ENHANCED DETECTION OF LEARNERS LEARNING STYLES FOR E-LEARNING

L.JEGATHA DEBORAH, P.VIJAYAKUMAR
Department of Computer Science and Engineering, University College of Engineering
Tindivanam, Melpakkam – 604 001
blessedjeny@gmail.com,

ABSTRACT

Learning Style is: "A particular way in which an individual learns". Different kinds of learners are distinguished according to their learning styles based on the explicit characteristics shown by the learners, during the earlier period. The latent nature of the learners in addition to the explicit nature, addressed by most of the traditional learning style models also influences the learning style of an individual and such identification could provide better E-Learning framework in terms of content delivery. This paper categorizes new kind of learners: "*Intelligent Learners*" who are identified by two varying dimensions: Uncovering the latent attitude (Browsing History in an E-Learning server) in them and testing of linguistic intelligence and are trained using a neural-network algorithm. The paper also provides a brief summary of the different categories of learning styles available in the past. The experimental results shown are compared with other models and are found to be promising.
Keywords: Learning style, E-Learning, neural-network, latent nature, Browsing History, Linguistic Intelligence.

I.INTRODUCTION

E-Learning is "*Electronic Learning*" which is deemed to be "Learning at ALL stages". E-Learning provides anytime and anywhere study saving lot of time, cost and effort. E-Learning had gained lots of attention since it greatly reduces the drawbacks of the traditional learning educational setting environment. [20] The success of any E-Learning framework is attributed by various factors like the learning objects, content delivery, information retrieval, efficient storage, performance evaluation and content restructuring based on the learning styles of the learners. The design of an E-Learning system is based on the common rules and features of the learners engaged in the learning process. In most of the existing E-Learning frameworks, the psychological level between the learners and the instructors could not be well balanced. This kind of the psychological level of the learners is greatly attributed by the learning styles of the learners involved in learning. The learning styles of an individual vary from one person to another and hence if some similar kind of teaching is provided to all the learners, the success of that E-Learning system degrades apparently. The design of the E-Learning system could be modified such that all the learners could be well benefited and the complete objective of the system could be satisfied. [21]

This paper exclusively speaks about the impact of the learning styles of the learners in the restructuring the E-Learning framework. According to Butler (1986) a Learning Style is defined as "A particular way in which an individual learns". Numerous learning styles in the past have acquired most attention in E-Learning and identified that learners learn in diverse ways and that single approach to teaching does not work for every and even most students. Several models and instruments have been made use in the past to identify the learning styles of the learners' efficiently through questionnaires, interviews, profile information, etc. [8] These metrics are labeled as explicit information given about the learners during the assessment procedure. The main concentration of this paper is to find out the individual learning style which is latent in nature.

1.1Authors Main Motivations
The main motivation of the paper had its origin from Flemming VARK learning style designed by Neil Fleming in the year 1987, which categorizes the learners into four viz. Visual, Auditory, Read/Write and Kinesthetic learners. This paper exploits the idea of meta-

cognition (i.e.) thinking about one's thinking. In most of the previous learning style models, the meta-cognition context was shallow in its idea. [9] The explicit evaluations of the learning style of the learners were very limited. However, a deep understanding of one's own way of learning integrated with the traditional metrics can lead to a great personal empowerment and self confidence. This kind of deep understanding is known by the implicit nature of the learners involved in an [12] E-Learning environment which are always latent and not explicitly shown outside. Several studies had revealed that the latent attitude within them which is explicitly not shown outside could also influence the learning style of the learner.

VARK model comprises of 4 different kinds of learning styles. Each learning style can be defined by the answers to the following queries.

1. Which sensory channel is preferred the most while the learners learn the course contents? – Eyes, Ears, Hands
2. What type of information does the learner prefer the most during learning? – Graphics, pictures, lectures, radio, power point presentations, dictionaries, thesaurus, case studies, practice applications, problem solving applications
3. Which style of learning will be helpful in making the learners retain the information they had studied? – Visual, Auditory, Read & Write and Hands-on experience. [16]

The general traditional metrics involved for identifying the learning style of a learner are many, inclusive of 1. Personality types, 2. Early Educational Specialization, 3.Professional career choice, 4. Adaptive competencies as indicated in Table 1. When considering the above metrics, from the authors' prior motivations, the learners can be identified as belonging to any one of the styles of learning viz. visual, auditory, read/write, kinesthetic as proposed in VARK learning style. However, these metrics are shallow in indentifying the learning styles and sometimes the results may not be accurate. [10]

