Design of a Neurofuzzy-based Model for Active and Collaborative Online Learning

Agbonifo, O. Catherine[1*], Adewale, O. Sunday[1] and Alese, B. Kayode[1]
[1]Department of Computer Science, Federal University of Technology, Akure, Nigeria

***Correpondence Author:**

Agbonifo, O. Catherine
montoyaan@yahoo.com

Abstract

An e-learning model that adapts instructional content to individual learning differences and creates new assessment parameters such as *studylevel, reviewstudylevel, collabotivelevel, assignments and finalexam* for a focused and improved study performance is proposed in this paper. The model was adopted from Honey and Mumford model learning style questionnaire with four classes (*activist, pragmatist, theorist and reflector*) which was used to determine the learners' learning preference and matched with the appropriate content presentation. Fuzzy c-means clustering technique was used to analyze the learners' responses stored in the learner profile database to obtain the degree at which learners belong to each of the four classes. The highest degree of membership value was selected among the four classes as the most acceptable pattern of learning for individual learner. The result of the analysis showed classification accuracy in the ratio of 96%:4% on the fifty learners' data collected. Furthermore, the learners' responses from assessment parameters as they gainfully engaged with learning process were obtained in form of *studylevel*, *reveiewstudylevel*, *collabotivelevel*, *assignments* and *finalexam* and stored in leaner profile database. The values of the assessment parameters of each learner were fed into neurofuzzy-based network where fuzzy logic technique was performed on a four-layer network. The stages are fuzzification of the input variables, realization of fuzzy relations and rule evaluation, fuzzy aggregation of the rule outputs and defuzzification. These were used to determine the learners learning capability. The results obtained from the implementation of this model showed that the varied learning rate of 0.05, 0.10, 0.15 and 0.20 has the best network classification performance of 97% at 0.05. The tools used for the implementation of this model include MySQL, PHP, HTML and Java.

Keywords: instructional content, individual learning differences, fuzzy c-means clustering, neurofuzzy based network, assessment parameters

Introduction

Education is the foundation upon which a free and just society is built. All the societies with varied groups of individuals acquire and exchange ideas, skills and values in their day-to-day life supporting interactions. It is necessary for a society to adopt suitable ways and means of satisfying the basic needs of mankind and resolving emerging problems in the course of their productive activities and relationships. To cope with the changing realities and uncertainties of human life, effective teaching and learning techniques with emphasis on educational technology should be systematically exposed to all and sundry as means to acquire relevant knowledge, and skills (Oyekan, 2000).

Educational system has been in existence over thousands of years before the advent of information technology era as supportive mechanism. Education is concerned with creating the kinds of experiences that will be productive and produce healthy people. The purpose of education is to build learning communities that bring moral into teaching and reconnect teachers with their fundamental purpose of making a difference in young people's lives and changing the quality of relationships throughout the system. Education is now focusing on the needs to foster lifelong learning, to transform the value place on what is already know, and to create new ideas for dialog, reflection and contextual applications of learning in the real world (Agbonifo, 2005).

The emergence of Information Technology (IT) has transformed the educational system from classroom education, which is also known as face-to-face learning; to the integration of technology into education to achieve high quality of teaching and learning. Before the advent of IT, educational perspective tends towards teacher-centred approach with teachers doing most of the talking and intellectual work while students are passive recipient of the information provided. This is not to indicate that the traditional lecture method is without value as it allows the teacher to convey lots of information to students and is a useful strategy for recall or note learning. However, it is not the most effective way to help students develop and use higher order cognitive skills to solve complex real world problems. As noted by Driscoll (1994), learner can no longer be viewed as "empty vessels" wanting to be filled, but rather as active organisms seeking meaning.

With respect to IT, there is a gradual shift from teacher-centred to learner-centred approach to education. The roles of teachers and students were changed dramatically. The employment of IT's potentials in the development of pedagogy objectives has opened unprecedented opportunities in enhancing the delivery of quality education independent of time, location and distance. This has made the educational institutions, public and private companies/industries to embark in the deployment of IT tools to design their educational products in order to compete effectively with the global market.

In the past, most of the e-learning applications are mostly developed to deliver educational materials to target a wide range of audience regardless of their background knowledge, interests, goals, learning styles and preferences. The focal point has been towards technology-centric rather than user-centric. Many existing e-learning systems are not taking advantage of the resources and power of the Internet and e-learning content are merely a replication of traditional learning contents. The e-learning evolving produces such term as personalization, adaptive or individualized instruction – learning environments that adapt to the changes or needs of the user to achieve learning objectives. This has become the growing concern and one of the most important requirements for successful student learning in the field of e-learning technology (Fang et al., 2007). The importance of personalization has been demonstrated by research endeavor in different areas, where individual differences such as prior knowledge, learning needs, the diversity of learning styles and learning goals provide a significant support for successful personalization. The close links between personalization and learning style are often seen by many researchers. O'Connor (1997) argued that students could learn best when their learning can be performed in the modalities which are in accordance with their learning styles. Federico (2000) also stated that an understanding of learning styles can improve the instructional procedures and strategies that are accommodated to students' preferences in order to enhance their learning, retrieval and retention. Furthermore, it is suggested that the learning style is the preferred and most effective way students process and acquire the instructional information. It is also one of the valuable resources which need to be utilized for personalizing the e-learning (Piombo et al., 2003).

The trend of e-learning technology evolution shows that the current learning environments have not absolutely deployed the potential of technological tools that would have accommodated the learning theories and styles that would reflect high personalization, collaboration and successful student learning.

Therefore, this paper proposes a new e-learning model that adapts instructional content to individual learning styles and preferences; new assessment parameters into the e-learning model for focused and improved study performance. This would allow for active participation and interaction on the part of learners engaging in the virtual educational community to take control of the learning.

Related Works

The field of e-learning technology has greatly revolutionized and improved the educational systems from classroom education to online delivery of courses. Nonetheless, numerous studies have been carried out that revealed the difficulties detected in the first wave of online learning environments. In fact, the general view is that there are few so called best practices (Bonk, 2002). The development of online learning environments, which emerged in diversified forms with varied notations according to instructional designers, has also been characterized with disappointments and frustration on the part of learners, which brought about high dropout rate on online courses. This is mainly because the traditional mode of instruction (one-size-fits-all approach) which exists in classroom education is being reproduced in the conventional educational technology where the same content is transmitted to all in the same manner and learners find it difficult to access and learn the content in their preferred way.

Several studies revealed other issues stating that education has not yet realized the full potential of the employment of IT, that the conventional educational technology with respect to traditional mode of instruction cannot fully accommodate the different learning and studying styles and preferences of diverse learners (Karagiannidis & Sampson, 2004). Several attempts have been made by instructional designers to develop learning environments in which the instruction could match individual preferred way of learning, but it was discovered that adaptive procedures have been mostly unsystematic and primitive (Wang, 1980). Instructional developers have failed to incorporate many valuable learning principles and instructional strategies invented by researchers and educators with emerging technology (Tennyson & Christensen, 1988). Psychometric measures of learner cognitive abilities could not be obtained due to improper built-in modality of assessment valuators within the learning context (Byrnes & Ellis, 2006; Khare & Lam, 2008). Assessment and grading remain fairly open and unresolved area of e-learning for instructors who want to embed constructivist and learner-centered activities into their online courses. Many online instructors are satisfied with traditional examinations and proctored or controlled testing centers while others are anxious about any Web-based testing and evaluation (Curtis et al., 2004).

Wolf (2002) proposed iWeaver, an interactive web-based adaptive learning environment. iWeaver uses the Dunn and Dunn learning style model and the Building Excellence Survey as assessment tool to diagnose a student’s learning preferences. Instead of focusing on student’s learning preferences and to match contents to learner learning style, iWeaver offers and encourages the trial of different media representations. The system does not adapt to the changes of the learner preferences. Agbonifo (2005) also developed a collaborative and distance education system for Nigerian students due to the increasing demand for university education especially for those who are qualified but could not get admission due to lack of facilities, enabling environment and shortage of personnel that exist in the conventional Nigerian universities. The mode of instructional strategy and content presentation was still one-size-fits-all approach, not tailored to individual learner preferences.

Adewale (2007) described extensively some of the well-known learning theories, styles, preferences and approaches as revealed in the fields of education and psychology. The author presented the model of the learning environment in which the Honey and Mumford learning styles was adopted for the educational presentation of content based on learner characteristics. Though, the implementation and evaluation of the model were not carried out to ascertain its performance, but it could be observed from the model that in the respect of determining what would be the likely learning preference, it could only be obtained using primitive technique that is not based on computational intelligence. Khairil and Nor (2010) proposed a new e-learning recommender system framework that used content-based filtering and good learners ratings to identify the most interesting and relevant learning items from a large number of items. Since the ratings of items by good learners had significant effect on the possible items to be recommended by the system, but this would also pose a challenge in cases where the system could not calculate or predict the good learners' ratings for such items because the good learners' ratings are unavailable.

