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AFCM MODEL TO PREDICT THE LEARNER STYLE BASED ON QUESTIONNAIRE AND FUZZY C MEAN ALGORITHM

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ABSTRACT

Every learner follows a special Learning Style (LS), which enables him to learn and understand efficiently; it is necessary to discover every learner's behavior and LS to offer him his specialized materials. The success of the E-learning systems comes from the ability to select and recommend the suitable subject contents to the learner. This paper suggested a new adapted technique for the Fuzzy C Mean (FCM) Algorithm named Adaptive Fuzzy C Mean (AFCM). Moreover, this paper proposed a new adapted E-learning model to predict the Learning Style through the process of learning, depending on the suggested AFCM. The suggested model can store the access data of the learner's navigation, finds out the behavior pattern that personalizes every learner, and then offers individualization due to the LS. The analysis of AFCM performance can be performed by the calculation of the two test accuracy; the performance of using the AFCM algorithm in the second test is much better with an overall performance of 88.7%. The AFCM introduced a preprocessing step before the FCM Algorithm to reduce the time and reduced the number of iterations taken by FCM. The proposed model assists the learners for an English course in the Faculty of Computer Science, October 6University, to maximize the E-learning advantage with high performance, in COVID 19 circumference.

Keywords: *Learning Style, Fuzzy C Mean Algorithm, Questionnaire, Adaptive E-Learning, Log File*

1. INTRODUCTION

Every learner has his own way of dealing with the learning material and using information. The differences from one learner and another can decide their special LSs. Therefore, every learner is known by his/her own LS which can show his/her own way to see, understand, and use information [1]. In fact, realizing the special LS can help the e-learning system to present individualized content to every learner which can match his/her own needs [2] and support his/her own learning process. Several solutions are suggested for identifying the LSs of learners. One conventional solution includes requesting learners to answer the questions in a questionnaire [3][4], but this solution has several defects[5]. First, answering questionnaires is boring and takes much time. Second, many learners are not generally conscious about their LSs, and do not value the importance of the questionnaire; therefore, they often give some inaccurate answers which result in having imprecise findings to the questionnaire which in turns reflect unsuitable LSs to learners. Third, the findings which questionnaires give are constant, but the LSs may change within the learning process.

To get over these drawbacks, some automatic concepts [6] [7] are suggested to find out the LS of learners automatically through their behavior while interacting with the e-learning system [8]. This automatic detection has several advantages above the conventional methods. First, it reduced the spent time on filling questionnaires, so it does not take much time since it gathers information through the interaction of learners with the system [9]. Also, detecting LSs by the automatic way is dynamic and changes due to the behavior of learners [10].

This behavior was observed through the e-learning log system; the log file consists of many sequences that stand for learning objects which are accessed by learners through the session[11], [12]. Such sequences, or learning objects, have been used as input to the FCM algorithm, which has been used for mapping the learning objects to the LSs. Then, these mapped learning objects can be used as data for predicting every learner's LS.

In Egypt, by the start of March 2020, COVID19 (corona virus) prevents study in traditional groups and closes all the universities until the students will come back; universities also have to continue using e-learning platforms and online classes. We designed a real system and applied our model for the English language course.

The contribution of this paper is suggesting a new adapted technique for the Fuzzy C Mean (FCM) Algorithm named Adaptive Fuzzy C Mean (AFCM). Moreover, this paper proposing a new model to predict the Learning Style (LS) through the process of learning, depending on the suggested AFCM, to enables the learner to learn and understand efficiently. Fuzzy C Mean (FCM) Algorithm finding the centroids with more than 70 iterations to reach 85.27% performance of correct clustering, and reach performance 93.41% by 210 iterations. While the proposed new adapted E-learning model overall performance is 88.7% by 6 iterations, that reduce the time taken and the number of iterations.

This paper is arranged as follows; Section 2 discusses the Background and some important algorithms. Section 3 discusses the related works about several techniques are used to define and categorize LSs through different LS models. Section 4 shows the proposed model AFCM for detecting LSs automatically though the behavior of learners. Section 5 discusses and presents the experiment and results. Finally, Section 6 presents the conclusion.

2. BACKGROUND

To build an adaptive e-learning system, some important models and algorithms that will be used in our approach were illustrated in details in this section.

2.1 The Felder and Silverman Learning Style Model (FSLSM)

A learning style can be described as the way in which the learner to study and easy understands information [13]. The FSLSM helps educational systems by presenting four dimensions of the learner LS (processing, perception, input, and understanding) as shown in figure1. Where each dimension consists of two categories, the learner behavior is near to one category. Selecting one category from each dimension form the learner LS [14].

