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Predicting Learning Styles Using an Adaptive Hierarchical Questionnaire with Machine Learning Techniques

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Abstract

An effective teaching-learning process is one in which instructional style and content are based on the learner's preference and learning style. The same holds true in the case of online Learning Management Systems and especially in Adaptive Education Hypermedia Systems(AEHS) which adapt themselves accordingly to the learning style of the user. Felder-Silverman's Learning Style Model is a commonly used model that provides a framework to classify the learners with the help of the Index of Learning Styles Questionnaire. The main challenge in predicting the learning style in AEHS using the Felder ILS questionnaire is the number of questions in the questionnaire that a learner has to respond to. Here due to a large number of questions in the questionnaire, there is a probability of users skipping certain questions. Such misinterpreted or unattempted questions can lead to inaccuracy in the evaluation stage of the questionnaire. The present study aims to bridge this gap by developing an adaptive ILS questionnaire. Decision Tree Algorithm J48 was used to identify the minimum number of questions that can be used to predict the learning style of the learners across the 4 dimensions of Felder-Silverman's Learning Style Model.

Keywords: *AEHS, Learning Styles, Learner Classification, ILS, Machine Learning.*

I. INTRODUCTION

Learning styles refer to various ways of receiving, processing, and maintaining the understanding of obtained information. Learners, whose learning styles complement the educator's teaching styles, are able to retain information for a longer period, and also tend to apply knowledge effectively (A H. & Utomo, 2019; Alzain, Clark, Jwaid, & Ireson, 2018; Brusilovsky, Methods and techniques of adaptive hypermedia, 1996; Akbulut, Yavuz, Cardak, & Cigdem, 2011) . Learners have been reported to experience problems when there is a mismatch found between the learning and teaching styles. (Andaloussi, Kenza, Laurence, & Ismail, 2017; Karagiannis, Ioannis, & Maya, 2018) Many studies have been conducted on learning style evaluation; researchers have identified various models of learning styles; that include Kolb's model, Myers–Briggs type indicator (MBTI), Herrmann Brain Dominance Instrument (HBDI), Felder and Silverman learning style model (FSLSM) and Dunn and Dunn model (Kolb, 1984; Pittenger, 1993; Herrmann, 2001; Felder; , Richard M.; , Linda K. Silverman, 1988; Dunn, 2003).

Researchers have found that the Felder-Silverman Learning Style Model (FSLSM) (Felder; , Richard M.; , Linda K. Silverman, 1988) is well-suited to be used as a learning model for providing personalized courses in learning systems.The authors have also stated in their studies that the FSLSM is used far more often than any other in educational systems, mainly because it offers an in-depth description of learning styles along with the ability to quantify students learning styles. (Nafea, François, & Ying, 2019) (Gomede, Everton, Rodolfo, & Leonardo, 2021) (Bernard, Jason; Ting-Wen, Chang; Elvira ,Popescu; , Sabine ,Graf., 2017)

There are systems such as Adaptive Educational Hypermedia Systems commonly known as AEHS are online learning systems that adapt a variety of educational resources to improve the learning process. AEHSs build a model of the goals, preferences, and knowledge of each user, and use this model throughout the interaction with the user, to adapt to the needs of that user. These systems go beyond the “one size fits all” approach by adapting the content to suit the learning requirements of individual learners. (Brusilovsky, Adaptive educational hypermedia: From generation to generation., 2004; A Q. , Benyoussef, El, & Elyadari, 2020; Akbulut & Cardak, 2012; Adeboje Olawale Timothy, 2020)

Most of the AEHSs segregate the learners into learning style dimensions, therefore it is required to take into consideration the common propensity of the learner and not the particular score predicted in each dimension. Within this frame of reference, the study proposes an approach to decrease the number of questions required to find out the learning style propensities/inclinations of each learner.

The rest of the paper is organized as follows. Section 2 describes the Felder-Silverman Learning Style Model (FSLSM); Section 3 discusses the goal of the study; the methodology is being explained in Section 4; Section 5 presents decision trees that were produced along with the results. Finally, section 6 concludes the study and scope of future work.