Gbolami et al (2011) developed a virtual collaborative learning that used the wikis technology. The system was evaluated base on how students were engaged in the process of peer collaboration and interaction with other fellows through the use of collaborative space-wikis and how they perceived instructor support in these processes. According to authors' findings from data gathered through questionnaire, semi-structured interviews, focus group and a reflection journal suggested that the students perceived the learning conditions in Wiki with high quality including support from instructor, collaboration, and self-regulation activities. Even though, the system was developed on the basis of mediating collaborative activities which focused on self-regulating control on the part of learners. The choice of individualized active learning that is motivated through the provision of instructional design principles such as learning theories and learning styles models is not taking into consideration.

Frick & Ramm (2011) developed a prototype of online self-assessment system that assists prospective students on the selection of course of study. This was used for the bachelor program "Computer Sciences in Media" at the University of Applied Sciences in Osnabrueck. The authors discussed that several studies investigated, discovered many factors that contributed to the high dropout rate in the course of study such as: performance problems, financial problems, lack of motivation, study conditions, failing exams, career change, family problems and disease. The evaluation of the prototype showed that it allayed misconceptions and false expectations and in addition, reduced the amount of dropouts. Nonetheless, the authors developed a system that matched the prospective students to the likely possible course of study on the basis of certain characteristic features that influenced the choice of selection process. But the aspect of sequencing the curriculum of the courses in the field of study to match individualized preferred way of learning was not incorporated in the system.

Rahimi et al (2013) proposed a framework to build web 2.0-based personal learning environments by combining the main elements of the students' control and the components of technology-based teaching process to enhance learning activities. The framework was not implemented to test the efficiency of the designed objective. Zhou (2013) proposed a model for utilizing an assisted personal learning environment (PLE) for middle school students to practice self-regulated learning. The author's model was based on the general reflection characteristics of PLE such as learner control, multiple formatting of educational materials/resources, etc. The model was not tested and evaluated to ascertain its performance.

System Design

The architecture of the system is shown in Figure 1 which consists of components which performs the functions of personalizing learning materials to meet individual learner's learning requirements. The access portal, pre-test selection of learning objects are functions that allow learners to interact with the system by giving or obtaining information through their use. The system builds a learner profile based on the learner information supplied through the user interface to enable the system to acquire and match his learning behaviour and preference that is appropriate for the learning material to achieve the learning objectives. There were eighty questions to identify the individual learner styles for formulating the parameters for the optimization algorithms using fuzzy c-means clustering technique for matching pattern or service. This technique classified learner into these four classes (Activist, Reflector, Theorist, Pragmatist) according to Honey and Mumford learning style model used in this research which is commonly used in the field of education compare to other models (Honey & Mumford, 2000; Coffield et al., 2004). The outcome of the analysis allows each learner to place higher priority on his strong learning preference, there is possibility of learners developing their weaker learning styles. The learners' responses are obtained as they engaged in the learning process of presentation of concepts path through learner concepts processes. The learner concepts processes are represented with various assessment parameters such as *studylevel, reviewstudylevel, collabotivelevel, assignments and finalexam.* The neurofuzzy inference engine is used as reasoning processes based on values of assessment parameters to infer learning capability.

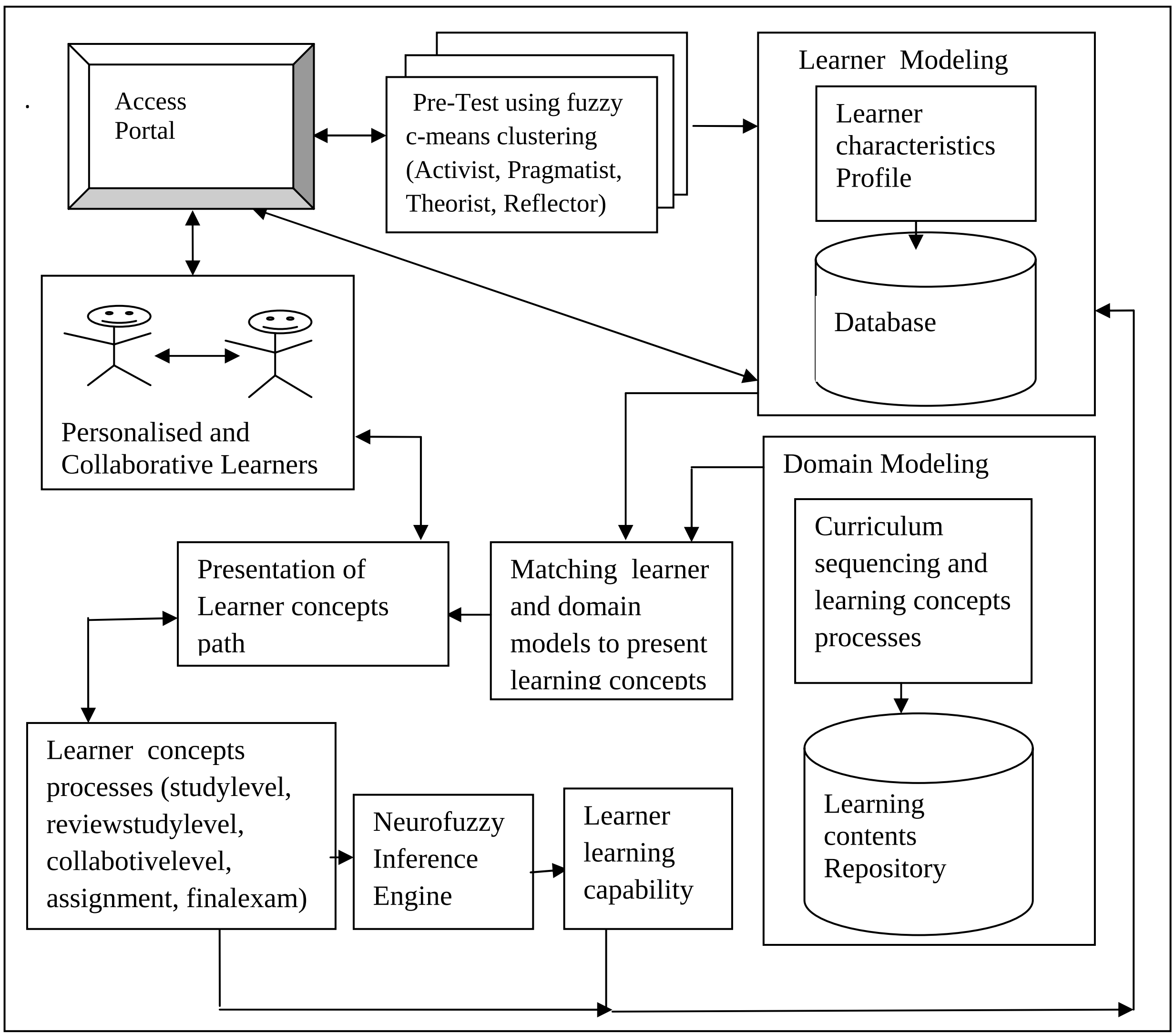

Figure 1: The architecture of active and collaborative online learning

Pre-Test: Modeling Questionnaire for Knowledge Representation

Each question item describes a feature x of the personality of a learner ls, in which the eighty questions ran through, selecting features that uniquely classify them into four different personalities. The technique adopted for classification of feature selection into four groups of individual learning style is fuzzy-c-means clustering. This is shown as

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}^{m}\left\|X_i - C_j\right\|^2 \qquad 1 \leq m \leq \infty \tag{1}$$

$$\sum_{j=1}^{c}\mu_{ij} = 1 \ \forall\, j = 1, \ldots, c;\, i = 1, \ldots, n \tag{2}$$

$$\mu_{ij} = \frac{1}{\sum_{j,k=1}^{c}\left[\frac{\left\|X_i - C_j\right\|}{\left\|X_i - C_k\right\|}\right]^{\frac{2}{n-1}}} \ \forall i = 1, \ldots, n;\, j,k = 1, \ldots, c \tag{3}$$

$$C_j = \frac{\sum_{i=1}^{N}\mu_{ij}{}^{m}.X_i}{\sum_{i=1}^{N}\mu_{ij}{}^{m}} \tag{4}$$

where input feature parameters are denoted as vector data sets $x_1, x_2, \ldots\ldots\ldots\ldots x_N$, which are in form of objects-attributes relation where objects denote the respondents and attributes are set of questions the learners respond to with option selection type expresses in linguistic terms of four point-likert scale: totally agree (4), partially agree (3), totally disagree (2) and partially disagree (1); attributes are the set of questions that learners respond to; m = 2, for each datum x_i, μ_{ij} is a coefficient denoting the degree of being in the *jth* cluster, the cluster is partition into four groups, $C_j = 1,2,3,4$. The sum of those coefficients is defined to be 1 as shown in equation 2. x_i is the *ith* of d-dimensional feature measured data, c_j is the d-dimension cluster of centroid. $\|*\|$ is any norm expressing the similarity between the feature measured data and the cluster centroid (i.e the Euclidean distance which is the distance between feature measured data and the cluster centroid). Fuzzy partition is carried out through iterative optimization of objective function J_m in equation (1), with updated membership function μ_{ij} and cluster centroid c_j in equations (3) and (4).The iteration will stop when $\max_{ij}\left\{\left|\mu_{ij}{}^{(t+1)} - \mu_{ij}{}^{(t)}\right|\right\} < \varepsilon$ where ε is the termination criterion and t are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m. It would be inferred at this point that the highest degree of membership the individual learner is associated with between the classes of groups is the actual class of group the learner belongs to.