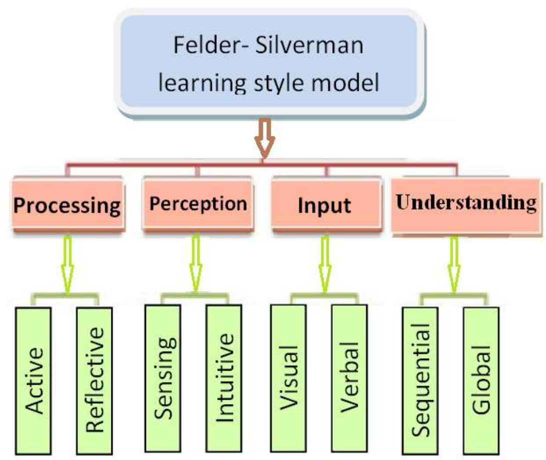

Figure 1: Felder-Silverman Learning Style Model[14]

The meaning of each category will be defined in the following points:

- Active (processing): learners almost study in teams and prefer to do something more than thinking.
- Reflective (processing): learners do not like to study in groups prefer to think about the learning material quietly first.
- Sensing (perception) learners like facts and more practical.
- Intuitive (perception) learners prefer to do mathematical calculations, and don't prefer normal calculations, and they. They may be better than sensors at innovating and grasping new concept.
- The visual (input) learners almost seeing visual representations (pictures and charts).
- Verbal (input) learners prefer to study with written words or spoken.

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- Sequential (understanding) learners prefer to learn course step by step from simple information to harder.
- Global (understanding) learners prefer to learn by taking over view first and access materials randomly.

2.2 Algorithm to Initial LS.

A lot of algorithms tried to predict LS of the learner, but the Ulearn questionnaire algorithm [15] is fast and does not waste the learner time. This algorithm calculates dynamically the initial LS of the learner even if the leaner answers a few questions at this dimension; now filling the questionnaire is not boring task, and saving the time.

It asks 11 question at each dimension to find the learner category, the learner choose from two answers ("a" or "b").

The Ulearn questionnaire algorithm:

```
Begin
/* we have four dimensions each dimension 11 questions */

For dimension = 1 to 4 do
A[dimension] = 0;
B[dimension] = 0;
Question = 1;
While (A[dimension] <7 and B[dimension] <7 and Question <=11) do
        Read the question answer;
        If (answer is "a") then
        A[dimension] = A[dimension] + 1;
        Else
        B[dimension] = B[dimension] + 1;
        End if
        Question= Question+1;
While end
End for
End
```

We can describe the input and the output of the algorithm as:

Input to the Algorithm: the learner questionnaire answers.

The process: count the number of answer "a" and the number of answer "b" in each dimension, then find the maximum number between ("a" or "b").

The output: at each dimension store the learner category.

For example in the processing dimension if the number of answer "a" greater than "b", the learner is active otherwise is reflective. This algorithm defines LS of the learner in each dimension according to answers of the questionnaire.

2.3 FSLSM Dimensions Learning Objects

At sec 2.1, four dimensions were defined by The FSLSM each dimension has two categories. According to each category, each learner prefers to study using certain objects. Table1, explain a combination of objects preferred at each category [16].

Table 1:Objects preferred at each category

Category	Objects preferred at each category
Active	Videos, PPTs, Demo, and Assignments
Reflective	Videos, PPTs, Announcements , and PDFs
Sensing	PDFs, Videos, Examples, Practical and Material
Intuitive	PDFs, Videos, PPTs, and Topic List
Visual	Images, Videos, Charts, and References
Verbal	PDFs, Videos, Announcements, and Email
Sequential	References, Assignments, Sequential, and Exercise
Global	References, Assignments, Topic Lists, and Exercise

2.4 Fuzzy C Means (FCM) Algorithm

The FCM technique used to assign membership to some sequence values (learner behavior), to a single cluster [17][18].As shown on figure 2, all points are clustered in to three clusters; each cluster has a cluster center point.

The goal is to find each cluster center. When any sequence becomes near to center of any cluster, declare this sequence to be member of this cluster. Total summation of all membership values almost near to one.

For each iteration, the membership and cluster centers are revised according to the membership equation [16].

Then comparing distance value with the threshold value. If the distance value is less than the

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threshold value, learner's sequence is defined as member of this cluster. In the end, the sequences are directed into sixteen clusters of FSLSM.

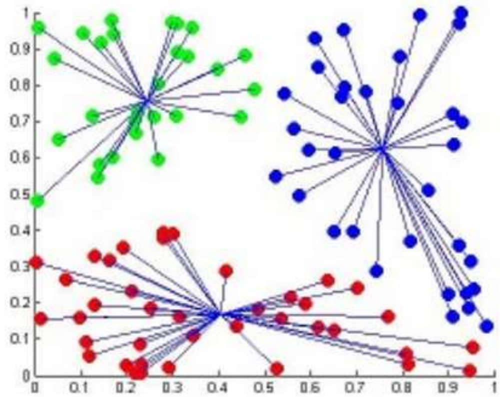

Figure 2: Result of Fuzzy c-means clustering

Fuzzy c-means clustering Algorithm can be written in steps:

Let $X = \{x_1, x_2, x_3 ..., x_n\}$ be the set of data points

1. Randomly select cluster centre

2. Initialize $U=[u_{ij}]$ matrix, $U^{(0)}$
Calculate the u_{ij} using:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \quad (1)$$

3. At k-step: calculate the centers vectors $C^{(k)}=[c_j]$ with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \quad (2)$$

4. Update $U^{(k)}$, $U^{(k+1)}$

5. If $\| U^{(k+1)} - U^{(k)}\| < \varepsilon$ or the minimum J is achieved, then STOP; otherwise return to step 2.

'*k*' is the iteration step.
'*β*' is the termination criterion between [0, 1].
'$U = (\mu_{ij})_{n*c}$' is the fuzzy membership matrix.
'*J*' is the objective function.

