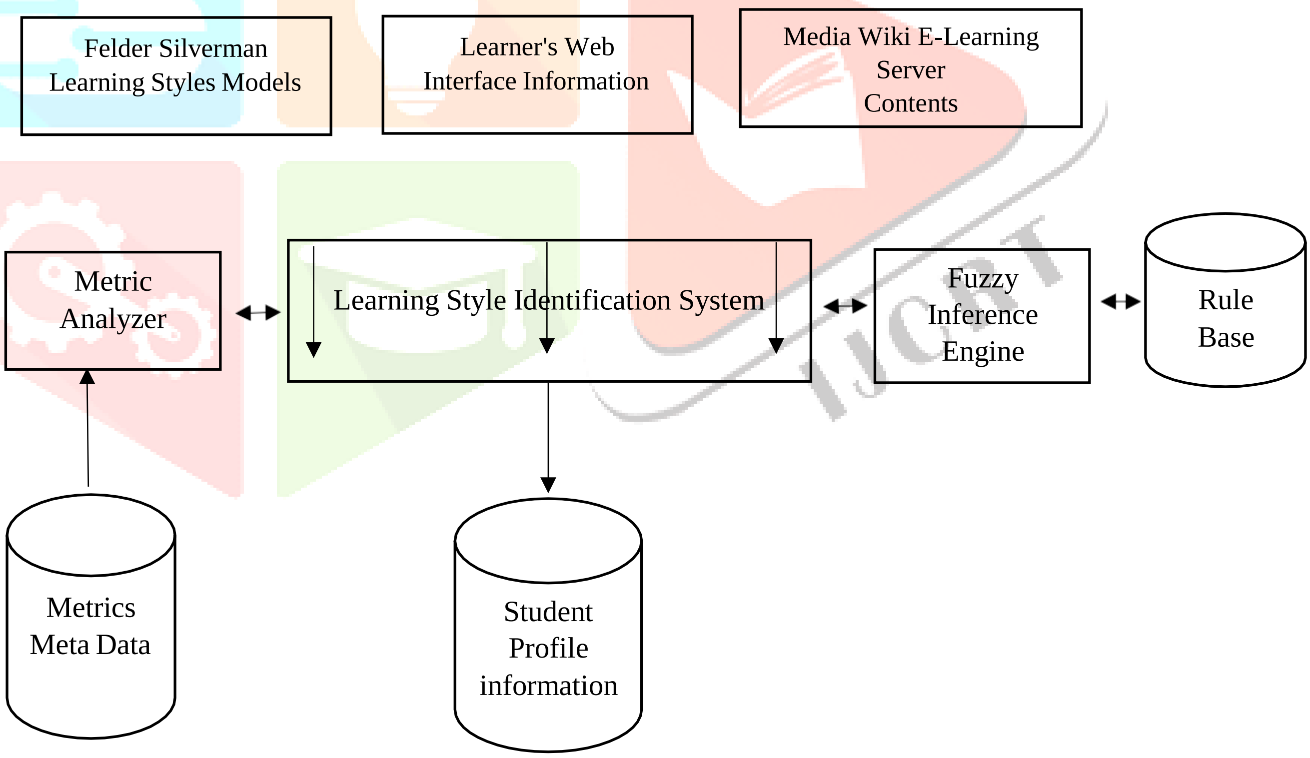

Figure 1., Model for identifying learning styles

List of the parameters
Number of mouse movement in the y-axis
Ratio of document length to the time spent on a page
Ratio of images area to document length and scroll distance
Number of visits to a document

Table 4. Parameters of learners web interface.

5.2 Measurement analyzer

Many measures listed in Table 5 are used to analyze the proposed model's learning style prediction. These metrics take into account both the students' web browsing history and some of their initial profile data. The metric analyzer in the proposed system would assess the learners' behavior using the data from Table 4 and can help categorize the learners according to their learning styles.

5.3 Rule base

In this study, a rule-based method for classifying learners who can manage unclear information is proposed. Additionally, using the identification of learning styles, this model helps in the recommendation and provision of appropriate e-learning materials. For the prediction of learners based on their learning styles using offline profile information and online web activity information, the knowledge editor rule base has about 30 fuzzy rules. This proposed work's setof rules is provided in rules of fizzy.