Therefore, the completion of the process of classification uniquely identify the learners ls, based on the attributes x into classes $C_j = 1,2,3,4$ as represented in equation 5.

$$ls_{i,\ x} \in C_j \tag{5}$$

where $i = 1\ldots m$ is the total number of learners that interacted and responded to the questions at a certain period of time; x = 1…..n is the total number of attributes; $j = 1,2,3,4$ (j is the number of classes the learners are grouped into).

Domain Modeling: Curriculum Sequencing and Learning Concepts Processes

Curriculum sequencing provides a learner, ls with the most suitable individualized sequence of knowledge units to learn, with a sequence of learning tasks such as examples, questions and problems (Brusilovsky, 1998). The curriculum sequencing as depicted in Figure 2 using knowledge tree contains the construction of course materials and domain concepts with link relationships that form concept networks.

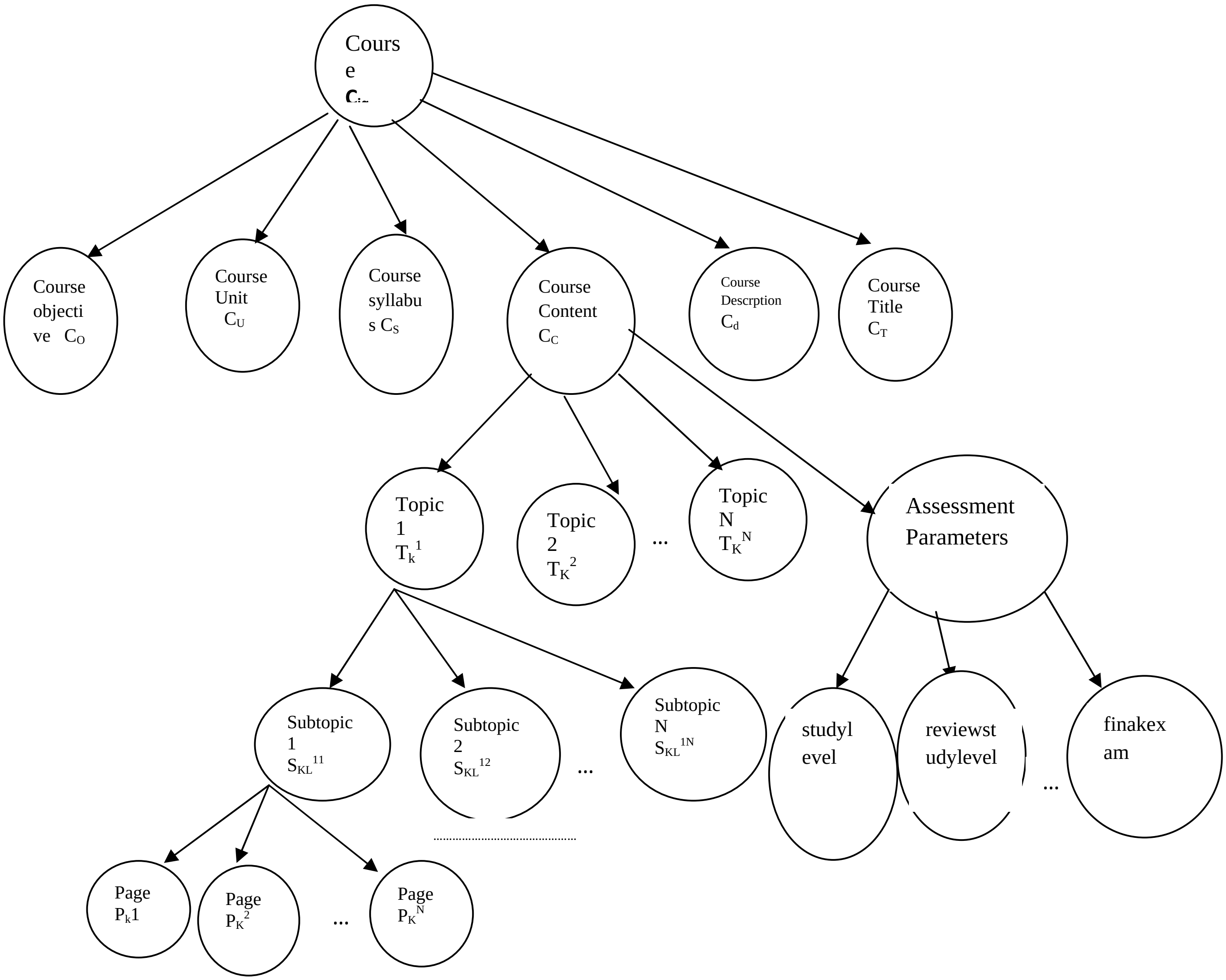

Figure 2: Curriculum hierarchical tree-structure of a domain
Source: Adewale & Agbonifo (2007)

Let C_{iq}, be courses to be learned by the learners where i =1, 2, 3, 4, 5 (current year of study) and q = 1, 3, 5,… first semester or q = 2, 4, 6, … second semester (l is the course number registered for the session). C_{iq} referred to as $M_j(t)$ that denotes the same material structured into jth instructional materials according to equation 5 and covers a semester of curriculum that the learner must complete and prove a level of mastering within a given function timeline, *t*. Let $T_k \subseteq C_{iq}$ and $S_{kl} \subseteq T_k$ where $k, l = 1,2,3,\ldots$ represent several topics and subtopics to cover. The page p_k of T_k and S_{kl} also denotes the concepts presented to the learners to learn. Each page p_k is modeled using learning objects with metadata scheme.

C_{iq} is disassembled into curriculum elements such as course title, unit, objective, syllabus, description, course content and assessment which are represented by the second level nodes of course tree structure, course content constitutes topics T_k and subtopics S_{kl} represented by the third and fourth level nodes of the course tree structure while the page p_k is represented by the lowest level nodes which denotes different multiple pages of T_k and S_{kl} that are presented to the learners based on their learner model.

From the above description, the following representations are given for domain modeling (teaching strategy) to suit individual learning characteristics in order to obtain learning concepts processes:

The matching of learner identification with appropriate content presentation is given as:

$$ls_{i,\ X} \in C_j \to M_j(t) \tag{6}$$

The left hand side of equation 6 is matched to a particular learning material M_j of C_{iq} which is a function of timeline, t associated with each p_k with a weighted range *[0,1]*, structured into concepts path presentations based on classes of learners C_j.

The description of accessing point to the learning material C_{il} into M_j synchronized with timeline *t* (associated with weights) based on C_j is through page p_k the last node in the hierarchical course tree structuring in Figure 2 is given as (Adewale & Agbonifo, 2007):

$$\left[P_k \subseteq S_{k,l} \subseteq T_k\right] \in M_j(t) \tag{7}$$

$$P_k(t) = \begin{cases} 1.00\ for\ 7mins \le P_k \le 10mins \\ 0.75\ for\ 5mins\ \le P_k \le 6mins \\ 0.50\ for\ 3mins\ \le P_k \le 4mins \\ 0.25\ for 1\ \text{min} \le P_k\ \le 2mins \\ 0.00\ for\ P_k < 1\ \text{min} \end{cases} \tag{8}$$

The description of the learning process in terms of *studylevel* of the individual learner within the group as relates to the learning material M_j. The *studylevel* is determined by finding summation of each page visited with associated weighted value for the time taken to study each page is given as.

$$ls_{i,\ X}(studylevel) = \sum_{k=1}^{N} P_k\ (t) \tag{9}$$

where i is the *ith* individual learner that interacted and responded to the learning material base on classification; X = is the learner attributes for learner category type; *k* is the number of pages in the learning material the learner goes through in studying, $P_k(t)$ is a function that returns the time taken to study each page with a weighted value as in equation 8.