3. RELATED WORKS

By taking a look at the literature review, it can be seen that several techniques are used to define and categorize LSs through different LS models.

Many papers are completely studied, and a lot of factors have been realized to be integrated in that work. The literature review can cover some various aspects of the behaviors and knowledge of learners which is considered by the authors for applying and testing those models.

Abdullah et al. [19] suggested one new approach for classifying the learners in a dynamic way relying on their own LS. This suggested approach is conducted on 35 learners for an online course on Data Structure that was prepared by Moodle. Due to FSLSM, every learner's LS were identified through realizing their behavior and data that was gained from Moodle log. In addition, there was a comparison between the behavior's LSs and the quiz results, which are conducted at the course end. However, the learner's LS changes over time while e-learning portal can only consider the static Moodle study. Therefore, the learning parts of portal; like the files and the pages that are important for defining FSLSM's LSs, were not considered.

Chang et al. [20] suggested a mechanism for classifying and identifying the learner's LS. This mechanism shows the classification algorithm of K-Nearest Neighbor (k-NN) and links it with the Genetic Algorithms (GAs). The result of the experiment shows that mechanism of classification has the ability to define and classify the learner's LSs. The LSs' definite aspects of LS model have not been considered by that mechanism while the LS model selection can enrich the main mechanism aspects. The Ls model use has not been considered by the authors for improving the e-learning system as well as for recommending a mechanism that is based on the learner's LSs.

D. HASSOUNA [21] suggested a platform was practiced on one 200 college from Canadian International College to improve the process of higher education and can be practiced on online or physically at the university. This work used VARK questionnaire [22], [23]. That presents to the students 16 questions in the type of choices questions. According to the learner preferences, he will choose the best answer. The results show that

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the success percentage was raised by 50% of the 200 learners.

Abdullah et al. [24] discussed the LSs impacts on the learning environment through Naive-Bayes Tree (NBTree). The classification system of Naive-Bayes Tree (NBTree) can be followed to show the learner's LS through FSLSM. Through this concept, LSs are realized through using FSLSM questionnaires' index that has limitations for considering the behavior of a learner's online use.

Latham et al. [25] showed a link between Multi-Layer Perceptron and Artificial Neural Network (ANN) for defining the data of learners. Through using FSLSM questionnaire index, the data of learners is gained and it shows four classifications of learners which are Active, Reflective, Sequential, and Global. Because algorithm considered the FSLSM questionnaire data, LSs cannot be called realistic ones for adaptive learning.

Bernard et al. [26] offered one approach which uses ANN for defining the LSs of learners. In this concern, the FSLSM questionnaire approaches have been considered by the authors for identifying the learners' LSs. Learners who took above 5 minutes for filling out the questionnaires were kept in the database. Therefore, such approach can be dynamically used for identifying LSs.

Huong Truong [27] checked several cited works which worked on integrating LSs with the adaptive e-learning system. In addition, he has checked the different aspects of LS theories. In reality, the predictors of LS, who are the major data source as well as the corresponding attribute, like log files may uses knowledge, history, ability, and background. All such matters have been discussed through the paper.

Quang Do [28] offered using Gravitational Search Algorithm (GSA) in NN and set a comparison with the classification of Back Propagation NN.

Xu and Zhang [29] have linked both GSA and NN, and checked the difference with classification data sets. The integration and linkage of GSA and NN has been approved for giving better precision, which can make it available for real time use of learner through e-learning portal for classifying the new learners as for LS model.

Deborah et al. [30] defined FSLSM as the proper model of predicting LS as in the Web environment. These authors offered using Fuzzy rules for managing uncertain points in the LS prediction. In spite of this, it was not considering the whole FSLSM learner classifications. In addition, fuzzy rules can be known on three parameters like the length of a document, the image area and the mouse movements.

Through this piece of work S. Kolekar [16], the web mining technique helps in capturing the learning behavior. Then, the learning behavior is prepared to change to XML format depending on the assessing content sequences. Such sequences get mapped to the FSLSM eight categories via the use of FCM algorithm. Then, An algorithm of gravitational search based back propagation NN (GSBPNN) can be used for predicting a new learner's LS. Through this algorithm, a modification to NN is done through making a calculation to the gravitational search algorithm weights.108 learners have participated in HTML online course; the GSBPNN classification algorithm accuracy is 95.93% for the 200 iterations. The more the iteration numbers increase, the more accurate the findings become. However, the algorithm needs longer tome for being executed.

O.El Aissaoui[1] illustrated that the log file of the e-learning platform has been pre-processed through the use of web usage mining technique for extracting the sequences of the 1235 learners. The sequences have been mapped to the LSs' combinations by using K-modes clustering algorithm depending on the FSLSM. These sequences, which are labeled, have been used as a training set for training the naive Bayes classifier and predicting a new learner's LS combination. For evaluating the classifier performance, the confusion matrix method is used. Although the algorithm accuracy is 93.7%, it requires longer time for its function.

