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RESEARCH ARTICLE

On Assessment of Students' Academic Achievement Considering Categorized Individual Differences at Engineering Education (Neural Networks Approach)

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Abstract

This work introduces analysis and evaluation of an interesting, challenging, and interdisciplinary, pedagogical issue. That's originated from categorization of the achievement diversity of students' (individual differences), equivalently students' Structure of the Observed Learning Outcome (SOLO). This students' academic diversity affected in classrooms by three interactive learning/teaching approaches (orientations) namely: surface, deep, and strategic.

Assessment of these approaches has been performed via realistic simulation adopting Artificial Neural Networks (ANN^{s}) modeling considering Hebbian rule for coincidence detection learning. That modeling results in interesting mathematical analogy of two effective learning performance factors with students' achievement individual differences.

Firstly, the effect of two brain functional phenomena; namely long term Potentiation (LTP) and depression (LTD). That's in accordance with opening time for crossing N-methyl-D-aspartate NMDA observed at hippocampus brain area.

Secondly, the effect of neurons' number associated with diverse learning/teaching environments comprise the dichotomy (extroversion/introversion).This dichotomy has been investigated as the external and internal environmental learning conditions. The obtained simulation results concerned with student's diversity attitudes (extroversion/introversion). They shown to be in well agreement with recently published results after performing a case study at an engineering institution in Egypt. Finally, introduced study, aims mainly to present interesting analysis of brain's functional development based students' individual differences, and learning abilities.

Introduction

The field of learning sciences is represented by a growing community conceiving knowledge associated with educational system performance as well as assessment of technology-mediated learning processes. Therefore, a recent evolutionary trend has been adopted by educationalists as well as learners due to rapid technological and social changes. So, they are facing increasingly challenges arise in this time considering modifications of educational field applications [1][2]. During the nineteenth of last century, computer scientists and educationalists, as well as neurobiologists[3][4][5]. All have adopted challenging and interdisciplinary research direction [6][7][8][9].That's in aiming to perform interpretational analysis, assessment, and systematic investigation for some observed educational field phenomena such as diversity of students' individual differences, learning creativity, and optimal Computer Aided Learning (CAL) packages. [10][11][12][13][14][15][16].

This paper deals with categorization of students' achievement diversity. Specifically, it considers the students' approaches and orientations to learning in one of three ways *surface, deep, and strategic* [10]. Herein, the analysis of diversity approaches to learning presented via two effective learning performance factors as follows.

A. First Student's Diversity Factor

This factor addresses quantitative analysis and evaluation of predicted behavioral brain function considering Hebbian rule for coincidence detection learning using mathematical modeling of artificial neural networks (ANN[$]). That's fulfilled by modeling of genetically developed two performances brain functions (learning and memory) [17][18][19][20]. Therefore, they have been adopted for relevant modeling of the patterned pedagogical issue of students' individual differences[9][11]. Accordingly, realistic ANN simulation of that issue has been inspired by the organization and functioning of students' brain organization and synaptic plasticity at hippocampus brain area [20][21][22][23]. Additionally, this work adopts a novel quantitative modeling approach for analysis and evaluation two essential brain functions namely (learning and memory). Since LTP and LTD are thought to play important roles in learning and memory [17][19][21][23][24]. Specifically, this work This paper motivated by obtained results after experimental work based on genetic engineering technology [21][22]. Interestingly, obtained results of presented ANN simulation have been supported by fairly predicted students' learning outcomes[25]. Such work is mainly concerned with investigational research for some brain functions development [18][6]. More specifically, the objective of that experimental research work is to build up smarter genetically reformed mouse on molecular basis [21][22]. Therein, brain functions (learning and memory), observed to have better performance following increase of synaptic connectivity (plasticity), in addition to improvement of forgetting factor [23].The long-term Potentiation phenomena (LTP) observed at hippocampus cortical brain area improves synaptic plasticity as well as memorization factor[21]. N-methyl-D-aspartate receptors (NMDARs) have well established roles in synaptic plasticity, causing the induction of some forms of both LTP and LTD of synaptic strength [17][19]. It is noticed that work obtained results were mostly evaluated qualitatively rather than,[19] [26][27].The presented mathematical model obeys the general research direction recommended for ANNs theorists to investigate brain functions phenomena [28].