The description of the learning process in terms of *reviewstudylevel* of the individual learner within the group as relates to the learning material M_j. It signifies number of times n_k revisiting some or all pages (concepts) especially in the course of solving problems, which is having causal-effect of gradual decaying weight value associating P_k with timeline t in equation 10 as given in equation 11:

$$P_k(t) = \begin{cases} 0.100\ for\ 7mins \le P_k \le 10mins \\ 0.075\ for\ 5mins\ \le P_k \le 6mins \\ 0.050\ for\ 3mins\ \le P_k \le 4mins \\ 0.025\ for 1\min \le P_k\ \le 2mins \\ 0.010\ for\ P_k < 1\min \end{cases} \quad (10)$$

$$ls_{i,\ X}(reviewstudylevel) = \sum_{k=1}^{N} \left(n_k\ .P_k(t)\right) \quad (11)$$

The description of the learning process in terms of assignments of the individual learner within the group as relates to the learning material M_j is given in equation 12:

$$ls_{i,\ X}(assignments) = F\left(Prob_{i,\ n}, Sol_{i,\ n}, \leftarrow P_k\right) \quad (12)$$

where F is the function that returns the cumulative score of the assignments of the *ith* individual learner to the *nth* number of problems attempted with the solution submission within a given page P_k.

The description of the learning process in terms of *collabotivelevel* of the *ith* individual learner within the group as relates to the learning material M_j is given in equation 13:

$$ls_{i,\ X}(collabotivelevel) = \left[ls_{i,x} \Rightarrow \left[\left(G_{n,j}\ \varepsilon\ C_j\right), Prob_{n,j}, Sol_{n,j}\right]\right] \quad n\ \varepsilon\ i \ \text{ where } G_{n,j} = \begin{cases} 0 & \text{if } ls_{\text{i,x}} \text{ MOD 5} \\ 1 & otherwise \end{cases} \quad (13)$$

where *n* is a member of *i* and is the number of groups formation with membership number 5 that depends on dividing the total number $ls_{i,x}$ in a particular C_j with MOD 5 that returns zero (0) if it is divisible and if returns one (1), group number will increase with the number of remainder to form another group member. The equation 13 returns the collabotivelevel score of an individual in a particular group of the learner category type. This demonstrates the level of learner's participation in contributing Sol to the problem posted Prob to the discussion group.

The description of the learning process in terms of *finalexam* of the individual learner within the group as relates to the learning material M_j is given in equation 14:

$$ls_{i,\ X}(finalexam) = R\left(Prob_{i,\ n}, Sol_{i,\ n}, \leftarrow P_k\right) \quad (14)$$

where R is the function that returns the score of the *finalexam* of the *ith* individual learner to the *nth* number of problems attempted with the solution submission within a given page P_k. The problems are in form of multiple choice questions, theory and fill in the blanks.

Learner Modeling: Learner Characteristics Profile

The architecture of the system in Figure 1 shows that the system maintains learner profile in the database. This is set of learner parameters that are captured at the initial learner login to the system which is stored as learner information in the database. Such learner information are: name, address, sex, age, background knowledge and responses obtained through the learners' interaction to the questionnaire which is used to determine learner preference type. As learner goes through the learning material presented to him based on the learner preference type, the system dynamically construct information that relates to learner's studylevel, reviewstudylevel, collabotivelevel, assignments, finalexam and overall performance.

Neural Network and Fuzzy Logic Approach for Modeling Learner Learning Capability

The technique to model learner learning capability is based on using neural network with fuzzy logic. Neural networks are trained to imitate human tutor's decisions regarding learner's characteristics and fixed weight neural networks are used to evaluate and aggregate membership functions. The network is trained with multivariate fuzzy input set (learner characteristics) and associated weights which are used to determine the learner learning capability (overall performance).

Fuzzy Logic based approach

Fuzzy logic techniques are used to provide human-like approximate diagnosis of learner's knowledge and learning concepts capability. It can be used to solve real world problems that involve human reasoning in making decision, evaluation and judgment. The learner information characteristics denoted as studylevel, reviewstudylevel, collabotivelevel, assignments and finalexam represent the fuzzy input variables that are described as attributes with values that are used to determine learner learning concepts capability (overall performance). The learner characteristics are defined as a set of quintuple as follows:

$$overall\ performance = \{studylevel, reviewstudylevel, collabotivelevel, assignments, finalexam\} \quad (15)$$

Each of the variables is defined with a trapezoidal membership function with which it belongs to a fuzzy set as follows:

The *studylevel* and *assignments* variables have membership function represented by linguistic terms such as [excellent, very good, good, average, poor] as depicted in Figure 3.

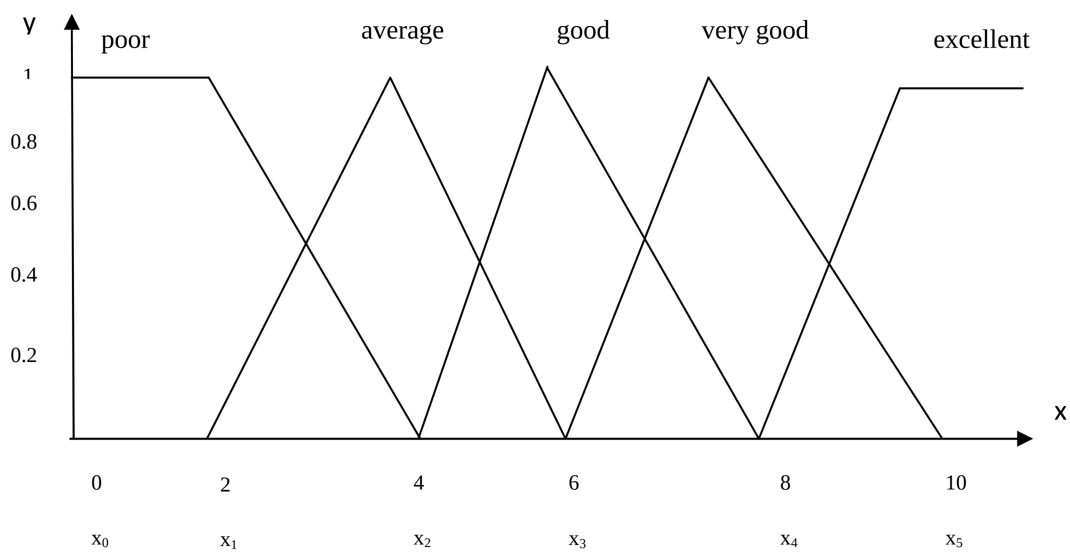

Figure 3: Graph of membership function (MF) for a given fuzzy variable (studylevel and assignments)

The *reviewstudylevel* variable has membership function represented by linguistic terms such as [no review, review, less review, more review, frequent review] as depicted in Figure 4.

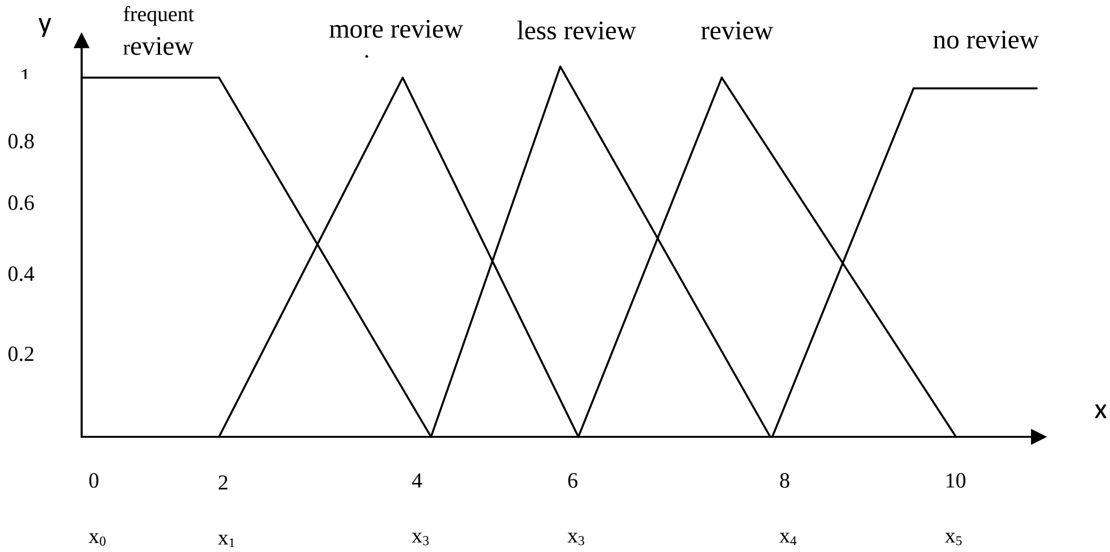

Figure 4: Graph of Membership function (MF) for fuzzy variable (reviewstudylevel)

The *collabotivelevel* variable has membership function represented by linguistic terms such as [highly collaborative, highly less collaborative, collaborative, less collaborative, no collaborative] as depicted in Figure 5.