Table 1.Learning styles Models – Metrics and Dimensions

Nature of Metrics	Inclusive Dimensions	Underlying Learning Theory	Learning Style Models Addressed
Static	Personality Type	Experiential theory model	Kolb Model
	Educational Specialization	Behavioral theory model	Honey and Mufford Model
	Professional career choice		
	Job role	Cognitive theory model	Gregoric model
	Adaptive competencies	Psychological theory model	Felder-Silvermann model
	Environmental factors		
	Emotional factors	Meta-learning theory model	Flemming VARK model
	Sociological needs		
	Physical needs		
Dynamic	Intelligence quotient factors	Personality model	Carl and Myers Brigg indicator model
	Biological factors	Intelligence theory model	Howard Gardner
	Inherent interests	Neuropsychological theory model	Chris Jackson

The major strengths of this paper are as follow

➢ Clear visualization of the varying dimensions of the different learing style models.
➢ Identification of the latent learning style of the learners registered in an E-learning serer.
➢ Categorization of "Intelligent learners" based on the learners latent attitude and linguistic intelligence test trained using a neural network back propagation algorithm. [2]

The meta-cognition of the learners could be identified by making the learners to provide comprehensive information of their own profile which would be always static in nature. Clear and deep identification of the learning style of the learner increases the measures for restructuring the design of an E-Learning environment. The performance level of the learners and the use of the E-Learning system are identified and hence the design of the E-Learning content shall be modified pertaining to the needs of the learners. [1] The rest of the paper is organized as follows. Section 2 provides a detailed summary of the existing learning styles models through visualization. Section 3 comments on the major critics of the existing systems and the drift of the future work from the past models. Section 4 explains the system architecture with good explanation. Section 5 shows the experimental evaluations of the system. The final section gives a crisp concluding remark of the paper.

II.PAST LEARNING STYLE MODELS AND INSTRUMENTS

Learning styles are different kinds of learning. The major objective of identifying the learning style is, to well educate the performance level of the learners and aiding them to find their best position to fit in the outside environments. Especially, in an E-Learning environment, the impact of the learning style causes a greater effect on the performance of the learners and in the design of the E-Learning systems. [29] [26] Several learning style assessment models and instruments are available online to effectively assess the learning style. Most of the learning styles discussed follow the metrics mentioned in Table 1. The generic categorization of the learning styles fall under four categories. Fig.1 shows the basic categorization of the traditional learning styles.

1. Synthesis Analysis – Processing information and organizing into taxonomy
2. Methodical Study – Careful study and completion of academic assignments
3. Fact Retention – Analysis of the correct output instead of understanding the logic behind
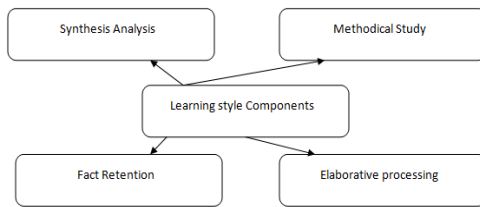4. Elaborative processing - Applying new ideas to the existing knowledge

Fig.1 Learning Styles – Basic Categorization

Fig. 2 provides a clear understanding of the various learning styles available to till date. The visualization has different colors to indicate the various features of the learning styles. Each of the concentric circle compartments illustrates the different features of the learning styles. [4] The picture also explains the idea of the drift from the earlier efforts. The various concentric circles of the above visualized picture are described below

1. Name of the Learning Styles along with the year of invention
2. Underlying learning theory model
3. Different kinds of learners of each model
4. Analysis of each of the metrics for the learning styles
5. Limitations of the individual learning style [14]

III. DRIFT FROM EARLIER EFFORTS

A complete scenario of learning styles was discussed in section 2. These learning styles had a great impact on the static behavior of the learners. Studies reveal that there were some hidden behavioral traits present within the learners which are not usually considered for learning styles assessments. Most of the learning styles discussed in the literature assess the learning style of a particular individual based on the profile information given by the learners themselves. On further analysis, it was identified that the explicit information given by the learners are alone not enough in identifying the learning style correctly. [37]
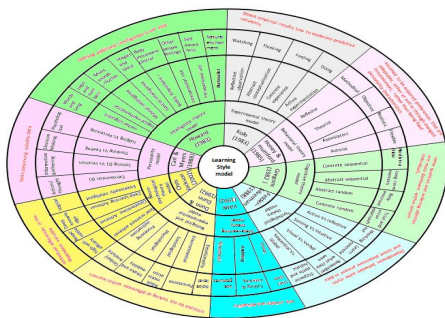