A. Second Diversity Factor

Herein, the adopted ANN model gives attention to simulate cognitive styles in addition to student's personality indicator.

Diversity of student's cognitive styles classified as his/her behavioral learning with either field dependant or independent performance. In neural networks context, both (field dependant and independent) styles have been realistically simulated via two learning paradigms respectively. Supervised (interactive learning with a tutor), and unsupervised (learning though students' self-study).

However, student's personality influences his/her way (approach) to learning after Myers-Briggs Type Indicator (MBTI) [29]. That MBTI based originally on Jung’s theory of psychological types [30]. According to one dichotomy flowing MBTI (extroversion/introversion) [29]. Both represent external and internal environmental learning conditions, including: teaching methodology, adopted educational technology, learning styles, prior knowledge, motivation, and cognitive traits [30][31]. Interestingly, both performance of extroversion and introversion student's attitudes have been realistically simulated respectively by learning rate and gain factor at ANN modeling.

Furthermore, student's cognitive style as well as his/her personality indicator (MBTI). Both have been evaluated under consideration of variable neurons' number. That's while these stimulated neurons where cooperatively contributing to performing learning processes convergence.

The rest of this paper is organized as follows. At the next section, revising of Pavlov-Hebbian modelling is presented. Mathematical modelling of coincidence detection learning in addition to a brief about NMDA receptors and its roles in forming two long term phenomena Potentiation (LTP) and depression (LTD) are introduced at the section III . At section IV., a generalized view for interactive educational process is presented. In addition to a block diagram of an interactive ANN model (with and without teacher) are introduced. A brief introduction for students' Structure of the Observed Learning Outcome (SOLO) along with summarizing of findings as simulation results in addition to obtained practical results engineering education are given in the fifth section. A macro level flowchart for the adopted ANN modelling program is presented In the sixth section. Furthermore, running of that program results in illustrative simulation of how the increase of neurons' number contributing to learning convergence process may correspond to diversity of student's approaches (surface, deep, and strategic) . Accordingly, both student's diversity attitudes extroversion and introversion as well as the three interactive learning/teaching student's approaches (surface, deep, and strategic) have been realistically simulated. Obtained results are given at the section VI. Finally, at the last section VII , some interesting conclusions, suggestions for future work are presented.

II. Revising Pavlov-Hebbian LEARNING model

Referring to the original psycho-experimental work of Pavlov [32]; coincidence detection learning process observed to be performed, after the fulfillment two vectors association as shown at Fig. 1.(adapted from[33]). More precisely, the coincidence process between input signal vector (X_1, X_2) provided to sensory neurons (A ,C) , and dynamically adaptive weight vector (W_1, W_2), associated with both neurons. The threshold value is denoted by θ(. The coincidence learning of input signals (with two vector components), is detected as an output salivation signal (Z), developed by motor neuron (B).

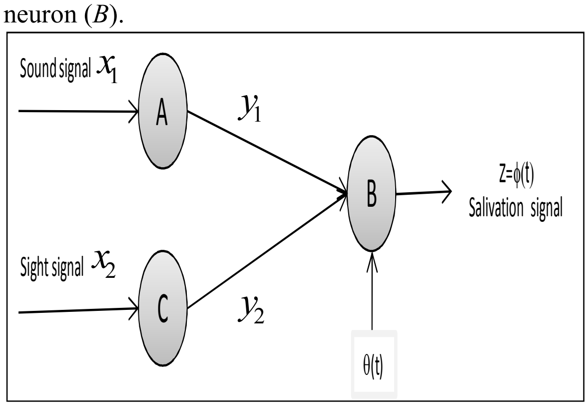

Fig. 1. The structure of the Hebbian learning rule model representing Pavlov's psycho-experimental work .