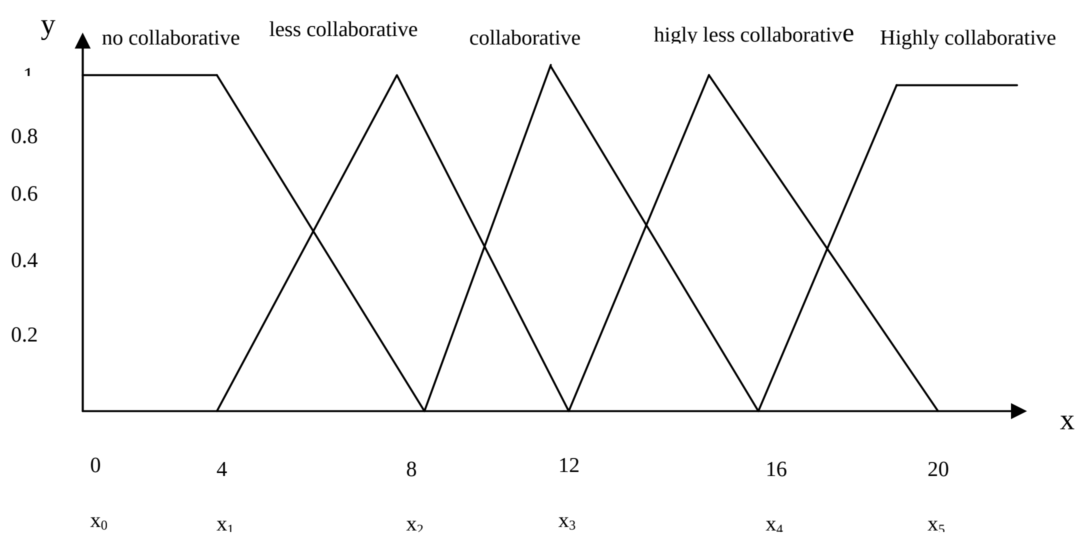

Figure 5: Graph of Membership function (MF) for a given fuzzy variable (collabotivelevel)

The *finalexam* and *overall performance* variables have membership functions represented by linguistic terms such as [excellent, very good, good, average, poor]. The *finalexam* has range values between 0%-50% that span through its linguistic terms and *overall performance (learning capability)* has range values between 0%-100% that span through its linguistic terms.

The example of mathematical representation of membership functions (poor, frequent review, no collaborative) in Figures 3, 4 and 5 can be described as in equation 16.

$$y^{poor\,/\,frequent\ review\,/\,no\ collaborative}(x; x_0, x_1, x_2) = \max\left(\min\left(\frac{x - x_0}{x_1 - x_0}, \frac{x_2 - x}{x_2 - x_1}\right), 0\right) \tag{16}$$

Neural Network-based approach

The combined features of neural network and fuzzy logic are used to model learner learning capability. It operates with the principle of performing fuzzy logic on neural network with the following stages: fuzzification of the input variables; realizing fuzzy relations and rule evaluation, fuzzy aggregation of the rule outputs and defuzzification. The neurofuzzy network structure used in this research is four-layer architecture as shown in Figure 6 consists of input layers, hidden layer and output layer.

The information on learner characteristics serve as fuzzy input variables (*studylevel, reviewstudylevel, collabotivelevel, assignments and finalexam*) with fuzzy values (excellent, very good, good, average, poor) determined by the membership function i.e the degree to which the values of fuzzy variables belong to the sets. The network is trained using at the input layers the multivariate fuzzy input variables with the associated weights W_k. The weights are interconnects between nodes of one layer to another. The network structure directly maps the weights of input layers into the required membership functions. Here, pseudo-trapezoidal shape for the membership function is used which can be calculated by the fixed weight neural networks.

The hidden layer forms the basis of realising fuzzy relations and fuzzy aggregation network operated with minimum composition to produce the generation of final fuzzy set using fuzzy rule base (knowledge drawn from the experts). The type of fuzzy relational realised is in rule based structure where the IF…THEN rules relate fuzzy inputs to fuzzy outputs in this form:

$$X_k \circ RE_{kc} = Y_c \tag{17}$$

where k is the kind of learner information characteristic and c is the learner learning capability. X_k is the learner observed characteristic from the set {excellent, very good, good, average, poor} or {no review, review, less review, more review, frequent review} or {highly collaborative, highly less collaborative, less collaborative, collaborative, no collaborative}; RE_{kc} is defined as (number of input nodes × number of output nodes) matrix representing the estimations of human tutor (expert knowledge) to the degree of association between an observed response and learner characteristic; $\circ$ is the min-max composition operator and Y_c is the fuzzy output of the learner characteristics which is learner learning capability.

Fuzzy rules grow exponential with the increase in the number of fuzzy sets and the number of input variables. Such a number makes the interaction between a model and system designer impossible. Therefore, reasoning rules for this research were extracted base on learning rule. This is because tutor's reasoning cannot be exactly described but is available in the form of case labeled patterns of learners' observable characteristic through which rules are extracted (rules are learned by the network). It is assumed that connection weights are symmetric and fixed at1 between the hidden and output layers. The activation function of the learning rules at the hidden layer that determines the firing strength threshold of the rules that satisfies finding each pattern in the dataset that classifies the fuzzified inputs as Y_c, is defined in equation 18 using the unit sum method.

$$A_{x_i w_j} = \frac{\sum_{i,j} W_{x_i w_j} Y_c}{N} \geq \varphi \tag{18}$$

where $A_{x_i w_j}$ is the minimum of the membership values from its antecedents of the rule that classifies them as Y_c within a threshold value φ of the learning rate, N is the number of data set.

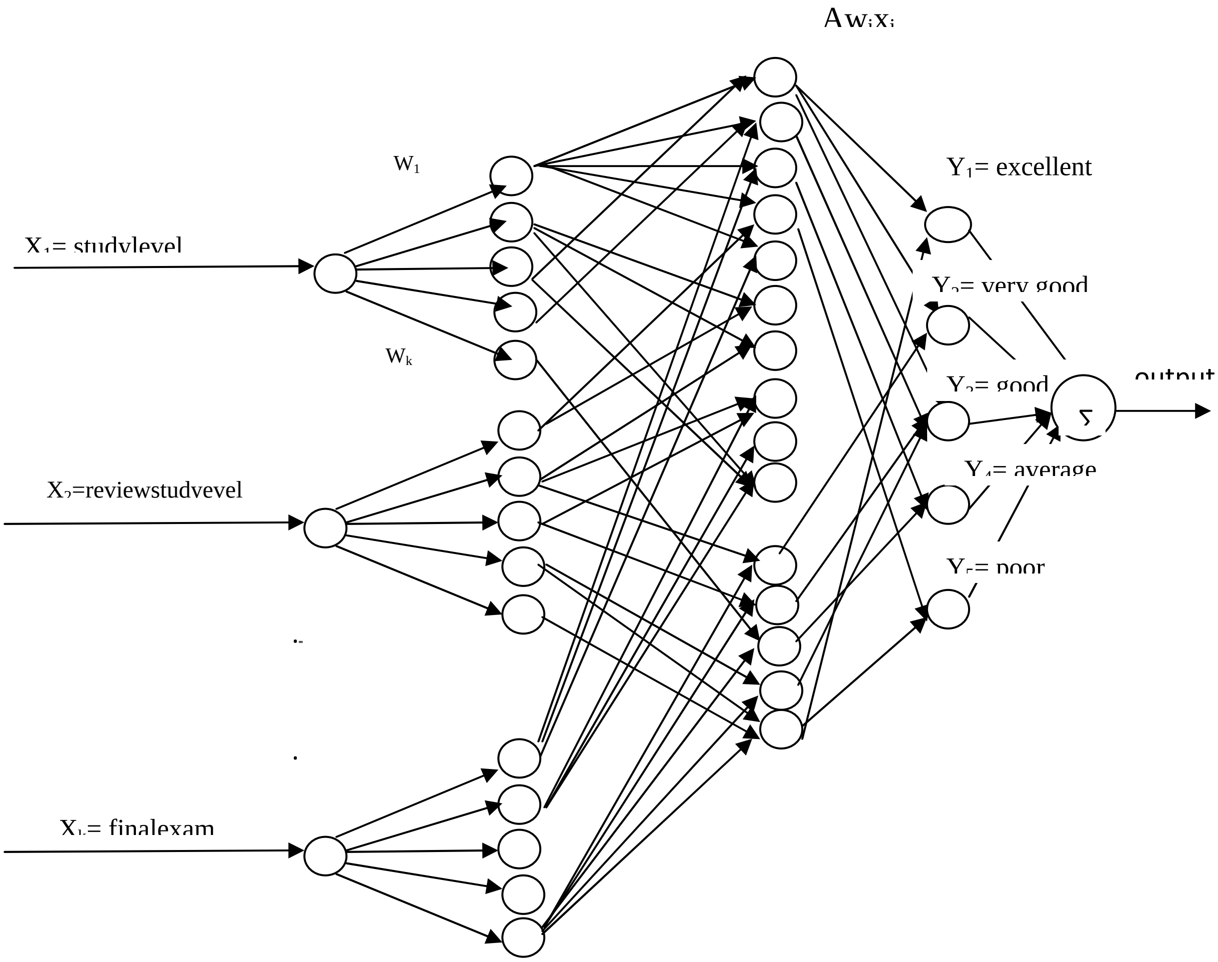

Figure 6. Neurofuzzy architecture for Learner's learning capability

Then, the activation values of all the consequents part at the level of truth value of the antecedents part of the fuzzy rules were aggregated as in equations 19 and 20 using union (maximum) operator because it allows all the fuzzy outputs of a specific characteristic to contribute to the final fuzzy set (Panagiotou et al., 1994).