Fig.2. Complete Visualization of different Learning Style

In the proposed work to be carried out, greater importance is given to identify the hidden nature of the learners which could aid in assessing the learning style of an individual efficiently. The existing learning styles are based on different dimensions of psychological, cognitive, multiple intelligences and personality models. However, in our proposed work a hybrid model of explicit and implicit nature of the learners are identified in assessing the learning style. The explicit information of the learners is identified using the profile information given in an interactive web environment as most of the existing learning style assessment tools perform. One of the methodology used to identify the implicit nature of the learners which are usually hidden within the learners are done by accounting their browsing pattern in any specific E-Learning servers. [31] This kind of browsing pattern is identified as one of the attributes in identifying the learning style in addition to the profile information attributes. As described earlier, the proposed work had its motivation from Flemming VARK learning style model which identified three kinds of learners including visual, auditory and kinesthetic type of learners. The proposed work identifies a new kind of learners called as "*Intelligent Learners*". There are two different dimensions in categorizing the "*Intelligent Learners*". They are identified by two kinds of attributes in addition to the learners own profile information given explicitly. [3] [32]

Dim 1: Identification of the browsing patterns of any E-Learning server

Dim 2: Testing the linguistic intelligence using any examinations like comprehension ability, word power, word build, essay writing, poetry etc.

The proposed model identifies four different kinds of learners. They are

1. Visual learners – sensitive to eye movements and can be taught using pictures, models, comics
2. Auditory learners – sensitive to sounds and can be taught using classroom lecture voice, tape-recorders, CD contents.
3. Practice learners – sensitive to actions and can be taught using hand on experiences, practice tool, practical sessions. [25]
4. Intelligent learners – Hybrid learners, skills are usually hidden in nature and can be taught using verbal and hands on experiences.

IV. SYSTEM ARCHITECTURE

Deep understanding of the behavior of the learners could effectively recover the learning styles of the individuals. On such analysis of the varying learning styles the design of the E-Learning framework could be restructured so that

the learners of an E-learning framework could be benefited utmost. A deep understanding of one's own way of learning integrated with the traditional metrics can lead to a great personal empowerment and self confidence. The proposed system framework ILS- Intelligent Learning Style Framework is depicted in Fig. 3. The learning style of an individual can be found by the following attribute values

1. Complete, self profile information of the learner
2. Browsing History pattern of an E-Learning server
3. Linguistic Intelligence test results of the learner
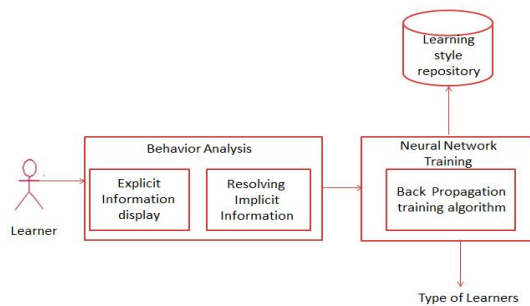4.

Fig.3 ILS framework

The learner's explicit and implicit behaviour analysis is performed. The different profile information metrics are 1. Educational background 2. Age 3.Hobbies 4. Heredity 5. Professional Background 6. Study Environment The implicit information is resolved by accounting the browsing pattern of the MediaWiki E-Learning server. [27] This MediaWiki E-Learning server contains different kinds of contents viz. documents, audio lectures, video lectures. The learners browsing pattern of these categories of E-Learning contents is accounted and stored in a repository. In addition to this, the learners' linguistic intelligence is also tested and the results are stored for analysis. The output of ILS framework gives the type of learning, the learners belong to. ILS resolves four different kinds of learners.

1. Visual Learners – interested in learning through pictures
2. Auditory Learners – interested in learning through videos
3. Practice Learners – interested in learning through software tools and exe files
4. Intelligent Learners – interested in learning through documents and exe files

V.PROPOSED APPROACH

Neural Networks –based Identification

5.1 Neural Network - Prelims

Artificial Neural Networks are simulations of the human brain. They are composed of many 'neurons' that cooperate to perform the desired function. These networks are usually used for applications like classification, noise reduction and prediction. According to Rumelhart et al. (1986) a neural network generally consists of the following components:

- a set of processing units,
- the state of activation of a processing unit,
- the function used to compute output of a processing unit,
- the pattern of connectivity among processing units,
- the rule of activation propagation,
- the activation function, and
- the rule of learning employed.

The generic background design of a neural network consists of 3 kinds of layers, 1. Input 2. Hidden 3. Output. The output of a neuron is a function of the weighted sum of the inputs plus a bias. Weights are assigned at random initially and later on the weights will be updated to get the desired output. The function of the entire neural network is simply the computation of the outputs of all the neurons. [19] [33]The two main phases of the neural network are 1. Training 2. Testing. Training phase is the act of presenting the network with some sample data set and modifying the weights to better approximate the desired function. An epoch is technically defined as one iteration through the process of providing the network with an input and updating the networks weights. [6] Typically many epochs are required to train the neural network. A learning rate is user-designated in order to determine how much the link weights and node biases can be modified based on the change direction and change rate. The higher the learning rate (max. of 1.0) the faster the network is trained.