- *Felder-Silverman Learning Style Model (FSLSM)*

FSLSM describes the learning style of a student in more detail, distinguishing between learning preferences on four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global (Graf, Sabine, Silvia, Tommaso, & Kinshuk, 2007). (Felder; , Richard M.; , Linda K. Silverman, 1988) The dimensions used in the FSLSM model are distinct and independent from each other. Active Learners always try something through experiments and they prefer learning in a group than alone. They are not much interested in theory classes or theory material. When acquiring information, they prefer to discuss, share and explain to others for better understanding. **Reflective Learners** are those learners who prefer to learn through thinking and they tend to learn independently. In addition, they are more inclined toward lecture learning which enables them to think about the information obtained while attaining any information they like to think before discussing or explaining to others. **Sensing Learners** are likely to be concerned with details, learning facts, and figures. They are good at doing hands-on and always prefer to crack the given problems using well-established methods. **Intuitive Learners** fall under the category of those learners who are conceptual and innovative. They always try to involve their innovative and creative nature in their work. These types of learners prefer to look for relevance and possibilities. **Visual Learners** learn new things more likely by watching instructional videos. They easily remember what has been seen as pictures, diagrams, or in-person demonstrations. They tend to learn via a lot of graphic presentations in the learning process. **Verbal Learners** are those learners who tend to learn through words or oral discussions conducted in a group. They generally like to read out the concept or learning material loudly and by repeating it several times. **Sequential Learners** are the learners who are more likely to understand and remember the concepts or learning material if they have been delivered by the instructor systematically and sequentially that is starting with easy, moderate, and then difficult levels. **Global learners** are those learners who like to relate one piece of information to another. They are keen to solve complex problems easily and can receive information in all the way possible without worrying about their organized manner (Felder; , Richard M.; , Joni Spurlin, 2005; Graf; , Sabine; , K. Kinshuk, 2007).

A questionnaire containing 44 questions with two choices, termed as Index of Learning Style (ILS) questionnaire is used to classify the learners in any one of the behaviors in the 4 dimensions (Felder; , Richard M.; , Linda K. Silverman, 1988).

To identify the style model of each learner majority of the AEHSs utilize the ILS questionnaire. ILS produces information about 4 dimensions of learning styles, using 11 questions for each dimension on a scale from - 11 to 11.While processing the data, all the students can be categorized into three categories on the basis of the scales: **High**(from 11 to 5), **Moderate**(from 3 to -3), and **Low**(from -5 to -11) (Graf; , Sabine; , K. Kinshuk, 2007; Allioui, 2019; Akbulut, Yavuz, Cardak, & Cigdem, 2011; Felder; , Richard M.; , Joni Spurlin, 2005).

- *Research Objectives-*

Mainly AEHSs that are based on FSLSM ILS questionnaire use this tool to predict the learning style model for providing the adaption. The questionnaire consists of 44 questions that represent each FSLSM dimension; once the questionnaire is assessed; the learners can be classified into learning style tendencies based on their scores. Although the ILS score leads to help in proper adaption in AEHS this process requires filling 44 questions as per the preferences of the learner which is time-consuming and can lead to inconsistency as well. Secondly, the FSLSM Model groups the learners into specific learning style categories on the basis of a range of values, instead of exact scores. Thus, knowing the learners class is more important than knowing the exact score. In this context, instead of asking a learner all the questions of the ILS, presenting them the relevant questions that provide suitable information will be sufficient.

The objective of the study is to propose an adaptive questionnaire based on Felder-Silverman’s Learning Style Model (FSLSM) by reducing the number of questions of the Index of Learning Styles (ILS) questionnaire. It is critical to consider that we are only selecting the more relevant questions to find the learning style of the learners and not to propose any new questions.