$$output_{aggregated} : Input_{hidden} \rightarrow A_{x_i w_j} = [Y_1, Y_2, \dots, Y_k] \quad (19)$$

$$Max[Y_1, Y_2, \dots, Y_k] = Y_c \quad (20)$$

The output layer forms the basis in which the fuzzy defuzzification process takes place. The defuzzification allows the creation of non-fuzzy assessments of learner's characteristics. The aggregated output was defuzzified which is a process of arriving at a single number using mean of maxima (MOM) as obtained from:

$$U = \sum_{i=1}^{R} \mu_i / R \quad (21)$$

where μ_i is the result of applying OR or union operation on all the rule outputs and R is the membership function under consideration. The output value of the output layer is the mean of activation values of all rule units it is connected to.

Example of Reasoning Rules of the Neurofuzzy Inference Engine

The following are some of the reasoning rules of the neurofuzzy inference engine to determine the learning capability of the learner:

RULE 1: IF studylevel=excellent and reviewstudylevel = no review and collabotivelevel = highly collaborativ) and assignments=excellent and finalexam = excellent THEN overall performance = excellent

RULE 2: IF studylevel = very good and reviewstudylevel = review and collabotivelevel = highly less collaborative and assignments=very good and finalexam = very good THEN overall performance = very good

RULE 3: IF studylevel = good and reviewstudylevel = less review and collabotivelevel = less collaborative and assignments=good and finalexam = good THEN overall performance = good

RULE 4: IF studylevel = average and reviewstudylevel = more review and collabotivelevel = collaborative and assignments= average) and (finalexam = average) THEN (overall performance = average)

RULE 5: IF studylevel = poor and reviewstudylevel = frequently review and collabotivelevel = no collaborative and assignments= poor and finalexam = poor THEN overall performance = poor

RULE 6: IF studylevel = excellent and reviewstudylevel = no review) and collabotivelevel = highly collaborative and assignments= excellent and finalexam = very good THEN overall performance = excellent

RULE 7: IF studylevel = excellent and reviewstudylevel = no review and collabotivelevel = highly collaborative and assignments= excellent and finalexam = very good THEN overall performance = excellent

RULE 8: IF studylevel = excellent and reviewstudylevel = no review and collabotivelevel = highly collaborative and assignments= very good and finalexam = very good THEN overall performance = very good

RULE 9: IF studylevel = excellent and reviewstudylevel = review and collabotivelevel = highly less collaborative and assignments= very good and finalexam = very good THEN overall performance = very good

RULE 10: IF studylevel = very good and reviewstudylevel = review and collabotivelevel = highly less collaborative and assignments= very good and finalexam = average THEN overall performance = very good

Results and Discussion

Fuzzy c-means technique is used for classification of learners and to obtain a distinct clear-cut pattern of learners without compromise. This was used to run on fifty learners' data collected through online submission of filling-in of their personal data and responding to the questionnaire provided via interfaces provided. The participants (learners) used for the purpose of this research were third year students of Computer Science students of Federal University of Technology, Akure. To achieve the objective function of the algorithm relative to identifying each learner learning preference, it was observed that the algorithm ran and iterated to converge and terminate at $\varepsilon = 0.00001$ with iterate count which is equal to

3. The output of the algorithm is depicted in Table 1 and which identified each of the learners' learning preference relative to four dimensions of the Honey and Mumford model (Pragmatist, Theorist, Activist and Theorist). Table 1 shows the distribution of the learners into various learning pattern that would be appropriate for content presentation. Each learner has varied degree of membership value of belonging to each of the four dimensions and the highest value was inferred as the likely class learner could belong to. This information would be useful by the instructor to advice the learner on how to develop weak learning style.

The accuracy of this algorithm is obtained considering the total number of learners' data that are used as input and out of which the algorithm is able to uniquely identify individual into various classes s/he belongs to with the varied degree of membership values. In this research, it is observed that out of fifty learners' data collected, the algorithm could identify and classify forty eighty (96%) into their respective learning preferences (Theorist: 5, Reflector: 19, Pragmatist: 22, Activist: 2) while two (4%) could not be classify which is probably due to inconsistent input responses pattern from the those learners (Learner profile 8 and 29 in Table 1).

Table 1: Fuzzy c-means membership distribution for Learners' Learning Preference

	FUZZY C-MEANS MEMBERSHIP DISTRIBUTION				
Learner Identity	**Pragmatist**	**Theorist**	**Activist**	**Reflector**	**Strong Preference**
Learner01	0.22845	0.25877	0.19494	0.31784	Reflector
Learner02	0.27404	0.24986	0.15674	0.31937	Reflector
Learner03	0.29554	0.24200	0.19530	0.26717	Pragmatist
Learner04	0.21480	0.24872	0.16058	0.37590	Reflector
Learner05	0.27264	0.25785	0.18276	0.28675	Reflector
Learner06	0.38251	0.20310	0.15938	0.25501	Pragmatist
Learner07	0.29989	0.18929	0.18929	0.25419	Pragmatist
Learner08	1.00000	0.00000	0.00000	0.00000	**NULL**
Learner09	0.33267	0.22095	0.14730	0.29907	Pragmatist
Learner10	0.28247	0.25037	0.20276	0.26440	Pragmatist
Learner11	0.25490	0.26286	0.22734	0.25490	Theorist
Learner12	0.27130	0.21354	0.13031	0.38486	Reflector
Learner13	0.25036	0.20237	0.13567	0.41160	Reflector
Learner14	0.25230	0.29015	0.28170	0.17585	Theorist
Learner15	0.14017	0.57190	0.08936	0.19857	Theorist
Learner16	0.23579	0.27626	0.19181	0.29615	Reflector
Learner17	0.25779	0.27077	0.18632	0.28513	Reflector
Learner18	0.21745	0.29729	0.18563	0.29963	Reflector
Learner19	0.32693	0.25337	0.20406	0.21564	Pragmatist
Learner20	0.30974	0.22700	0.19381	0.26945	Pragmatist
Learner21	0.23733	0.25085	0.17307	0.33875	Reflector
Learner22	0.12131	0.12636	0.69530	0.09303	Activist
Learner23	0.32512	0.23336	0.19420	0.24732	Pragmatist
Learner24	0.26177	0.28028	0.21021	0.24775	Theorist
Learner25	0.30181	0.25151	0.18172	0.26495	Pragmatist
Learner26	0.27341	0.20920	0.12844	0.38894	Reflector
Learner27	0.24703	0.31066	0.16144	0.28087	Theorist
Learner28	0.30391	0.22932	0.21197	0.25480	Pragmatist
Learner29	0.00000	0.00000	0.00000	1.00000	**NULL**
Learner30	0.29688	0.19727	0.13568	0.37018	Reflector
Learner31	0.31645	0.24469	0.24469	0.18379	Pragmatist
Learner32	0.32996	0.21919	0.19299	0.25787	Pragmatist
Learner33	0.21698	0.28186	0.21031	0.29038	Reflector
Learner34	0.25713	0.24465	0.14823	0.34999	Reflector
Learner35	0.27541	0.27251	0.19320	0.25888	Pragmatist

Learner36	0.38603	0.20374	0.16299	0.24723	Pragmatist
Learner37	0.31236	0.20758	0.30652	0.17353	Pragmatist
Learner38	0.32990	0.23474	0.15583	0.27953	Pragmatist
Learner39	0.29696	0.22109	0.16643	0.31552	Reflector
Learner40	0.25762	0.25556	0.26185	0.22497	Activist
Learner41	0.24280	0.22345	0.14342	0.39033	Reflector
Learner42	0.36666	0.26915	0.14795	0.21624	Pragmatist
Learner43	0.29170	0.24309	0.18331	0.28190	Pragmatist
Learner44	0.29417	0.22813	0.15525	0.32245	Reflector
Learner45	0.27698	0.25140	0.14525	0.32238	Reflector
Learner46	0.29964	0.27310	0.17454	0.25472	Pragmatist
Learner47	0.22958	0.24224	0.15050	0.37868	Reflector
Learner48	0.29401	0.24048	0.21859	0.24892	Pragmatist
Learner49	0.32800	0.25185	0.23913	0.18222	Pragmatist
Learner50	0.30437	0.24243	0.18580	0.26440	Pragmatist

Learners' Learning Outcome from their Learning Concepts Processes

The curriculum sequencing of the teaching material (Introduction of Java Programming Language) was structured according to learning preference of the learners, using four dimensions of Honey and Mumford learning style. With this, thirty five students out of fifty learners that registered and enrolled to participate in this system were gainfully engaged in the learning concepts paths presentation. The following assessment parameters such as *studylevel*, *reviewstudylevel*, *collabotivelevel*, *assignments* and *finalexam* were obtained and stored in learner profile as depicted in Table 2. Through this, the system was able to infer the learners' learning outcome which forms the basis of how well the knowledge is acquired and to deduce that the requirements of learning objectives have been met.