5.2 Behavior Analysis

This module of the ILS framework is the initiator of the framework. This module has two components viz. explicit information display and resolving implicit information. The learner can enter his self profile information during the registration of an E-Learning server. The assumed non-functional requirements of the ILS is that, the learner provides correct information of him/her since this information is one of the important attributes in resolving the learning style of him/her. The second measure of implicit attitude of the learner can be obtained using two metrics by taking an account of browsing history pattern in an E-Learning server and results of any kind of linguistic intelligence test viz. word power, comprehension test, essay writing, etc. The module is shown below. [17] [13]

5.3 Modeling Learning Styles using Neural Network

In our proposed model, there are 9 input nodes of the neural network and they are designated as the metrics of the learning styles both explicit and implicit designed for the training module. These metrics are obtained from the learners directly and taken from the pattern of his/her behavior. The explicit input node metrics are- 1.Educational Background, 2.Professional Background, 3.Heredity, 4.Age, 5.Hobbies, 6.Study Environment, and the implicit input nod metrics are 7.Reading time, 8.Marks, 9.Browsing Pattern History. [34]
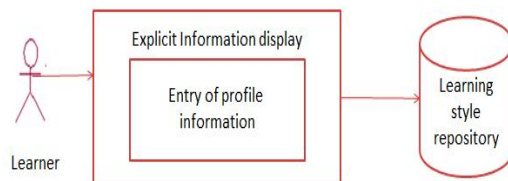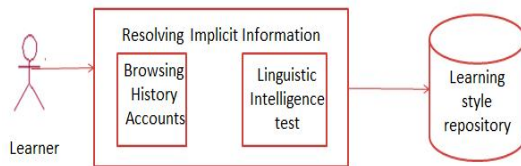

Fig. 4 Explicit Information - Behavior Analysis

Fig. 5 Implicit Information - Behavior Analysis

We have considered 2 hidden layers with 10 nodes in each layer for efficient training and testing. We had used 2 hidden layers for correctly back propagating the errors occurring in the neural network. The output nodes are 4 in number and they are the type of target learners based on their style of learning. These nodes are 1. Visual, 2. Auditory, 3.Practice, 4.Intelligent. The inputs, hidden and the output nodes of the neural network in shown in Fig 6. The input and the output node metrics defined earlier cannot be processed as such in the training and testing phases of the network, and hence the node values have to be transformed appropriately to be trained. The implicit input node value 'reading time' is not transformed and the other values are transformed appropriately. [30] The values of the input and output node transformations are shown in Table 2.

The mathematical model of the underlying Back Propagation Neural Network algorithm is given in [40]. The algorithm back propagates the error values till the expected network output and the obtained network output is more or less the same.
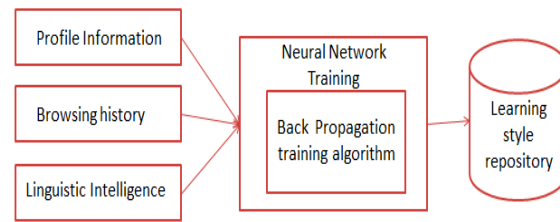

Fig.6 Back Propagation Neural Training

We have used Matlab toolbox for neural network training and testing. 'train' is a neural network training function in the Matlab toolbox. The mathematical function of train is given in equ 2. train(net,P,T,Pi,Ai)   (2)where
net – network , P – network inputs , T – network targets,
Pi – initial input delay conditions
Ai – initial layer delay conditions.
The function 'train' returns (net,TR,Y,E,Pf,Af)
where
net – new network, TR – training record (epoch and performance function), Y – Network outputs
E – Network Errors
Pf – Final input delay conditions
Af – Final layer delay conditions

4.4Training & Testing Phases
The above input attributes of the behaviour analysis modules is trained using Back Propagation Neural Network algorithm. The input node attributes are trained using the Back Propagation Neural network for the students' database of Anna University College of Engineering Tindivanam. Our test bed environment for the training phase consisted of 50 students belonging to the Department of Computer Science and Engineering. The training neural function used is the gradient descent momentum with back propagation, traingdm present in the Matlab Toolbox. 'traingdm' is a network training function that updates weights and bias values according to gradient descent with
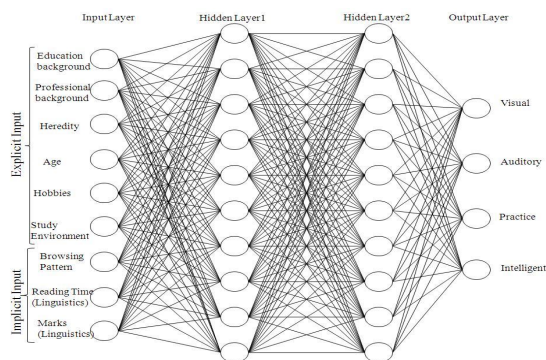