II. METHODOLOGY

To predict the learning style is an important factor of any learning model but the traditional approach of measuring the learning styles using the ILS questionnaire with all 44 questions does not fit well in AEHS because factors such as not being able to understand the questions properly, non-attentive approach towards the questions of the learners, going through all the 44 questions in one go leads to the tiresome attitude in the learners. The study involves the application of the J48 decision tree classifier algorithm to classify the learners into specific learning style dimensions. For this purpose, a sample of 320 Computer Science students was taken who were asked to fill the traditional ILS comprising of 44 questions. The data collected was then used to assess the LS of each student. This data was used to apply the decision tree algorithm for achieving the objectives of this research.

A Decision Tree classification algorithm comprises of a root node, branch (edge or link), and leaf node. The root node represents the test condition for various attributes, the branch node represents all possible outcomes in the test, and the leaf node represents the class to which it belongs. The root node is located at the beginning of the tree, commonly known as the top of the tree (A O. , Paredes, & Rodriguez, 2010).

J48 algorithm is a Java implementation of the basic C4.5 decision tree algorithm. J48 that employs a predictive machine-learning model to determine the consequent value of a new sample using various attribute values from the available data. The nodes in the network of a decision tree represent the diverse features; the branches between the nodes indicate the possible values for these attributes in the observed samples, while the terminal nodes indicate the dependent variable's ultimate value (classification) (Kalhoro, et al., 2016; A Q. , Benyoussef, El, & Elyadari, 2020; Witten, et al., 2005).

To complete the objective of this paper the Decision Tree is learned by dividing the main node into subsets which are based on the gain factor. This is a recursive process and does not require any pre-knowledge of data attributes and has high accuracy. The decision tree in the algorithm process forms the root based on the calculation of the highest gain value. After the roots have been formed, then the next step will be to make a branch for each value and this particular process will be iterated until all cases on the branch have the same class. This approach when applied to the sample data helped to reduce the number of questions in the ILS questionnaire and enhance the classification of students which can be separated into 4 different categories based on their learning style as fetched by the ILS questionnaire. Then to determine the learning style of the learner, the classification method is used in data mining.

III. RESULTS

Decision trees were produced with the classification algorithm J48 by splitting the data on the basis of maximum information gain. This explicit representation of data is shown below in the figures for all the 4 dimensions i.e. 1 (Active/Reflective), 2 (Visual/Verbal), 3 (Sensing/Intuitive) and 4 (Sequential/Global) respectively and these decision trees can be interpreted in a top-down approach. The notation used for representing the question is within a circle (Q xx) where xx is the number of questions in ILS. The question will always have 2 dedicated paths and it will be depending on the answer of the learner (a or b).