Referring to the weight dynamics described by the famous Hebbian learning law [34], adaptation dynamical process for synaptic interconnections given after [35], by the following equation:

$$\frac{d\omega_{ij}}{dt} = \eta z_i y_{ij} - a(z_i)\omega_{ij} \qquad (1)$$

Where, the first right term corresponds to learning Hebbian law and η is a positive constant. The second term represents active forgetting; a (z_i) is a scalar function of the output response (z_i). Referring to the structure of the model given at Figure1 the adaptation Eq. of the single stage model is as follows.

$$\dot{w}_{ij} = -aw_{ij} + \eta z_i y_{ij} \qquad (2)$$

Where, the values of η , zi and yij are assumed all to be non-negative quantities [34], η is the proportionality constant less than one, a is also a less than one constant. The solution of the above Eq.2 given as follows:

$$w(t) = \frac{\eta}{a}(1 - e^{-at}) \qquad (3)$$

The above solution considered herein, for investigation of two synaptic plasticity factors (forgetting and learning).That is following both long-term phenomena Potentiation (LTP) and depression (LTD) observed at hippocampus brain area.

III. Modeling of Coincidence Detection Learning

The model based on transferring of dot products of coincidence detection vectors, into learning process curve that closely similar to the well-known sigmoid transfer (output) function.

Considering normalized two weight and input vectors, it seems a good presentation of coincidence detection learning process given as:

y = cos (α) (4)

Where y coincidence learning value presented by cosine of the angle α between weight and input vectors. Therefore, the relation given as:

$$x = f(y)$$

Where

$$x = \frac{y}{1-y} \qquad \text{For } (0 <= y<1) \qquad (5)$$

This Eq. inversely equivalently given by inverse y = f(x) as:

$$y = \frac{x}{1+x} \qquad (6)$$

This function could be easily as an approximation of

$$y \approx (1 - e^{-x}) \qquad (7)$$

When only two terms of e^{-x} expansion are considered

However, this exponentially saturated function behaves as the sigmoid function at the range $0 \le x < \infty$ at the next section. Considering generalization of this function, individual differences represented well by relevant choice the parametric value λ in the following Eq.:

$$y = (1 - e^{-\lambda x}) \tag{8}$$

This value corresponds to the learning rate factor suggested when solving Hebbian learning differential equation using Mathematica [35]. Considering the view of coincidence detection learning, the angle α is a virtual learning parameter that controlling individual differences factor. So the parametric value λ expressed as:

$$\lambda = \frac{1}{\tan\alpha} \tag{9}$$

The special case where ($\alpha = \pi / 4$), learning is virtually corresponding to the natural state (normalized). Consequently, brainier performance supposed to start at ($\alpha > \pi / 4$), and exceeded up to the limit at ($\alpha = \pi / 2$). At this limit, learning curve reaches to hard limiter performance, simulating maximum brainier (smartest) performance. Conversely, knockout brain functions cases considered for ($0 \le \alpha < \pi / 4$).

These two-brain state functions are in well correspondence with electrically practical stimulating signal observed at hippocampus brain area. That by either higher or lower frequencies than the normalized learning curve ($\alpha = \pi / 4$). These two states of frequencies results (after stimulation) in long-term Potentiation (LTP) long term Depression (LTD) respectively [21][27]. More precisely of presented above analysis for coincidence detection learning. The angle α between training /learning weight vector and an input vector have to be detected in accordance with cosine of the angle α. Consequently. In case of ideal detection learning ; tan (α) equals zero. However, on the extreme value impossibility of learning detection occurs when α equals Π /2. So, under the above assumption given at equation(9) ($\lambda = \frac{1}{\tan \alpha}$) , the value of λ ranges from zero to infinity.