Fig 7. A Simple Neural Network

momentum. The mathematical function of traingdm is given below traingdm(net,TR,trainV,valV,testV) where net – neural network, TR – initial training record created by train, TrainV – training data created by train , valV – validation data created by train, testV – test data created by train. The function traindgm returns (net,TR) where net –

Trained network, TR – Training record of various values over each epochs. [40] The mathematical model used for the training and testing in our proposed work is the back propagation algorithm with gradient descent momentum. The back propagation algorithm in this approach is used to calculate derivatives of performance 'perf' with respect to the weight and bias variables "X". Each variable is adjusted according to gradient descent with momentum.

$$dX = mc * dXprev + lr * (1-mc) * dperf/dX \quad (4) where$$

lr – learning rate

dXprev – derivative of the previous change to the weight or bias dpref – derivative of the performance function

Assumptions of our Neural Network
1. Learning rate - 0.05.
2. perf (Performance function) – Mean Squared Error (MSE)
3. Epochs – 40,000
4. Bias Weights
   Initial – (-1.5121, 1.5121)
   Final – (0.2249, -0.0985, -0.2497, 0.5215)
5. Initial Weights Assignments –
   1. 1 Input layer (9 nodes) – 2 Hidden layers (10 + 10 nodes)
      0.3730, 0.8605, -0.6771, -0.4543, -0.4604, -0.4805, -0.2811, -0.4664, -0.0500
      0.6589, 0.0796, -0.5912, 0.5743, 0.5298, 0.7236, -0.5114, 0.1956, -0.2500

2. 2 Hidden layers (10 + 10 nodes) – 1 Output layer (4 nodes)
   0.8933, 0.5382, -0.2475, -0.2823, -0.7656, 0.1689, 0.0280, 0.0698, 0.6595, 0.8673
   -0.8503, 0.6357, 0.2260, 0.4773, 0.0725, -0.4896, 0.3778, -0.6844, -0.4698, -0.2629
   -0.2889, -0.6744, -0.0151, 0.6203, 0.7468, 0.3332, 0.6641, -0.6506, 0.6807, -0.6580
   -0.1204, 0.1192, 0.5144, -0.7402, -0.2055, -0.4088, 0.7492, -0.3264, -0.4125, -0.3889

The testing phase of the network is done using the mathematical model given below. 'sim' is the testing function of the Matlab toolbox used in our approach.

sim(net, P, Pi, Ai, T) (5)

where
net – network, P – Network inputs, Pi – initial input delay conditions, Ai – initial layer delay conditions, T – Network targets. 'sim' function returns (Y,Pf,Af,E,perf) where
Y – Network outputs, Pf – final input delay conditions, Af – final layer delay conditions
E – Network error, perf – network performance

Educational Background	Professional Background	Heredity	Age	Browsing Pattern	Hobbies	Study Environment	Marks	Learning Styles
Arts - Science – 1 Visual communication – 2 Architect – 3 Teacher Training – 4 Management – 5 ITI – 6 Higher Secondary - 7 Engineering – 8 Diploma – 9 Law – 10 Medicine – 11 Chartered Accountant – 12 IAS – 13 IPS – 14	Film Industry -0 Artist – 1 Multimedia – 2 Manager – 3 Accountant – 4 Musician – 5 Teacher – 6 Student – 7 Engineer – 8 Professor – 9 Marine – 10 Government Institutions – 11 Lawyer – 12 Judge – 13 Doctor – 14 Self Employment – 15 Police – 16 Architect - 17	Architect – 0 Web Designer – 1 Journalist – 2 Film Industry -3 Labor – 4 Choreographer – 5 Clerk – 6 Government Institutions – 7 Teacher – 8 Engineer – 9 Doctor – 10 IAS - 11 IPS – 12 Professor – 13 Manager – 14 Self Employment – 15 Others - 16 Police – 17 Lawyer – 18 Judge – 19 Accountant - 20	15 – 18 -> 0 18 – 20 -> 1 20-21 -> 21 – 23 -> 32 4 – 26 -> 42 6 – 30 -> 5 > 30 – 6	None – 0 Video Files – 1 Audio Files – 2 Documents – 3	Painting – 0 Watching TV – 1 Surfing Internet – 2 Stamp Collection – 3 Reading Books – 4 Music Collections – 5 Dancing – 6 Playing Games – 7 Coin Collections – 8 Gardening – 9 Playing Mind Games - 10 Puzzle Solving - 11	Urban – 0 Rural - 1	D – 0 C – 1 B – 2 A – 3	Visual – 0 Auditory – 1 Practice – 2 Intelligent - 3