Table 2: Learners' Learning Outcome from their Learning Concepts Processes

Learner Identity	**Learning style**	**Assessment Parameters**	**Group No/Number of collaborators**	**Learning Outcome**
Learner26	Reflector	studylevel: 10 assignmenst: 9.29 collabotivelevel: 20 reviewstudylevel: 6.92 finalexam: 22.5	1/5	68.71
Learner03	Pragmatist	studylevel: 9.62 assignments: 10 collabotivelevel: 20 reviewstudylevel: 3.33 finalexam: 22.5	1/5	65.45
Learner02	Reflector	studylevel: 9.23 assignments: 10 collabotivelevel: 20 reviewstudylevel: 7.25 finalexam: 31	1/5	77.48
Learner06	Pragmatist	studylevel: 10 assignments: 10 collabotivelevel: 0 reviewstudylevel: 6.92 finalexam: 20	1/5	46.92
Learner07	Pragmatist	studylevel: 10 assignments: 10 collabotivelevel: 0 reviewstudylevel: 6.67 finalexam: 20	1/5	46.67
Learner01	Reflector	studylevel: 9.34 assignments: 10	1/5	66.55

		collabotivelevel: 20 reviewstudylevel: 4.21 finalexam: 23		
Learner16	Reflector	studylevel: 3.04 assignments: 9.29 collabotivelevel: 20 reviewstudylevel: 4.62 finalexam: 10	1/5	46.95
Learner05	Reflector	studylevel: 10 assignments: 10 collabotivelevel: 20 reviewstudylevel: 6.67 finalexam: 30	1/5	76.67
Learner04	Reflector	studylevel: 5 assignments: 4.48 collabotivelevel: 20 reviewstudylevel: 5.64 finalexam: 12.5	2/5	47.62
Learner21	Reflector	studylevel: 6.96 assignments: 1.65 collabotivelevel: 20 reviewstudylevel: 4.36 finalexam: 10	2/5	42.97
Learner42	Pragmatist	studylevel: 10 assignments: 10 collabotivelevel: 20 reviewstudylevel: 6.67 finalexam: 22.5	1/5	69.17
Learner12	Reflector	studylevel: 3.53 assignments: 7.65 collabotivelevel: 20 reviewstudylevel: 5.9 finalexam: 22.5	2/5	59.58
Learner10	Pragmatist	studylevel: 10 assignments: 10 collabotivelevel: 20 reviewstudylevel: 5.64 finalexam: 15	1/5	60.64
Learner18	Reflector	studylevel: 7.36 assignments: 2.45 collabotivelevel: 0 reviewstudylevel: 4.87 finalexam: 12.5	2/5	27.18
Learner13	Reflector	studylevel: 9.5 assignments: 4.87 collabotivelevel: 20 reviewstudylevel: 1.79 finalexam: 5	2/5	44.96
Learner35	Pragmatist	studylevel: 3.82 assignments: 3.82 collabotivelevel: 0 reviewstudylevel: 2.56 finalexam: 15	2/5	25.20
Learner09	Pragmatist	studylevel: 10 assignments: 10 collabotivelevel: 20 reviewstudylevel: 7.18 finalexam: 17.5	2/5	64.68
Learner37	Pragmatist	studylevel: 4.81 assignments: 4.81 collabotivelevel: 20 reviewstudylevel: 4.1 finalexam: 7.5	2/5	41.22
Learner19	Pragmatist	studylevel: 7.63 assignments: 6.84 collabotivelevel: 15 reviewstudylevel: 4.1 finalexam: 12.5	2/5	46.07

Learner32	Pragmatist	studylevel: 5.93 Assignments: 4.81 collabotivelevel: 0 reviewstudylevel: 3.59 finalexam: 12.5	2/5	26.83
Learner11	Theorist	studylevel: 10 assignments: 10 collabotivelevel: 20 reviewstudylevel: 6.67 finalexam: 12.5	1/5	74.17
Learner28	Pragmatist	studylevel: 7.23 assignments: 3.5 collabotivelevel: 0 reviewstudylevel: 5.38 finalexam: 15	3/5	31.12
Learner24	Theorist	studylevel: 4 assignments: 8.67 collabotivelevel: 20 reviewstudylevel: 5.64 finalexam: 25	1/5	63.30
Learner33	Reflector	studylevel: 5.83 assignments: 8.67 collabotivelevel: 15 reviewstudylevel: 2.82 finalexam: 10	3/5	42.32
Learner23	Pragmatist	studylevel: 4.33 assignments: 8.67 collabotivelevel: 0 reviewstudylevel: 1.79 finalexam: 2.5	3/5	17.29
Learner31	Pragmatist	studylevel: 6.43 assignments: 3.1 collabotivelevel: 0 reviewstudylevel: 3.59 finalexam: 2.5	3/5	18.12
Learner15	Theorist	studylevel: 10 assignments: 10 collabotivelevel: 20 reviewstudylevel: 5.13 finalexam: 15	1/5	60.13
Learner34	Reflector	studylevel: 10 assignments: 10 ollabotivelevel: 15 reviewstudylevel: 4.62 finalexam: 15	3/5	49.62
Learner20	Reflector	studylevel: 7.61 assignments: 5.91 collabotivelevel: 0 reviewstudylevel: 1.79 finalexam: 5	3/5	20.31
Learner34	Reflector	studylevel: 8.88 assignments: 1.21 collabotivelevel: 0 reviewstudylevel: 3.85 finalexam: 5	3/5	18.94
Learner27	Theorist	studylevel: 9.29 assignment: 9.29 collabotivelevel: 20 reviewstudylevel: 6.15 finalexam: 27.5	1/5	72.23
Learner36	Pragmatist	studylevel: 4.29 assignment: 3.71 collabotivelevel: 0 reviewstudylevel: 5.64 finalexam: 7.5	3/5	21.14
Learner30	Reflector	studylevel: 9.23 assignment: 10 collabotivelevel: 15	3/5	40.32

		reviewstudylevel: 3.59 Finalexam: 2.5		
Learner14	Theorist	Studylevel: 10 Assignment: 10 Collabotivelevel: 0 Reviewstudylevel: 4.1 Finalexam: 15	1/5	39.10
Learner25	Pragmatist	Studylevel: 10 Assignment: 10 Collabotivelevel: 0 Reviewstudylevel: 6.92 Finalexam: 20	3/5	46.92

Neurofuzzy-based Classification

The dataset of learners' profile was obtained during learners' interaction with the learning environment. This comprises of their assessment parameters values on the outcome of learners' actions in a given learning tasks was fed into neurofuzzy network to be trained. The learning rule of network classification was defined at the varied value between 0.05 and 0.20. The network classification for fuzzy assessment result for varied value was obtained using classification accuracy (i.e the actual total number of each class of learners' learning capability in the dataset is compared against the computed number of the class that are correctly classified over the computed number of correctly and wrongly classified).

The classification results of varied learning rate were then compared to determine the best of its network classification performance as shown in Table 3 and Figure 7. It was observed that the classification result of the learning rate at 0.05 gave the highest classification accuracy of 97% in the ratio of correctly to wrongly classified as described thus: Poor (100:0%); Average (100%:0%); Good (100%:0%); Very good (100%:0%); Excellent (75%:25%). The Figure 7 showed that the performance of network classification was at its best at learning rate of 0.05.