The results of learning process considering Hebbian rule are shown by following the equation(8). In other words ,the value of λ corresponds to the gain factor (slope) in classical sigmoid function at ANN models[36].

$$y(t) = \frac{1}{1 + e^{-\lambda t}} \tag{10}$$

The exponentially increasing function (8) behaves in a similar way as the sigmoid function as it saturated at unity value ($y(t) = 1$) when learning / training time approaches to infinity. However, the equation (8) is closely similar to the odd sigmoid function given as

$$y(t) = \frac{1 - e^{-\lambda t}}{1 + e^{-\lambda t}} \tag{11}$$

$$For \ 0 \le t \le \infty$$

At Fig. 2. , three curves are shown representing various individual levels of learning approaches(surface, deep, and strategic) . Curve *(Y_2)* is the equalized representation of both forgetting and learning factors [21]. However curve (Y_1) shown the low level of learning rate (learning disability) that indicates the state of angle ($\alpha < \Pi /4$) conversely, the curve *(Y_3)* indicates better learning performance that exceeds the normal level of learning at curve *(Y_2)*. When NMDA receptors time open more than normal time this leads to better level of intelligence. That means the saturation level has been reached more rapidly than the normal learning curve *(Y_2)*. More probably, as the slope {tan (α)} increases as the opening receptor time increases. Consequently, learning convergence time decreases as shown at Fig. 2 (t_1, t_2, and t_3). Three different levels corresponding to learning performance curves representing: normal, low, and better cases shown at curves Y_2, Y_1, *and* Y_3 respectively. Interestingly, the obtained simulation graphical results (given by graphs:Y_1, Y_2, *and* Y_3) are realistically corresponding respectively to three students' academic diversity approaches (orientations) namely: surface, deep, and strategic.

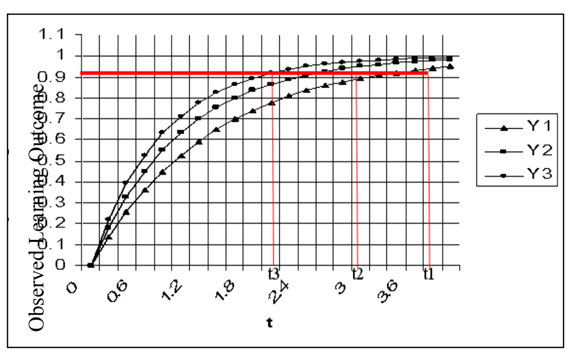

Fig. 2 shows three different learning performance curves Y_1, Y_2 and Y_3 that converge at time t_1, t_2 and t_3 considering different NMDA receptor opening time represented at different slope values corresponding to λ_1, λ_2, λ_3 respectively.

IV. REVISING OF GENERAL LEARNING MODEL

In general - from neurophysiologic P.O.V. - performing of learning process in practical field utilises two basic and essential cognitive functions. Both functions are required to perform efficiently learning /teaching interactive process in accordance with behaviorism [32][33][37] as follows. Firstly, pattern classification/recognition function based on visual/audible interactive signals stimulated by CAL packages. Secondly, associative memory function is used which is originally based on classical conditioning motivated by Hebbian learning rule.

Referring to Fig. 3., it illustrates a general view of a teaching model qualified to perform simulation of above mentioned brain functions. Inputs to the neural network teaching model are provided by environmental stimuli (unsupervised learning). However, correction signal(s) in the case of learning with a teacher given by output response(s) of the model that evaluated by either the environmental conditions (unsupervised learning) or by supervision of a teacher. Furthermore, the teacher plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of model pattern input. That is in accordance with tutor's experience while performing either conventional (classical) learning or CAL. Consequently, he provides the model with clear data by maximizing its signal to noise ratio [6]. Conversely, in the case of unsupervised/self-organized learning, which is based upon Hebbian rule [34], it is mathematically formulated by equation (18) given in below.