4. THE METHODOLOGY

The goal of the AFC model is to predict the LS and to increase learner knowledge. As shown in figure 3.The proposed model starts with creating an account for each learner and asks him to fill the questionnaire to classify and cluster the LS into 16 learner clusters. After that, the model will recommend materials to be studied and store all activities in the learner log file; then, they take a test. The AFCM calculates the start values of the Centroids based on the feature values (total spent time to each object) for the learners who fill the questionnaire, then modifies FCM Algorithm and applies them to the activities log file to update the LS. Finally, the model will recommend materials based on the new LS followed by test 2. The methodology of the proposed model can be written in the following algorithm:

AFCM Model Algorithm

1- For each learner
   a. Create an account andfill the questionnaire.
   b. Classify the LS using Ulearn Questionnaire.
   c. Clustering LS into one of 16 learner clusters
   d. Matching learning objects to each learner cluster.
2- For two weeks
   a. Recommendation learning objects to each LS cluster.
   b. Store all learner activities in the learner log file.
   c. Each learner computes the total time spent on each object.
3- Each learner takes the first test.
4- For each dimension from the FSLSM, four dimensions
   a. Find the centroid points using a log file and Ulearn Questionnaire.
   b. Use the FCM algorithm to update the centroid points.
   c. Update the LS of all learners.
5- Repeat step 2.
6- Each learner takes the second test.

The proposed model can be illustrated in the following three phases.
Phase 1, Identifying the learner profile and initial LS.
Phase 2, Recommend Learning Objects to Each Learner Cluster.
Phase 3, Updating the LS and repeat phase2.

The three phases will be described in detail in the following three sections.

4.1 Phase1: Identifying the Learner Profile and Initial LS.

This phase aims to create the Learner profile, includes the learner personal information and uses FSLSM questionnaire to identify the LS in to 16 clusters. Then our model matches the learning objects to each LS cluster. The first phase can be divided in to three steps will be described in details in the following 3 points.

4.1.1 Initializing the LS

In this step, create the Learner profile includes the learner personal information; if the learner visits the system, and it is the first login, then the ID is student_id, and the password is set to the current year, to be changed at the second login, the model starts with collecting personal data of the learner such as (Name-Id, GPA, Birth date, Password, Email, Mobile Number, Course Code).

After registration, the learner fills out the Ulearn questionnaire [15] to discover the four dimensions of FSLSM. Using the algorithm described at (sec2.2), this algorithm presents the 44 questions, 11 questions to each dimension of the learner LS (processing, perception, input, and understanding), the suggested model calculates dynamically the initial learner cluster (Active or Reflective, Sensing or Intuitive, visual or Verbal, Sequential or Global) from the answers of 11 questions, by selecting one category from each dimension.

For example the LS cluster (Reflective, Intuitive, Verbal, Global) summered by taking the first one or two letters (R,I,Ve,G) and this Cluster_ID is C1. We will obtain sixteen clusters of LS.AFCM calculates dynamically the initial LS of the learner even if the leaner answers a few questions at this dimension; now filling the questionnaire is not boring task, and saving the time.

4.1.2. Matching learning objects to each learner cluster

The goal of this step is to find the objects that will be recommended to the learner by each learner cluster [1]. From table1, Each Category was defined by some preferred objects where each learner prefers to study using it. Such as Reflective category preferred objects Videos, Microsoft PowerPoint (PPTs), portable document format

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(PDFs), and Announcements. Continue with the same example, the learner cluster C1 (Reflective, Intuitive, Verbal, and Global). Using table1, we can find the objects that will be recommended by each category of this cluster, as shown in table2.

Table2: the objects will be recommended by the Cluster C1

Categories of C1 Cluster	Objects preferred
Reflective	Videos ,PPTs ,PDFs ,and Announcements
Intuitive	PDFs ,Videos ,PPTs , and Topic List
Verbal	PDFs , Videos ,Announcements , and Email
Global	References, Assignments, Topic Lists, and Exercise

So, the cluster C1 will recommend the objects (Videos, PPTs, PDFs, Announcements, Topic List, Email, References, Assignments and Exercise), as shown in the first raw of Table 3, the model uses Table1 to find the objects will be recommended by each cluster.

4.1.3 Cleaning data

Some objects are not needed when we apply the system to English course such as charts-mail, and Practical Material. Table 3 illustrates the result of mapping the learning objects to each LS combination after cleaning some objects.

4.2 Phase 2: Recommended the Learning Objects to Each Learner Cluster

In the previous phase, we notice that some learners do not fill the questionnaire, so they do not have an initial learner cluster. This phase aims to recommend the course materials to all learners based on the LS and present all materials to those who do not fill the questionnaire. After training and study, the learners take a first-test to measure the adaptation effect on the learning process. And store all learner activities into the log file. This phase can be divided into two steps that will be described in detail in the following 2 points.

4.2.1 Initial preparation period to increase the learner knowledge

The target of this step is increasing the learner knowledge by adapting the online course materials. The system will recommend the preferred objects to each LS combination, as shown in table3, and also presents the links to all other materials (not recommended),using the blue color for the recommended objects; the learner can choose one object or some to study it, as shown in figure 4.