Table 3: The varied learning rates for the neurofuzzy-based classification accuracy

Class of Membership grade / varied learning rate	**Poor**	**Average**	**Good**	**Very good**	**Excellent**	**Average classification rate**
0.05	100%	100%	100%	100%	75%	97%
0.10	100%	75%	100%	100%	50%	87%
0.15	100%	89%	100%	75%	100%	89%
0.20	100%	66%	100%	75%	100%	82%

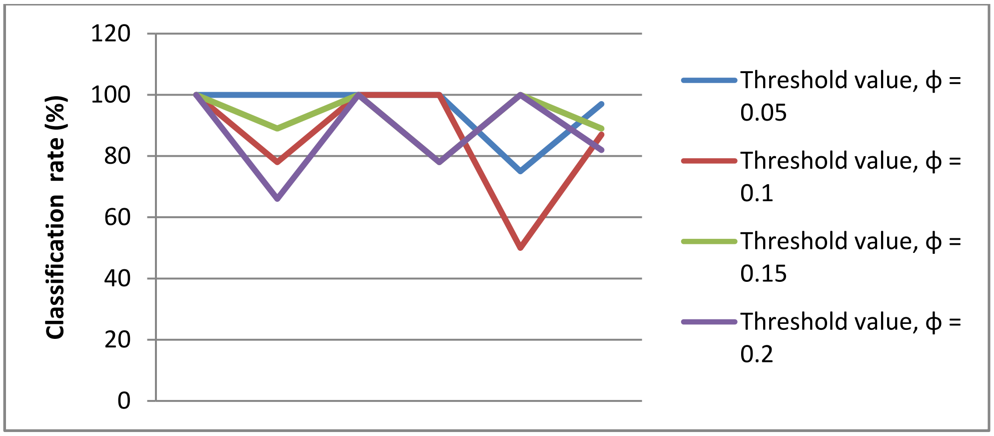

Figure 7: Average classification rate in categorizing learners with respect to their learning capability

Conclusion

Education is the bedrock that drives the economic strength of any society. It has been a great experience of attaining a trail of new phase lift in teaching and learning as a result of technological development. The trend has been from computer-based instruction or computer-mediated instruction to web-based instructional learning in which the mode of delivering instruction is similar to classroom education. The researchers in the field of education and psychology also observed the wide gap existing between the concepts of learning theories and technology. This showed that education has not fully employed the potentials of existing Information Technology. Some online programs exhibiting the feature of “one-size-fit-all” instruction made online enrolled learners’ experience characterized with frustration and disappointment. Moreover, some developers in the educational system also made an attempt to develop individualized instructional programs with artificial intelligence. These programs were not based on the principles of learning theories and styles alongside with stringent learning disciplines. Hence, in this research paper, a new learning model was developed that employed fuzzy c-means clustering technique to identify and classify learner learning preference and match learner with appropriate content presentation that meet his requirements. Furthermore, new assessment parameter modalities were built into the model with respect to *studylevel* and *reviewstudylevel* alongside with other parameters such as *assignment*, *collabotivelevel* and *finalexam*. Neurofuzzy expert reasoning was used to evaluate learner learning capability relative to the learning concepts processes obtained and stored in the learner profile during the interaction of the learners with the system.

The result of the implementation of the model shows that the fuzzy c-means clustering was relatively sufficient to identify and classify learner-learning preference. From the fifty learners data collected, forty eighty were correctly identified and classified into their learning preferences while two were result of the assessment performed by the learners over the given learning tasks saddled with questions and exercises relevant to individual learning preferences was moderately sufficient to demonstrate the performance of the system (Excellent: 4; Very good: 8; Good: 1; Average: 12; Poor: 10). This obeys the law of normal distribution. The neural network implementation of fuzzy model was trained at varied learning rates of 0.05, 0.10, 0.15 and 0.20 which was found to have the best network classification performance of 97% at the learning rate of 0.05. The research could further be extended to model additional demand learning tasks that would motivate the learners to engage on the cognitive activities in order to promote knowledge acquisition and critical thinking ability for attention and retention.

References

Adewale, O. S. (2007).University Digital Libraries Adaptive, Personalized E-learning System, Yerimah Prints, ISBN 978-3410-2-5.

Adewale, O. S. & Agbonifo, O. C. (2007). Internet-Based Collaborative and Distance Education System, Journal of Computer Science and its Application, vol. 14 No 1 pp. 86-95.

Agbonifo, O. C. (2005). Design and Implementation of Collaborative and Distance Learning System, M.tech. thesis submitted to the Department of Computer Science, Federal University of Technology, Akure,

Bonk, C. J. (2002). Online training in an online world. Bloomington, IN: CourseShare Available at: http://www.publicationshare.com, Retrieved on August, 2006.

Brusilovsky, P. (1998). Adaptive Educational Systems on the World-Wide-Web: A Review of Available Technologies. In Proceedings of Workshop "WWW-Based Tutoring" at 4th International Conference on Intelligent Tutoring Systems (ITS'98), San Antonio.

Byrnes, R. & Ellis, A. (2006). The prevalence and characteristics of online assessment in Australian universities. Australian Journal of Educational Technology, 22.1, 104-125.

Coffield, F., Moseley, D., Hall, E. & Ecclestone, K. (2004). Learning styles and pedagogy in post-16 learning: A systematic and critical review, published by the Learning and Skills Research Centre , ISBN 1853389188, Available at: www.LRSC.ac.uk.

Curtis, J. B., Robert, A. W. & Ji-Yeon, L. (2004). Moderating Learner-Centered E-Learning: Problems and Solutions, Benefits and Implications. In Timothy, S. R. Online Collaborative Learning: Theory and Practice, Information Science Publishing (an imprint of Idea Group Inc.) 701 E. Chocolate Avenue, Suite 200, Hershey PA 17033, Web site: http://www.idea-group.com

Driscoll, M. P. (1994). Psychology of learning for instruction. Allyn and Bacon, Boston.

Fang, L., Jasna, K. & Lorna, L. (2007). Breaking the Traditional E-Learning Mould: Support for the Learning Preference Approach, Human-Computer Interaction, Part IV, HCII 2007, LNCS 4553, pp. 294-301.

Federico, P. (2000). Learning styles and student attitudes toward various aspects of network based instruction. Computers in Human Behavior 16, 359–379.

Frick, N. & Ramm, M. (2011). Online Self-Assessment Before Enrollment: A solution for high dropout rates? Results of an Evaluation. In Brastians, T. and Ebner, M. (Eds.), proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications, pp. 142-151, Chesapeak, V. A: AACE.

Gbolami, K., Saadatmand, M. & Mobaraki, M. (2011). Web-Enhanced Instruction in Higher Education: A case of Blended Learning using Wikis in an undergraduate course. In T. and Ebner. (Eds.), Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications, pp. 760-767, Chesapeake, VA: AACE, Available at: http://www.editlib.org/p/37952.

Honey, P. & Mumford, A. (2000). The learning styles helper's guide, Peter Honey publications Ltd, maidenhead.

Karagiannidis, C. & Sampson, D. (2004). Adaptation rules relating learning styles research and learning objects meta-data. In *Proceedings of the AH 2004 Workshop*, (Magoulas, G. & Chen, S., Eds.). The 3rdInternational Conference on Adaptive Hypermedia and Adaptive Web-based Systems, The Eidhoven University of Technology, The Netherlands

Khairil, I. G. & Nor, A. A. (2010). Measuring Learner's performance in E-learning Recommender Systems, Australasian Journal of Educational Technology, 26(6), pp. 764-774.

Khare, A. & Lam, H. (2008). Assessing student achievement and progress with online examinations: some pedagogical and technical issues. International Journal on Elearning, 7 (3), 38–403.

O'Connor, T. (1997). Using learning styles to adapt technology for higher education, Indiana State University Centre for Teaching and Learning, Available at http://web.indstate.edu/ctl/styles/learning.html.

Oyekan, S. O. (2000). Foundations of Teacher Education, published by Negro City press, Lagos.

Panagiotou, M. Grigoriadou, M. & Philokiprou, G. (1994). Knowledge and Learning Student Model. In Vosniadou S. (Eds). Technology-based Learning Environments, NATO ASI series F, Springer, p. 243-249.

Piombo, C., Batatia, H. & Ayache, A. (2003). A Framework for Adapting Instruction to Cognitive Learning Styles. In: Proc. The 3rd IEEE International Conference on Advanced Learning Technologies(ICALT'03), pp. 434–435.

Rahimi, E., Van den Berg, J. & Veen, W. (2013). A framework for designing enhanced learning activities in web 2.0-based Personal Learning Environments. In Jan Herrington et al. (Eds.), Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications pp. 2222-2231. Chesapeake, VA: AACE. Available at: http://www.editlib.org/p/112281.

Tennyson, R. D. & Christensen, D. L. (1988). MAIS: An intelligent learning system. In D. Jonassen, (Ed.), Instructional designs for micro-computer courseware, pp. 247–274. Mahwah, NJ: Lawrence Erlbaum Associates.

Wang, M. (1990). Adaptive Instructions: Building on diversity. Theory into Practice 19, pp 122-128.

Wolf, C. (2002). iWeaver: towards an interactive web-based adaptive learning environment to address individual learning styles. European Journal o f Distance Learning (EuroDL), Available at: http://www.eurodl.org/materials/contrib/2002/2HTML/iWeaver.

Zhou, H. (2013). Utilizing an Assisted Personal Learning Environment for Middle School Students to Practice self-Regulated Learning. In . Jan Herrington et al. (Eds.), *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications* pp. 2395-2400. Chesapeake, VA: AACE. Available at: http://www.editlib.org/p/112304.