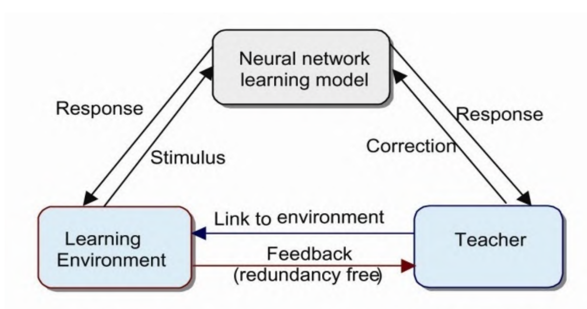

Fig. 3. A general view for interactive educational process

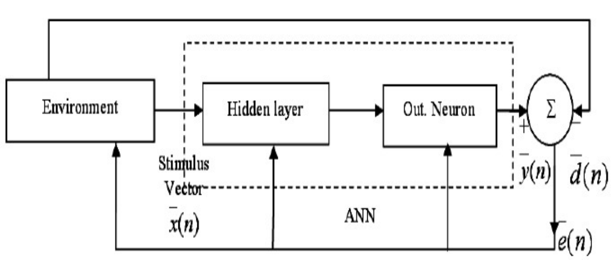

Fig. 4. Generalized ANN block diagram simulating two diverse learning paradigms.

The presented model given in Figure 4 in below generally simulates two diverse learning paradigms. It presents realistically both paradigms: by interactive learning/ teaching process, as well as other self organized (autonomous) learning. By some details, firstly is concerned with classical (supervised by a tutor) learning observed in our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between a teacher and his learner(s) [16]. However, secondly other learning paradigm performs self-organized (autonomously unsupervised) tutoring process [34][38].

Referring to above Fig. 4. ; the error vector $\bar{e}(n)$ at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \tag{12}$$

Where...... $\bar{e}(n)$ is the error correcting signal controlling adaptively the learning process, and $\bar{y}(n)$ is the output signal of the model. $\bar{d}(n)$ is the desired numeric value(s). Moreover, the following four equations are deduced:

$$V_k(n) = X_j(n) W_{kj}^T(n) \tag{13}$$

$$Y_k(n) = \varphi(V_k(n)) = (1 - e^{-\lambda V_k(n)})/(1 + e^{-\lambda V_k(n)}) \tag{14}$$

$$e_k(n) = |d_k(n) - y_k(n)| \tag{15}$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \tag{16}$$

Where..... X is input vector and W is the weight vector.

φ is the activation function. Y is the output. e_k is the error value and d_k is the desired output. Noting that ΔW_{kj}(n) is the dynamical change of weight vector value. Above four equations are commonly applied for both learning paradigms: supervised (interactive learning with a tutor), and unsupervised (learning though students' self-study). The dynamical changes of weight vector value specifically for supervised phase is given by

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \tag{17}$$

Where η is the learning rate value during the learning process for both learning paradigms.

However, for unsupervised paradigm, dynamical change of weight vector value is given by:

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n) \tag{18}$$

Noting that e_k(n) in (17) is substituted by y_k(n) at any arbitrary time instant (n) during the learning process.

V. STUDENTS' ADEMIC ACHEIVEMENT DIVERSITY

Referring to the original RICHARD M. FELDER work for understanding student differences [10]. Therein, that work examines in details three categorized aspects of student diversity. They have important implications for teaching and learning are differences in students' Namely: learning styles (characteristic ways of taking in and processing information), approaches to learning (surface, deep, and strategic), and intellectual development levels (attitudes about the nature of knowledge and how it should be acquired and evaluated). Herein, at the next subsection, the analogy describing diversity of quality levels of the learning outcomes is introduced including some experimental results. However, at the following subsection *B;* experimental results obtained after performing a case study at an engineering institution in Egypt are presented . At the last subsection *C,* obtained simulation results shown to be in well agreement with case study published results [25].

A. *Structure of the Observed Learning Outcome (SOLO)*

Referring to the work of Van Rossum and Schenk [39]used the Structure of the Observed Learning Outcome (SOLO) taxonomy to describe the quality of the learning outcomes of 69 first-year psychology students. The SOLO taxonomy consists of five structural categories of learning outcomes, going from the lowest level: 'pre-structural' (an irrelevant response), to the most complete level, called 'extended abstract' [40]. Their results show a clear positive relationship between the observation of a deep study approach and high quality learning outcomes. The difference in quantitative learning outcomes (using average exam scores) between students using the surface or the deep approach was only significant for questions measuring insight, not for questions measuring the reproduction of knowledge.