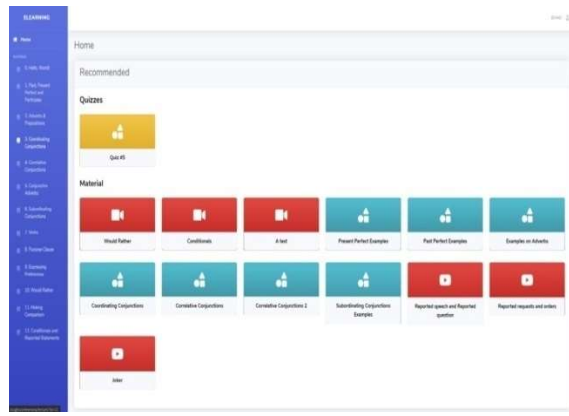

Figure 4: the recommend objects to the each LS combination

At the same time, with the training process, each learner at any time can access any object for a certain time; this operation can be defined as the learning sequence. The learning sequences are stored at the log file; each sequence containsid_Sequence, id_session, id_learner, the set of objects, and total time spent on the object, as shown in table 4.

Table 4, the sequences log file

Student ID	id_Sequence	id_session	object_num	object name	time In min
202011068	1200	1	ob12	Examples lec 9	12
202011068	1201	1	ob16	image 3	6
202006285	1223	2	ob19	pdf9	47
202006378	1224	3	ob19	pdf9	26

4.3 Phase 3: Updating the LS and Repeat Phase2.

Phase 3 is the most important phase because the proposed adaptation technique AFCM introduced a preprocessing step before FCM Algorithm, to reduce the time and reduced the number of iterations taken by FCM, then using data stored at the log file to update The LS. The model will recommend the course materials to all learners based on the updated LS.

For each dimension, the FSLSM's sequences of learners are given as an input to the FCM algorithm with M=2,threshold value ε=0.0001, a number of clusters = 2, the FCM algorithm assigns membership to each learner sequence, to one category of each FSLSM dimension, which is near to the category center. After examining the four dimensions, update all LSs. Finally, the learner must take a second-test. The difference between the second test and the first indicates the performance of the proposed model. The last phase can be divided into three steps that will be described in detail in the following 3 points.

4.3.1 Grouping the learning objects

The proposed model aims to group the learning objects for each dimension to be an input to FCM Algorithm; from table1, we can find all active and reflective learners prefer to study using videos and ppts. The difference come from active learners prefer Demo and Assignments but the reflective learners prefer to study using PDF.

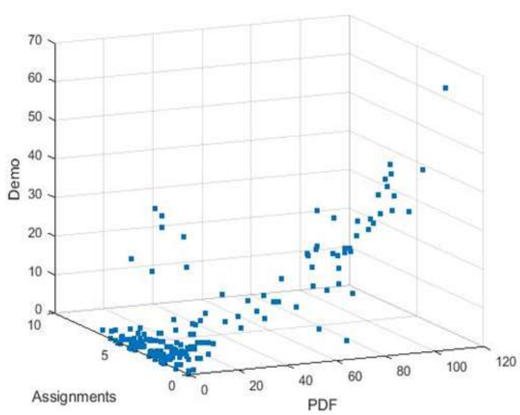

Figure 5: objects values (in minutes) from log file, which Assigned to Fuzzy C Mean Algorithm to detect (Active – reflective) learners.

Using the log file to find the total time spent by the learner at (Demo, Assignments, and PDF) objects, to distinguish between the active and reflective learners.

At figure 5, each point represents the time spent by one learner on 3 objects (Demo, Assignments, and PDF), the goal of FCM algorithm is to cluster all points in to 2 categories (Active or reflective). Learning objects are grouped for each dimension in table5 to indicate the new cluster for each dimension.

Table5: Feature values (objects) assigned to each dimension.

The log file			The learner has One cluster from two clusters	
Object 1	Object 2	Object 3	Cluster 1	Cluster 2
Assignm ents	Demo	PDFs	Active	Reflective
Topic list	Examples	PPTs	Sensing	Intuitive
Images	PDFs	Announc ements	Visual	Verbal
Topic list	Sequential		Sequential	Global

It is noticed that active learners spend a lot of time reading Demo and solve Assignments, but the reflective learners spend a lot of time to study using PDF; from the total spent time, the proposed model can compute the initial centroids point.

To make it clear, For example, one centroid points to active and another centroid points to reflect, which is the average to the total spent the time to each object from table 5.

4.3.2 The proposed adaptation technique for FCM

The old process of finding the centroids takes more than 70 iterations to reach 85.27% performance of correct clustering, and reach performance 93.41% by 210 iterations [32]. The centroid's values at FCM are randomly initiated.

The proposed system will reduce the time taken and reduce the number of iterations by calculating the start values of the centroids based on the feature values (total spent time to each object) for the learners who fill the questionnaire. Followed by, finding the center of each category as declared at sec 2.4.

The newly proposed adaption technique depending on the following steps:

For each dimension from four dimensions of the learner LS (processing, perception, input, and understanding)

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Step1: for the learners who fill the questionnaire, calculate the total time spent on the cleaned objects of the same category (cluster); the centroids point is the average to the total spent time.

Step 2: find the distance for all learners they did not fill the questionnaire with the centroids and update the membership function. Then find the new centroids.