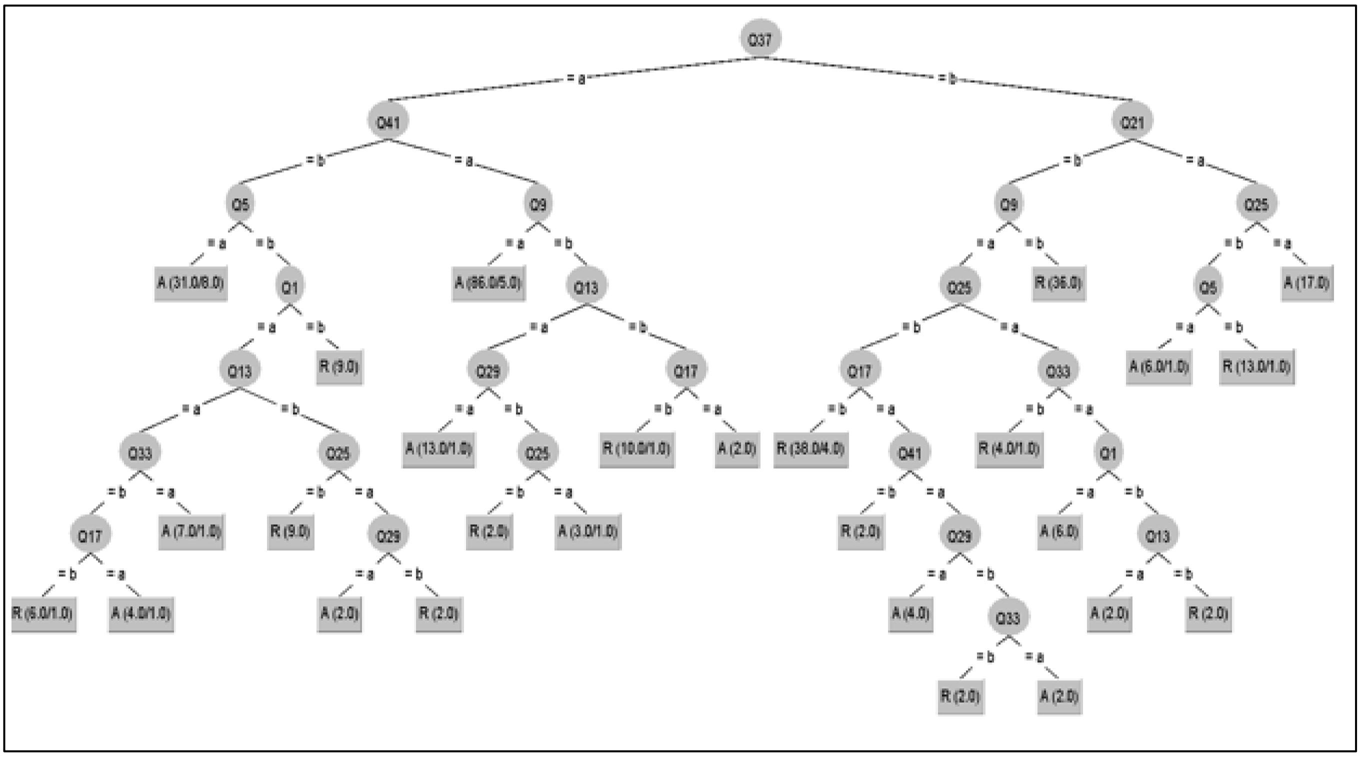

Fig 1 Active/Reflective Dimension Tree

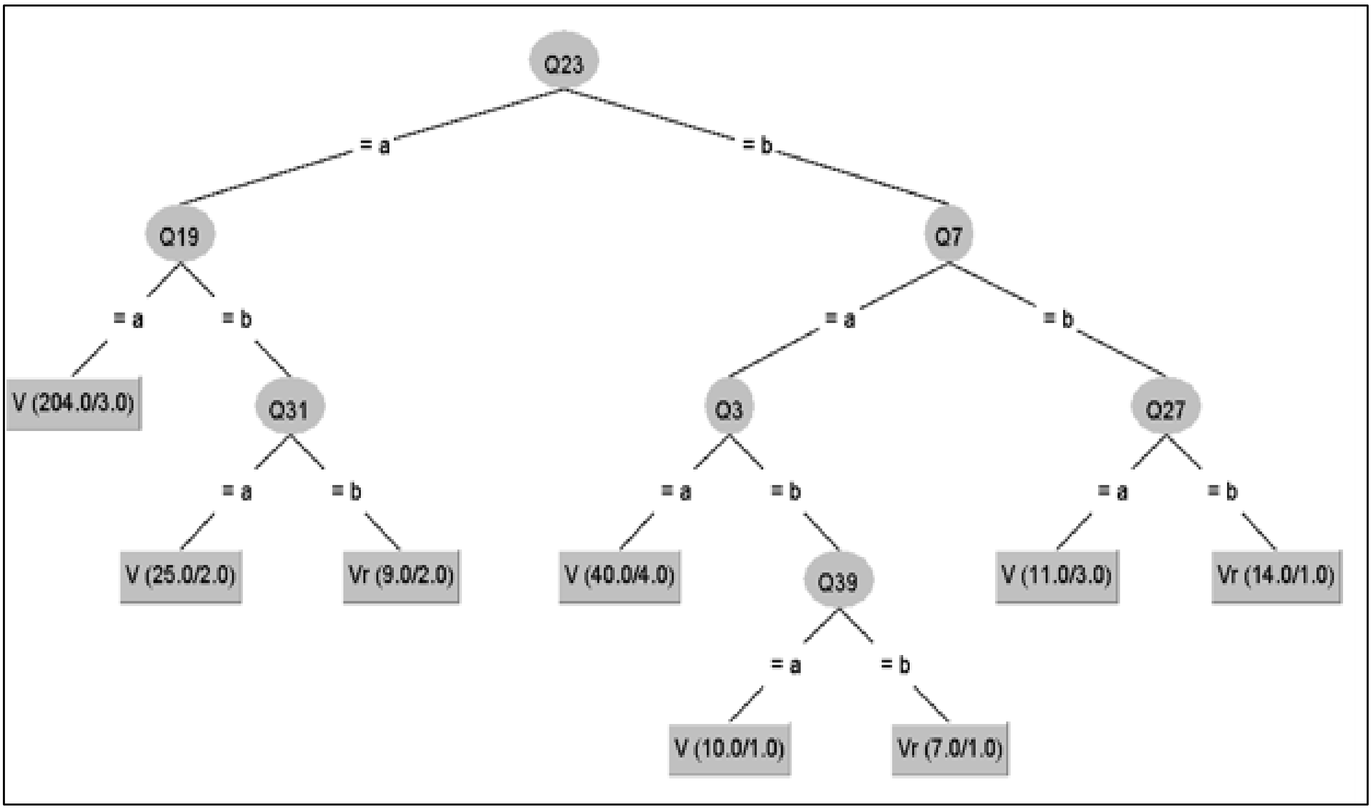

Fig 2 Visual/Verbal Dimension Tree

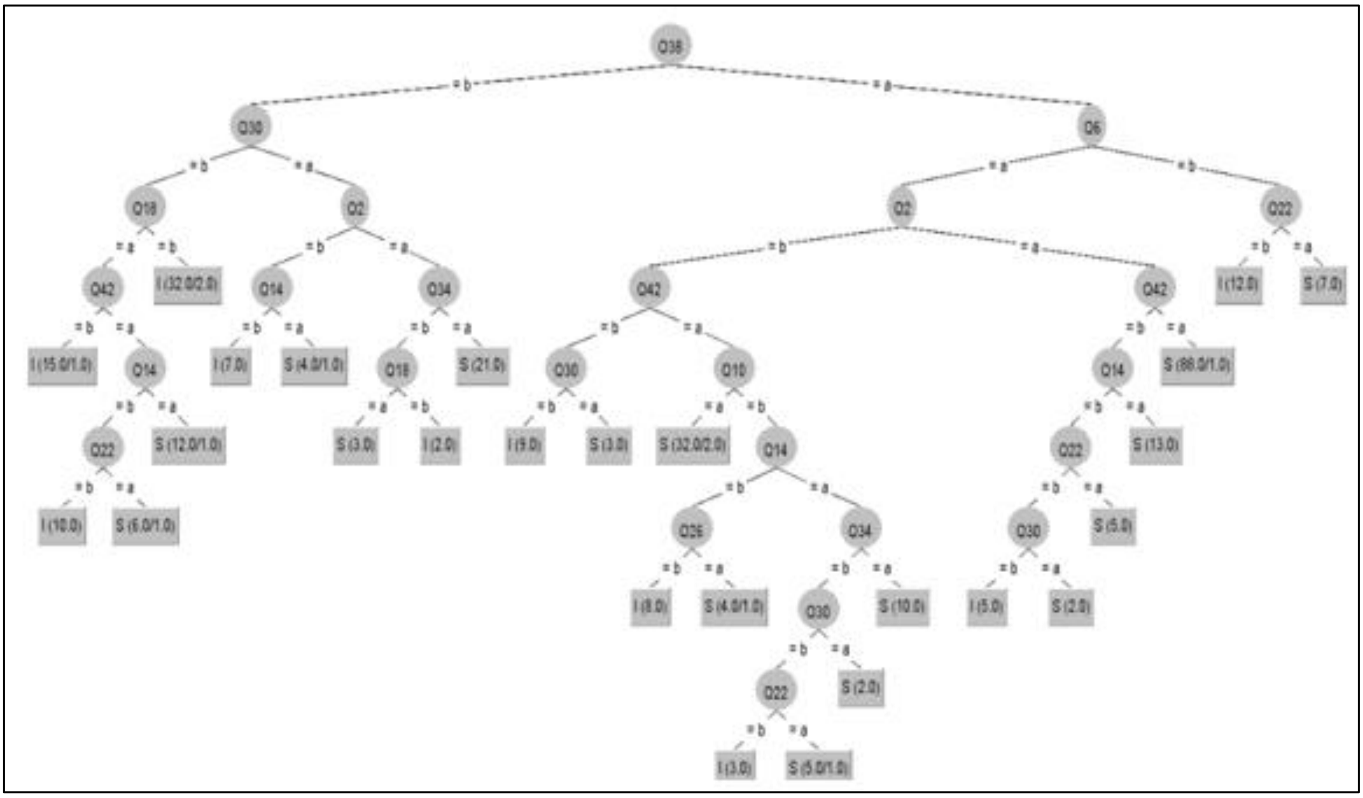
Fig 3Intuitive/Sensitive Dimension Tree

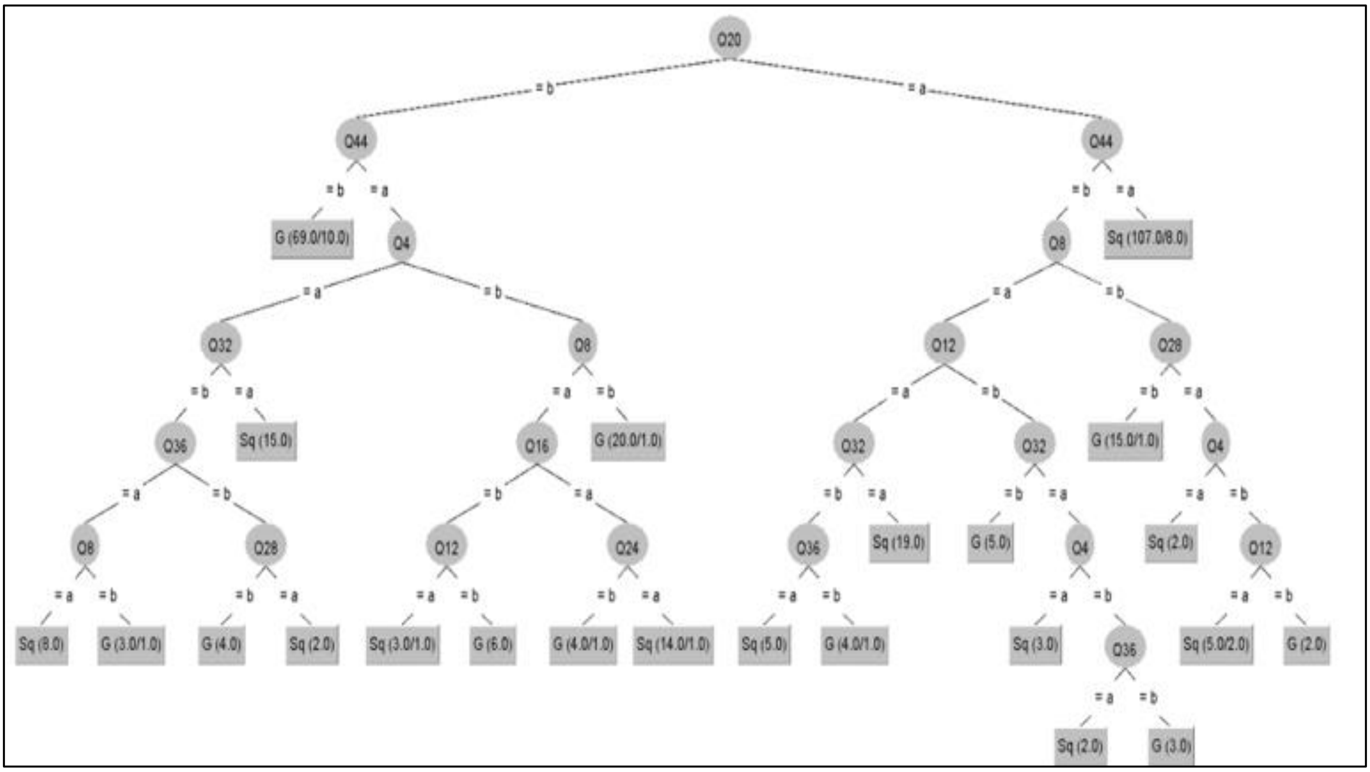

Fig 4 Global/Sequential Dimension Tree

The reduced number of questions is demonstrated in Table 1 for each learning style dimension. Each dedicated path in the decision tree for the respective dimension represents the anticipated number of questions the AEHS ought to ask or inquire before being able to classify the learner.

Table 1 Average Number of Questions for Each LS Dimension in Adaptive Questionnaire

	Active/Reflective	**Sensing/Intuitive**	**Visual/Verbal**	**Sequential/Global**
Questions	5.5	5.3	3.25	5.17