Table 2 Training Data

5.5 How Learning Styles are inferred using Neural-Networks

The results of the training and testing of the neural training module is stored in the Learning Style repository. The values of the training and testing are analyzed and computed for identifying four different kinds of learners. The output network nodes have to be transformed appropriately as indicated in Table 2 for interpreting the type of learners. The inference of the neural training and testing is that various kinds of input attributes and combined with the hidden layer values to interpret the type of learners present in the output nodes. The algorithm for interpreting the output values from the neural network is given below. [11] The combinations of input attributes for visual and intelligent kinds of learners are evaluated according to the algorithm given below and the corresponding results are shown in fig 7, 8 (single sample input).

Algorithm: Learners Type Interpretation

Input: Neural Network Output Node values – (o_1, o_2, o_3, o_4)

Output: Type of Learners – (Visual, Auditory, Practice, Intelligent)

Procedure

Begin

Declarations

Learning style = {visual, auditory, practice, intelligent}

Index = 0

Begin

Network output = {$|o_1|, |o_2|, |o_3|, |o_4|$}

Network output = Σ(i=1 to 4) |i-network output (i-1)|

Min value = network output (0)

for i = 1 to 3

Begin

    If Min value > network output (i)

    Min value = network output (i)

    index = i

    End

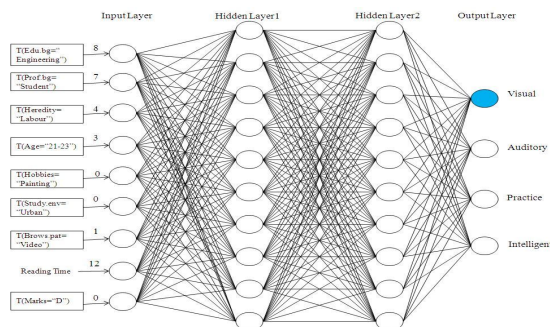Type of learners = learning style (index)

Return (type of learners)

End

Fig 8. Inference of a Visual Type of Learner

VI. EXPERIMENTAL RESULTS

In view of the implementation, the learners provide their profile information at the outset through a web interactive application. The learners are then allowed to view the contents of the E-Learning server after appropriate authentication. In our proposed work, MediaWiki is used as the E-Learning server. A variety of E-learning servers are present which includes Moodle, Joomla, Xerte, Dokeos and Claroline. The E-learning server shall contain a variety of contents in visual, audio lectures, document files and exe files format. In order to obtain the hidden attitude of the learners, the browsing pattern of the E-learning content is obtained and stored. [7]
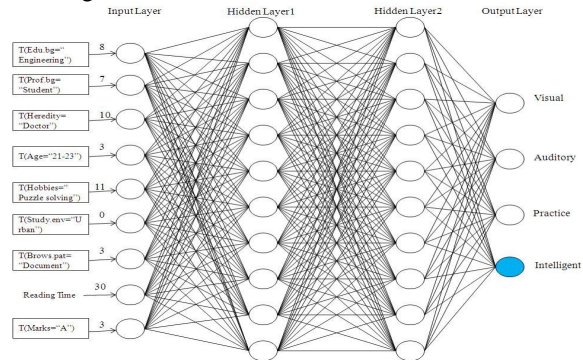

Fig 9. Inference of a Intelligent Type of Learner

In addition to this, as a second aspect of hidden dimension for assessing the learning style, the learners linguistic intelligence is also tested using a comprehension test. The results of the comprehension test are also recorded. The entire contents for the assessment are stored in a database and are considered to be attributes. [24] These attributes after necessary data transformation are trained using a back propagation neural network algorithm and tested against a new data set. The training dataset is the students' database of Anna University College of Engineering Tindivanam consisting of 31 students. The training dataset consists of approximately 87,000 records with different combinations of input attributes. [28] The application domain used for training and testing is "C programming language" course taken by the Department of Computer Science and Engineering. Students are presented with the variety of course materials (documents, audio and video) in the E-Learning server and they are not restricted to view any of the contents of the server. Also, in these cases, no prerequisites were made mandatory to the students. At the end of the final course session, the students must attend a final examination. [38] [39]

Fig.6 shows the categorization of the students based on the ILS questionnaires provided by Flemming VARK model according to the three dimensions: Visual, Auditory and Practice. Fig.7 shows the percentage of

students pertaining to the above dimensions when the individual browsing history patterns of an E-Learning server were resolved.