Step 3: find the distance for all the learners and the centroids, and update the membership function. Then find the new centroids.

Step 4: Repeat step 3 until the threshold becomes less than or equal to 0.0001.

4.3.3 The second test

After the training process, the learner is ready to do the second-test to discover the new Knowledge level; the system provides a link to the online exam consists of multiple-choice questions, and select the questions randomly from the test bank. The number of questions is decided by the doctor; the learners can access the test by mobile /laptop and can see the results immediately after the allowed time for the test is terminated. The score of the second test and the Knowledge level are stored at the learner profile to be compared with the results of the test1, figure 6 displays sample learner profile including the results of two tests, personal data, and the four dimensions were defined by The FSLSM.

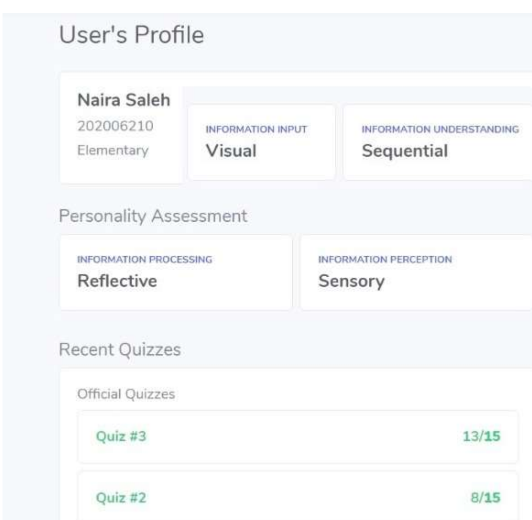

Figure 6: learner profile after 2 tests

The results will be shown in the following section.

5. EXPERIMENT AND RESULTS

In Egypt by the start of March 2020, COVID-19(corona virus) prevents study in traditional groups and closes all the universities until the students will come back; universities also have to continue using e-learning platforms and online classes.

It is a great opportunity to design a real system and apply the proposed model for First-Year English course of the Faculty of CS, October 6 University was made available for a duration of five weeks, and the learners can access the system by a mobile /laptop. A total of 249 learners participated in the online course with 4304 sequences and stored all learners' activities in the weblog data.

The first week: Create a learner profile and fill the questionnaire to indicate the LS for all learners and divided into 16 groups. Only 210 learners fill the questionnaire. And 39 leaner does not fill the questionnaire. The second two weeks (training): The FSLSM mapped learning objects to each style. Also, the characteristics of the web page are identified based on objects of FSLSM. At the end of this period, all learners take test1 then the system takes the objects of FSLSM from log file are then send it to FCM Algorithm to find the new LS for 249 Learner and update The LS for all learners. The last two weeks (training): The FSLSM mapped learning objects to the new LS calculated from FCM Algorithm. At the end of this period, all learners take test2.

5.1 Clustered Learners Based on Questionnaire

Only 210 learners fill the questionnaire and 39 leaner does not fill the questionnaire. The results are shown in figure7. For each dimension there are 210 learners were clustered into two categories.

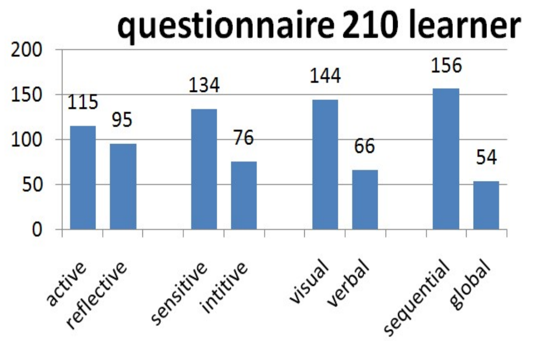

Figure 7: the number of learners at each dimension using questionnaire

5.2 Clustered Learners Based on AFCM Model.

The proposed model is trained using the results of questionnaire and log file sequences; the algorithm is repeated for six iterations, as it requires 6 iterations of the questionnaire and modified FCM algorithm to find the centroids, by using threshold value ε=0.0001.

The old and new LS for 249 Learners using AFCM model are shown in figure8.

5.3 The Knowledge Level of Learners after Tests

To test the System, the 249 learners solved two tests, one after the training according to the LS computed from the questionnaire and the second after AFCM Model.

After test1, the learner's knowledge levels numbers and percentages are shown in Figure 9. From 249 learners, the knowledge level of 122 learners is elementary with percentage 49%, 97 learners are at intermediate level with percentage 39%, and 30 learners are at the advanced level with percentage 12%.

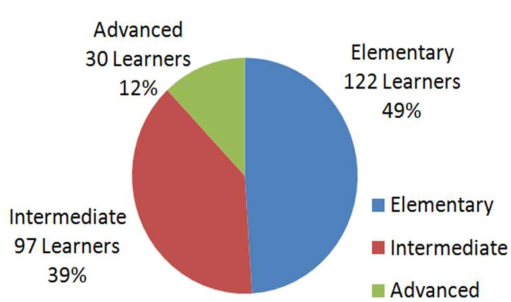

Figure 9: The learner's knowledge levels, after test1

The last two weeks (training): The FSLSM mapped learning objects to the new LS calculated from the AFCM model. At the end of this period, all learners take test2.After test2, the learner's knowledge levels numbers and percentages are shown in Figure 10.