A 10-fold cross-validation method was used to find out the predicted classification error. The Table 2 illustrates the predicted classification in terms of the correctly and incorrectly classified dimensions.

Table 2 Classification of Nodes

	Active/Reflective	**Sensing /Intuitive**	**Visual /Verbal**	**Sequential /Global**
Correctly Classified (%)	79.37%	86.875%	90.31%	78.12%
Incorrect Classified (%)	20.62%	13.12%	9.68%	21.87%

IV. CONCLUSIONS AND FUTURE WORK

In this study, an approach is proposed to reduce the number of questions in the existing ILS questionnaire of the FSLSM model for different learning style dimensions. This concludes that some questions are directly relevant in terms of providing more facts about the general preference of the learner. For better performance and higher accuracy, increasing the number of samples in the dataset is highly recommended. Although the sample used in this paper is mainly focusing on the higher education learners, a similar study can be done on various sets of sample groups of diverse age groups as well as education groups.

For future study, an association of learning styles with clustering algorithms can lead to group observations in such a way that pre-determining the learning style of the learners will not be required. Involving the advanced and hybrid algorithms may produce better results and higher accuracy for predicting the learning style of the learners.

In near future, the present work is to be compared with different approaches by analyzing the data on various age groups of students.

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REFERENCES

[1]. A, H., & U. V. (2019). An Architecture of Adaptive Online Module System Based on Felder-Silverman Learning Style Model. Proceedings of the International Conference on Online and Blended Learning. 440, pp. 70-73. Advances in Social Science, Education and Humanities Research.

[2]. A, O., P. P., & R. P. (2010). AH-questionnaire: An adaptive hierarchical questionnaire for learning styles. Computers & Education, 54(4), 999-1005.

[3]. A, Q., B. A., E. K., & E. M. (2020). Toward an Adaptive Educational Hypermedia System (AEHS-JS) based on the Overlay Modeling and Felder and Silverman's Learning Styles Model for Job Seekers. International Journal of Emerging Technologies in Learning (iJET), 15(8), 235-54.

[4]. Adeboje Olawale Timothy, I. A. (2020). Reviews on Machine Learning based Adaptive Mobile Learning System. International Journal of Computer Applications, 176 (38), 0975 – 8887.

[5]. Akbulut, Y., & Cardak, C. S. (2012, 2). Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011. Computers and Education, 58(2), 835-842.