In order to assess the precision of our approach we compared the learning style detected by the Neural-based approach against the learning style obtained with the ILS questionnaires given by Flemming VARK Learning Style model. However, the testing data for the neural network back propagation algorithm is completely different from the original training data used for determining the parameters of the neural network. [35] Table 2 shows the results that are obtained using the experiments conducted by ILS questionnaires and the neural-network algorithm. The table describes for the different users, the dimensions of the learning styles assigned by the proposed approach and by the ILS questionnaires given by Flemming VARK. The different dimensions for the evaluation of the learning styles are visual, auditory and practice. In addition to the above dimensions, a new kind "*Intelligent*" is also resolved by the proposed model. [22] [23]

Table 3 Experimental results

User	VARK Model	Neural Network Model	# experiments
1	V	V	20
2	RW	P	24
3	T	P	15
4	V	V	16
5	A	A	19
6	T	P	24
7	T	I	28
8	RW	I	12
9	RW	I	16
10	RW	P	18
11	T	T	16
12	A	A	17
13	RW	P	14
14	V	I	21
15	A	A	35
16	A	A	26
17	RW	P	38
18	A	A	19
19	A	A	14
20	T	V	17
21	T	T	22
22	RW	P	24
23	T	T	28
24	A	A	26
25	T	I	27
26	RW	I	20
27	RW	I	24
28	T	I	15
29	RW	V	16
30	A	A	19
31	V	V	24
32	V	V	28
33	A	A	12
34	RW	A	16
35	T	P	18
36	V	I	16
37	T	T	17
38	RW	P	14
39	A	A	21
40	RW	V	35
41	V	V	26
42	T	I	38
43	V	P	19
44	RW	I	14
45	T	A	17
46	A	V	22
47	RW	P	24
48	RW	I	28
49	T	V	26
50	T	P	27

6.6Experimental Screen shots

Back propagation gradient descent algorithm is used in the training and testing phases of our neural network. The iterations during the training phase extends to a maximum

of 50,00,000 epochs. The screen shot of the neural training at the 69,985[th] epoch is shown in Fig 10.
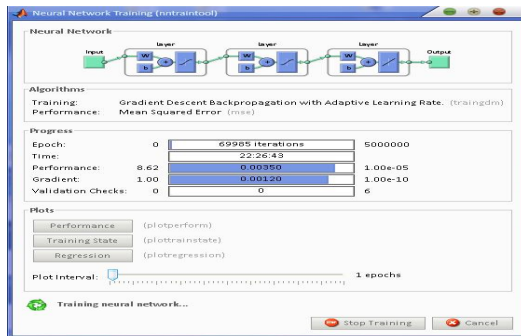

Fig. 10 Neural Training Phase

The performance function in the neural algorithm is Mean Squared Error (MSE). The screen shots of the performance function, gradient descent and the regression are shown in Fig. 11, 12, 13.
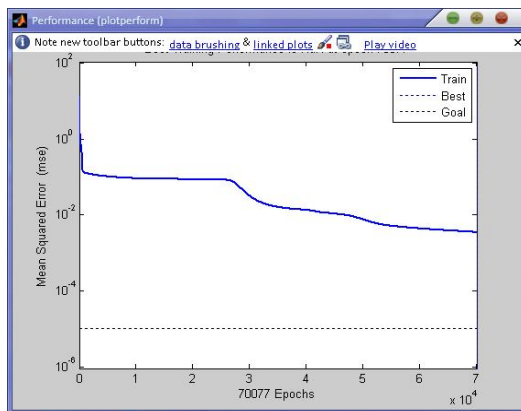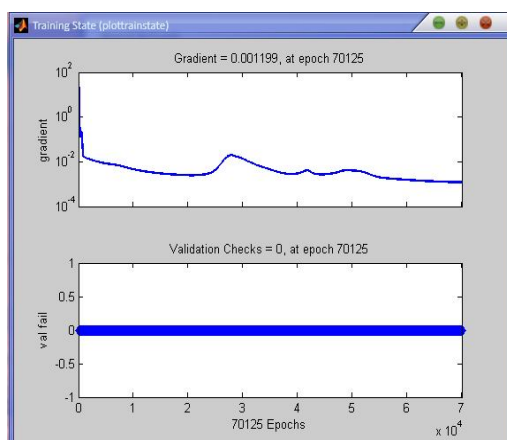