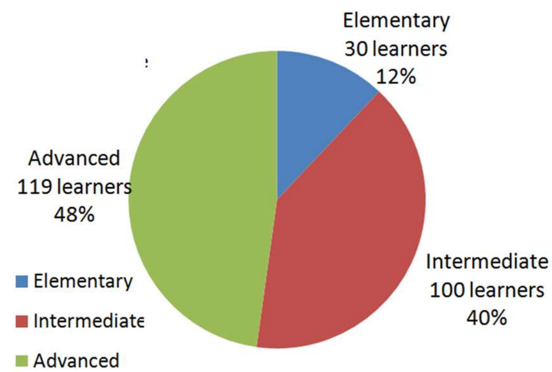

Figure 10: The learner's knowledge levels, after test2

From 249 learners, the knowledge level of 30 learners is elementary with percentage 12%, at intermediate level with percentage 40%, and at the advanced level with percentage 48%.

5.4 Effectiveness of AFCM System

The effectiveness of the applied system can be seen from the performance of the second test score value, as illustrated in Table 6.

According to the results, in the first test, the total number of learners got score less than 60% is 122 learners (low knowledge level),and the second test and the number of learners with elementary-level to 12.05 % of total students (30 out of 249 students).

Table 6 proficiency level after the second test

	Knowledge level 0:60	Knowledge level 60:80	Knowledge level 80:100
The learner's knowledge levels, after test1	122	97	30
learners got marks on test2 more than of test1	117	80	24
Percentage of students got	95.90	82.47	80

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marks on test2 more than on test1			

At test2 117 out of 122 (low level learners from test 1) got marks more than of test1 with 95.90%, the 82.47% of learners with intermediate performance at test1 got more marks at test 2,and 80% of the learners with high performance at test1 got more marks at test 2.

Overall performance is 88.7% at the second test, and the number of learners with elementary-level to 12.05 % of total students (30 out of 249 students). In the future the proposed model will be applied on widely large number of learners.

Finally, in the second test, updating of the memberships takes a few time, as it requires six iterations of the questionnaire and modified FCM algorithm to find the centroids, by using threshold value ε=0.0001.

6. CONCLUSION AND FUTURE WORK

Identifying the learner LS can help the e-learning system to present individualized content to every learner who can match his/her own needs to learn and understand efficiently. This paper aims to design a real, applicable system based on the proposed model that can adapt automatically to the preferences of a learner depending on the learner's knowledge and LS. The proposed model can identify LS automatically into sixteen groups through their conduct in the e-learning course using the ULearn questionnaire and FCM. Computing the knowledge of a learner can be done through the first test and finished after the second test training. Capturing the learning behavior of a learner was from the log file. The learning object time has been calculated due to the total time spent. At that moment, old LS from the questionnaire and total time spent are used in these sequences as the AFCM algorithm input data. This approach has been tested by conducting two tests as being applied in an English course. The results show that the performance of using the proposed Model (AFCM) in the second test is much better. The overall performance of the proposed model is 88.7% at the second test, and the number of learners with elementary-level to 12.05 % of total students (30 out of 249 students). The main limitation for E-learning systems is the responsiveness period during online learning was shorter than the responsiveness period during the physical lectures which will be handling in the future work to increase the overall performance of the proposed model.

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APPENDIX:

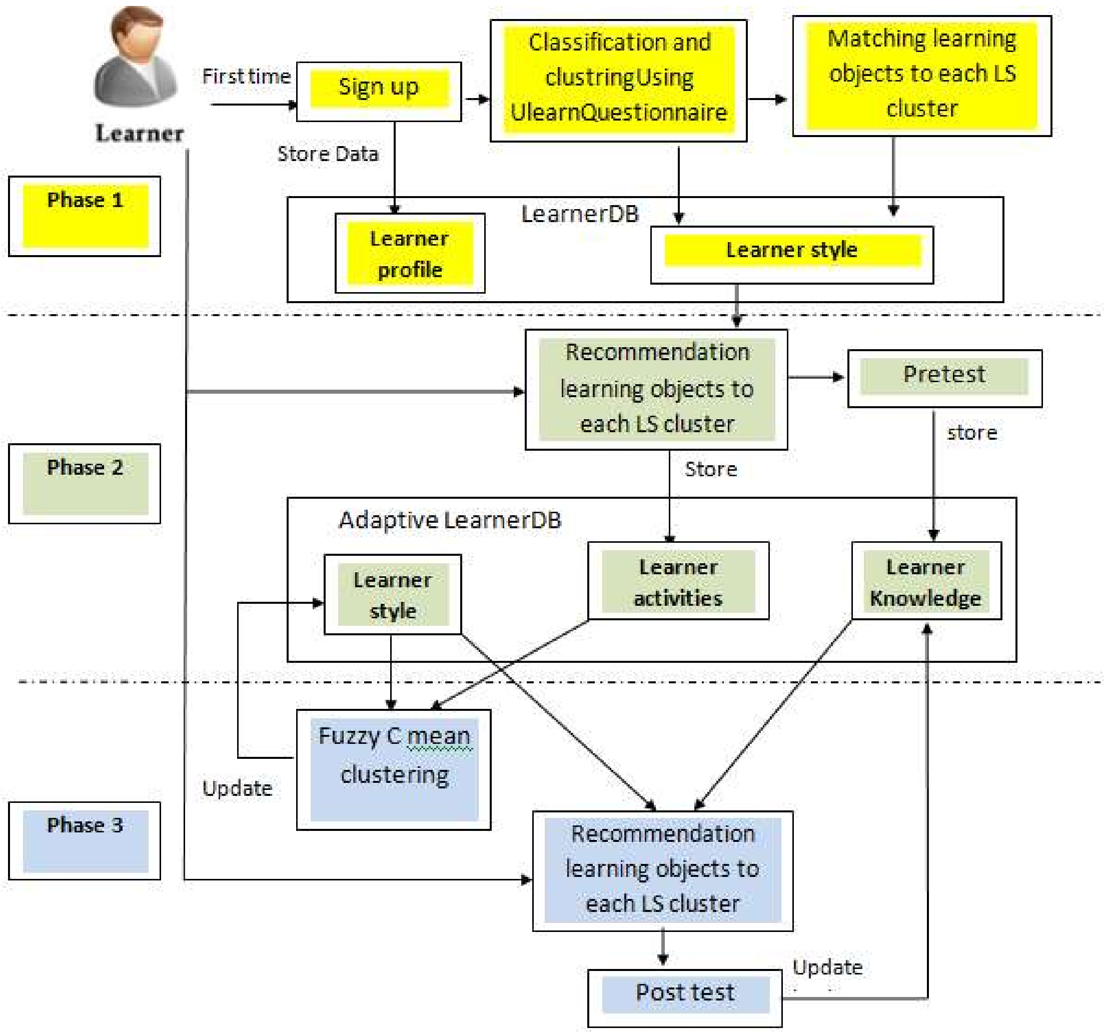

Figure 3: LS Identification Frame work

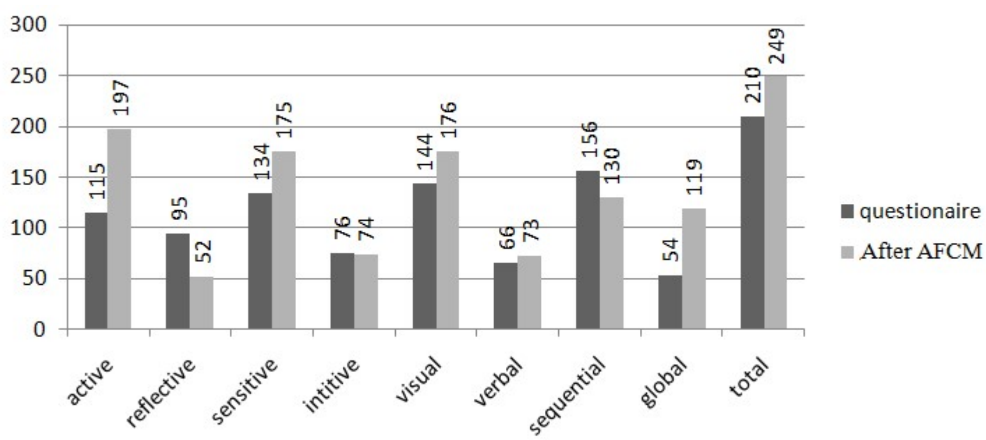

Figure8: the number of learners at all dimensions using a questionnaire or AFCM model

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Table 3 the 16 learning style combinations after cleaning

Cluster ID	Cluster meaning	Videos	PPTs	Demo	Exercise	PDFs	References	Examples	Topic list	Images	Announcements	Assignments	Sequential
C1	R,I,Ve,G	Y	Y	N	Y	Y	Y	N	Y	N	Y	Y	N
C2	A-I-Ve-G	Y	Y	Y	Y	Y	Y	N	Y	N	Y	Y	N
C3	R-S-Ve-G	Y	Y	N	Y	Y	Y	Y	Y	N	Y	Y	N
C4	A-S-Ve-G	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N
C5	R-I-Vi-G	Y	Y	N	Y	Y	Y	N	Y	Y	Y	Y	N
C6	A-I-Vi-G	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y	N
C7	R-S-Vi-G	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N
C8	A-S-Vi-G	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N
C9	R-I-Vel-Seq	Y	Y	N	Y	Y	Y	N	N	N	Y	Y	Y
C10	A-I-Ve-Seq	Y	Y	Y	Y	Y	Y	N	N	N	Y	Y	Y
C11	R-S-Ve-Seq	Y	Y	N	Y	Y	Y	Y	N	N	Y	Y	Y
C 12	A-S-Ve-Seq	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y
C13	R-I-Vi-Seq	Y	Y	N	Y	Y	Y	N	N	Y	Y	Y	Y
C14	A-I-Vi-Seq	Y	Y	Y	Y	Y	Y	N	N	Y	N	Y	Y
C15	R-S-Vi-Seq	Y	Y	N	Y	Y	Y	Y	N	Y	Y	Y	Y
C16	A-S-Vi-Seq	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y