[6]. Akbulut, Yavuz, Cardak, & C. S. (2011). Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011. Computers \& Education, 58(2), 835--842.

[7]. Allioui, Y. E. (2019). Advanced prediction of learner's profile based on Felder-Silverman learning styles using web usage mining approach and fuzzy c-means algorithm. International Journal of Computer Aided Engineering and Technology, 11(4-5), 495--512.

[8]. Alzain, A. M., Clark, S., Jwaid, A., & Ireson, G. (2018). Adaptive education based on learning styles: Are learning style instruments precise enough? International Journal of Emerging Technologies in Learning, 13(9), 41-52.

[9]. Andaloussi, K. S., L. C., & I. B. (2017). Adaptive educational hypermedia systems: current developments and challenges. In Proceedings of the 2nd international Conference on Big Data, Cloud and Applications (pp. 1-8).

[10]. Bernard, Jason; Ting-Wen, Chang; Elvira ,Popescu; , Sabine ,Graf. (2017). Learning style Identifier: Improving the precision of learning style identification through computational intelligence algorithms. Expert Systems with Applications, 75, 94-108.

[11]. Brusilovsky, P. (1996). Methods and techniques of adaptive hypermedia. Kluwer Academic Publishers.

[12]. Brusilovsky, P. (2004). Adaptive educational hypermedia: From generation to generation. In Proceedings of 4th Hellenic Conference on Information and Communication Technologies in Education, Athens, Greece (pp. 19--33).

[13]. Brusilovsky, Peter. (2004). Adaptive educational hypermedia: From generation to generation. Proceedings of 4th Hellenic Conference on ICT in Education., 19, p. 33.

[14]. Dunn, R. (2003). The Dunn and Dunn learning style model and its theoretical cornerstone. New York: R. Dunn & S. Griggs .

[15]. Felder; , Richard M.; , Joni Spurlin. (2005). Applications, reliability and validity of the index of learning styles. International journal of engineering education, 103-112.

[16]. Felder; , Richard M.; , Linda K. Silverman. (1988). Learning and teaching styles in engineering education. Engineering education, 78(7), 674-681.

[17]. Felder; , Richard M.; , Linda K. Silverman. (1988). Learning and teaching styles in engineering education. Engineering education, 78(7), 674-681.

[18]. Gomede, Everton, R. M., & L. d. (2021). Deep auto encoders to adaptive E-learning recommender system. Computers and Education: Artificial Intelligence, 2, 100009.

[19]. Graf, Sabine, S. R., T. L., & Kinshuk. (2007). In-depth analysis of the Felder-Silverman learning style dimensions. Journal of Research on Technology in Education, 40(1), 79-93.

[20]. Graf; , Sabine; , K. Kinshuk. (2007). Providing adaptive courses in learning management systems with respect to learning styles. In E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (pp. 2576-2583). Association for the Advancement of Computing in Education (AACE).

[21]. Herrmann, N. (2001). Measurement of brain dominance. Retrieved from www.herrmannsolutions.asia

[22]. Kalhoro, A. A., Rajper, Samina, Mallah, & Ghulam. (2016). Detection of E-Learners Learning Styles: An Automatic Approach using Decision Tree. International Journal of Computer Science and Information Security, 14(8), 420.

[23]. Karagiannis, Ioannis, & M. S. (2018). An adaptive mechanism for Moodle based on automatic detection of learning styles. Education and Information Technologies, 23(3), 1331-1357.

[24]. Kolb, D. A. (1984). Experiential learning: Experience as the source of learning and development.

[25]. Nafea, S. M., F. S., & Y. H. (2019). On Recommendation of Learning Objects Using Felder-Silverman Learning Style Model. IEEE Access, 7, 163034-163048.

[26]. Pittenger, D. J. (1993). The utility of the Myers–Briggs type indicator. Review of Educational Research, 467–488.

[27]. Witten, I. H., Frank, E., Hall, M. A., . . . M. (2005). Data mining–practical machine learning tools and techniques (Vol. 2).