Fig. 11 Performance Function (perf)
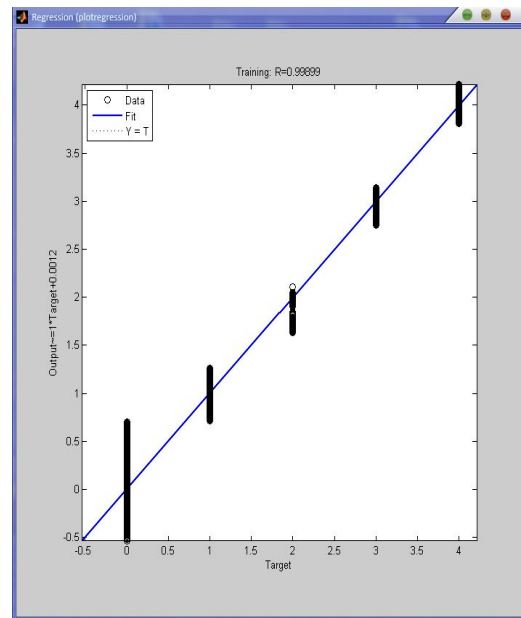

Fig. 12 Gradient

Fig. 13. Regression

The output algorithmic evaluation described in section 5.5 is evaluated and found to be "*Intelligent Learner*". [5] The output screen shot in Matlab toolbox for the "*Intelligent*" type of learners is shown below.

Fig. 14 Intelligent Learner – Neural Output

6.2.Results Findings
Based on the observations done in Table 3, it was found that a number of mismatches were found in the learning style of the learners resolved by VARK questionnaire version 7.1 and neural network models. The authors found that when the number of experiments done on the learners increases, this kind of mismatch occurs. Hence, the

number of experiments performed on the learners should be increased in order to obtain appropriate results. The learners were surveyed again in order to be assured of the results obtained. They were asked to fill in a different questionnaire other than VARK model which was based on a general scenario. The results of the questionnaire indicated that each learner preferred different kinds of learning and that single method of learning content delivery for all the learners is not sufficient enough in an E-Learning scenario. Thus, the design of the E-Learning systems can be done in such a way that course contents can be posted in various kinds in order to obtain the full benefit of such frameworks. [6]

To evaluate the precision of the ILS framework, the values are evaluated against equ 1. The precision of the model is calculated using the formula

$$Precision = \frac{\sum_{i=1}^{n} equal(LS_{VARK}, LS_{NNM})}{n}$$

(6)

In this equation, n is the total number of learners in the experiment. 'equal' is 1 if the values obtained from VARK and NNM learning styles are equal, 0 if they are opposite, and 0.5 if NNM is intelligent and VARK containing any other style. The system produced a precision of 63%. The results of the Neural Network model and VARK learning style model were compared. [41]

The main observation is that, the VARK model obtains only the explicit information given by the learners themselves. However, it is experimentally found that the explicit information alone is not enough and the latent attitude of the learners is also important during learning Style analysis. Through the questionnaires method of analyzing the learning style, only limited information were to be given by the learners. This kind of profile information is found to be shallow in nature. When using this kind of procedure, the learning style of the learner of an E-Learning framework may not be accurate. Hence, the traditional questionnaires methodology should be added to the behavioral aspects of the individual for resolving the correct (original) learning style of the learners. [15]

To summarize the experimental results obtained above, it is concluded that neural-network based back propagation algorithm is well suited to find the learning style of the learners. This is appropriate since the training module of the Back propagation algorithm covers the attributes of both the explicit and implicit information about the learners. The explicit profile information given by the learners during the registration in an E-Learning framework alone cannot give appropriate results. The latent attitude present within the learners combined with their original profile information of them can give better results when resolving the Learning Style. In addition to this, the proposed learning style model categorizes a new

kind of learners called "*Intelligent Learners*" and they are identified using linguistic intelligence test. [36]

VII.CONCLUSION

Designing the E-Learning system based on desired type of content delivery can be beneficial to the students whose main mode of learning is through web environments. In such cases of designing, a lot of issues had to be considered regarding the information exchange, mode of transmission, performance evaluation, security issues, etc. The authors decided to provide a scheme of E-Learning system which could serve best to all kinds of learners from various disciplines and backgrounds.

The learning styles of the learners are very essential since web learning comprises of a variety of people belonging to different kinds of disciplines. In the midst of several predefined questionnaires available in the past, this paper focuses on how the learning style could be derived from the learners' explicit and implicit attitudes. Neural-based back propagation with gradient descent algorithm is used in the propose approach, [18] since the information had to be trained initially and then tested against a new set of data. This algorithm is tested for "C programming" language course learned through E-Learning servers. Ongoing testing is handled for other programming languages liken C++, C#, Java.

The future work is planned to incorporate the use of agents in this framework. Hence, the ongoing work deals with delivery of contents according to the learning styles of the learners with the help of intelligent mobile agents.

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