5.4 Fuzzy inference engine

The degrees of learners' membership in the active and reflective aspects were tested. The symmetric Gaussian membership function (Swati Chaudhari & Manoj Patil 2014) for a fuzzy set A that represents the learners' learning preferences is represented by the following when the e-learning course materials for the C programming language are successfullyprovided.

$f(x;\sigma,c) = e^{-(x-c)2/2\sigma 2}$

Online web information	Offline profile information
Number of mouse movement in the y-axis Ratio of document length to the time spent on a page Ratio of images area to document length and scroll distance Number of visits to a document	Domain of interest Educational backgroundProfessional career

Table 5. Metrics for learning styles prediction

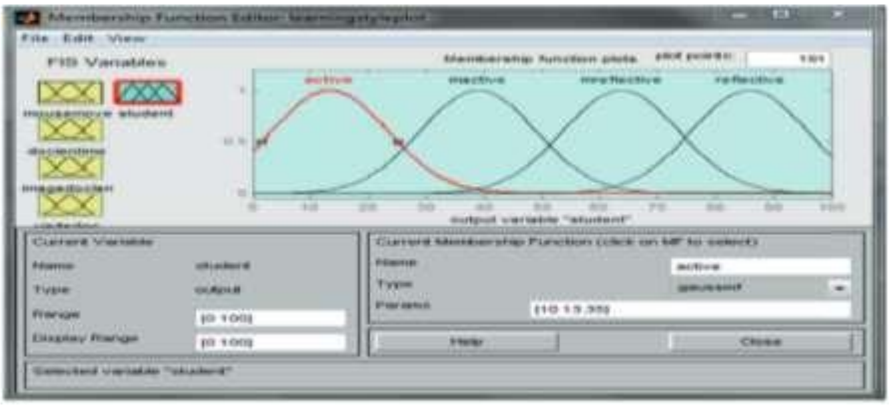

Figure 2. Symmetric Gaussian fuzzy function

Based on the input value x, the parameters (width) and (c) change the width of the fuzzy set A's membership function curve. The parameter c denotes the mean of the membership function curve in this function, while the fuzzy set A represents the learning style. Figure 2 depicts the symmetric Gaussian fuzzy membership function that was employed in the suggested model for the four types of learners, including active, medium active, medium reflective, and reflective. The suggested model's rule base and the use of the symmetric Gaussian fuzzy membership function stated in Eq. 1 allowed for the prediction of the appropriate learning styles for the students.

6.PERFORMANCE ASSESSMENT

Several e-learning settings have evaluated this model's applicability. The proposed model is evaluated for learners interested in studying a C programming language course with a variety of learning methods based on the authors' area of expertise. The model's major goal is to accurately classify learners into the four categories of active, medium active, medium reflective, and reflective, which are contained in Felder and Silverman's first dimension of their learning style model preferences. The results of testing and comparing the given objective withother current algorithms are shown in this section.

6.1 Experimental arrangement

The learners are asked for their original profile information, such as their age, gender, educational background, area of interest, professional career, and hobbies, throughout the verification process. The learners are then given access to a variety of C programming language course materials from e-learning platforms including Media Wiki, Moodle, and Joomla. Nonetheless, the e-contents published on MediaWiki's e-learning servers served as the foundation for our studies. Students from diverse branches were used in the experiments. A set of 30 fuzzy rules for predicting learning type were put in the rule base. In this study, Matlab R2009a was used to predict learning styles. The trials were replicated, analyzed, and contrasted with alternative models offered by (Sanders & Bergasa-Suso,2010). To assess the proposed model's notable differences in accuracy, it is also contrasted with the conventional Bayesian classification process. Based on the students' e-learning of C programming language course materials, the learners' learning styles were predicted in all of the repeated experiments. Yet this effort is still in progress. The preferences in the Felder-Silverman learning style model serve as the foundation for the proposed work, which is restricted to predicting only the first dimension of learning styles (active/reflective).

6.2 A brief evaluation

The experiments done in this work on predicting learners' learning styles using offline profile information and online web activity information yielded the experimental assessment results that are displayed below. With an online portal, the students give their complete information. They then use Media Wiki e-learning servers to access the textual course materials for the C programming language. The metric analyzer examines the metrics that can be used to predict learning style after properly gathering and logging this data.

X = The quantity of mouse movements along the y-axisY = ratio of document length to page load time

Z = Document length to picture area and scroll distance ratio

In our trials, these metrics take into account data from both profiles and online browsingbehavior. The fuzzy inference engine is in charge of categorizing the learners into four groups using these metrics: active, medium active, medium reflective, and reflective. This fuzzy inference engine uses a rule base that is fully loaded with 30 fuzzy rules for input and output. The proposed model's evaluation was expressed as a percentage of accuracy. The three- dimensional view of the many learner types, including active, medium active, medium reflective, and reflective, is shown in Figure 3. The first three parameters listed in Table 4 arerepresented by the X, Y, and Z axes.

6.3 Findings and conclusions

This work has been assessed using an accuracy percentage taking into account the whole population of the sample. For 30, 60, 90, and 120 numbers of learners, Table 6 compares the results of our work to those of other current methods. As may be seen from The table demonstrates that, in comparison to the dead band algorithm, the bergassa algorithm, and the bayesian algorithm, the proposed model exhibits a higher accuracy %. This is because the fuzzy inference engine, which is effective at processing unclear information, was used in this work. When compared to the conventional Bayesian algorithm and the algorithm proposed by Bergasa-Suso et al., the accuracy of the dead band algorithm proposed by (Sanders & Bergasa- Suso ,2010)Suso's model added a new category named "unknown" for learners who could notbe accurately anticipated.

Reflective Medium Reflective Medium Active

Acive

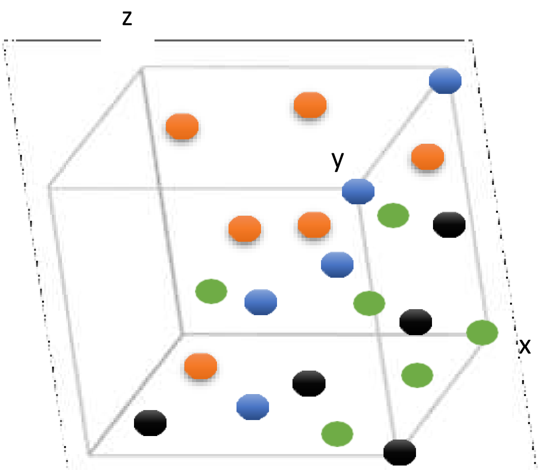

Figure 3. Three dimensional view of learners.

Accuracy(%)				
No. of users	Fuzzy-logic based Algorithm	Deadband Algorithm	Bergasa Algorithm	Bayesian Algorithm
30	59	52	48	42
60	69	64	55	47
90	84	75	65	52
120	92	81	71	57

Table 6. Accuracy evaluation results for active/reflective dimension.

In order to increase the accuracy of forecasting students based on their learning styles, this effort intends to resolve this "unknown" category so that it can once again be categorized into any one of the four groups, namely active, medium active, medium reflective, and reflective. The goal of achieving fine accuracy in the learning style prediction of the unsure learners who are studying through web environments has thus been accomplished.

7.CONCLUSION AND FURTHER STEPS

Our innovative fuzzy-logic-based learning style prediction is presented in this research and is based on the online learning of C programming language course materials. The key benefit of this suggested model is that it effectively manages the learners' unpredictable behavior using data gathered from their profile data and online web usage activities. Even with inadequate data, the fuzzy inference engine accurately classified the learners using the rule base. However, this new work only takes into account the first dimension, active/reflective, of the Felder- Silverman learning style model. The ongoing research tries to address the problems with the sensing/intuitive, visual/verbal, and sequential/global elements of the learning style paradigm. Next research will take into account additional participants, giving a more accurate picture of the overall population. The proposed work was tested for a online learners.

8.RULES OF FUZZY:

- If there are more mouse movements, more document time, more document images, andmore document visits, then (student is reflective)
- If the mouse motion, document time, document image, and document visits are allreduced, then (student is active)
- If both mousemove and doclentime are lower, then (student is active)
- If both (visitsdoc is more) and (imagedoclen is more), then (student is active)
- If both mousemove and doclentime are higher, then (student is reflective)
- If both (visitsdoc is more) and (imagedoclen is more), then (student is reflective)
- If mousemove is lower and visits to the doctor are lower, then (student is active)
- If mousemove is higher and fewer people visit the doctor, then (student is mediumactive)
- If both the imagedoclen and the doclentime parameters are lower (student is mediumreflective)

- If mousemove is higher, Doclentime is higher, Image Doclen is lower, and Visits Docare lower, then (student is medium active)
- If (mousemove is greater), (doclentime greater), (imagedoclen greater), and (visitsdocgreater), then (student is mreflective)

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