Referring to [41], therein a study of relationship between the observed approaches to learning and the learning outcomes of 122 first-year nursing students has been presented. Using the SOLO taxonomy, they found a positive correlation between a deep approach to learning and high qualitative levels in learning outcomes, but no such correlation to quantitative differences in outcome. There were no relationships found between surface approaches to learning and qualitative or quantitative outcome measures. In a later study in the field of biology. Finally, by referring to [42]. Therein, the SOLO taxonomy adopted to analyze the learning outcomes, complemented with concept maps and phenomenon graphic methods. The 272 students involved in this study ended up in two clusters. In the first cluster, there was a relationship between low outcome measures, low scores on deep approaches and high scores on surface approaches. On the other hand, the second cluster reported high outcome scores related to low surface approach scores and high deep approach scores.

B. *Experimental Results*

By considering Structure of the Observed Learning Outcome (SOLO) relevant to describe student's diversity quality levels of the learning outcomes . SOLO taxonomy consists of five structural categories of learning outcomes, going from the lowest level: 'pre-structural' (an irrelevant response), to the most complete level, called 'extended abstract' [40].

This subsection presents obtained the case study (experimental) results at Modern Academy for Engineering , and Technology (Cairo, Egypt). These results have been normalized and introduced in tabulated forms (Tables I, II, III, and IV). At tables I &II, normalized distribution values for Students' GPA , and Students' achievements at two prerequisite courses are given respectively. Correlation Coefficients of Electrical Engineering prerequisites are shown at Tables III, Moreover these Coefficients for Mechanical Engineering are given at Table IV. Finally, at Table V., the realistic obtained simulation results are presented after running of suggested ANN model program (see algorithmic steps flowchart at Fig.5., in the next section IV.).

TABLE I. ORMALIZED DISTRIBUTED VALUES OF STUDENTS' GLOBAL SOLO (GPA)

SOLO / Specialization	Pre-Structural	Fair	Good	Very Good	Extended Abstract
Electrical	0.08	0.12	0.44	0.28	0.08
Mechanical	0.08	0.11	0.27	0.43	0.11

TABLE II. **NORMALIZED DISTRIBUTED VALUES OF STUDENTS' SOLO PREREQUISITES**

SOLO / Specialization	Pre-Structural	Fair	Good	Very Good	Extended Abstract
Electrical	0.08	0.2	0.32	0.28	0.12
Mechanical	0.08	0.16	0.27	0.38	0.11

The following tables (III &IV) illustrate statistical results analysis for correlation coefficients of suggested case study:

TABLE III. **CORRELATION COEFFICIENTS OF ELECTRICAL ENGINEERING DEPARTMENT**

Variables	Math. / SOLO	Phys. / SOLO	Prerequisite / SOLO
Correlation Value	0.61	0.65	0.66

Table IV Correlation Coefficients Of Mechanical Engineering department

Variables	Mechanics / SOLO	Eng. Drawing /SOLO	Prerequisite / SOLO
Correlation Value	0.5	0.57	0.59

TABLE IV. **SIMULATION RESULTS FOR STUDENTS GLOBAL SOLO (GPA)**

Pre-Structural 35%	Fair 50%	Good 65%	V.G. 75%	Extended Abstract 90%
0.06	0.25	0.4	0.24	0.05

C. Analysis of Obtained Results

At the above Table V., the simulation results shown to be in agreement with experimental results. presented after ANN modeling. The results of the experimental work showed considerably high correlation between learning style and student results. Tables (III , IV) depict this correlation. Moreover, tables (I , II) show considerably good results for students who properly chosen their majors according to the results of the prerequisites. That means the proper choice of specialization that fits high marks in the prerequisite courses leads to better grade point average. The higher marks student achieves in the prerequisites, the better are the global student's SOLO (GPA). The simulation technique using artificial neural networks (ANN's) produced results that are in good agreement with the results produced by the case study. The input to the network is the marks obtained in the prerequisites (learning style) and the output is the Global SOLO (GPA) achieved.

VI. SIMULATION RESULTS

The presented results (in three items), at this section are obtained after running of adopted ANN computer simulation program. Its algorithmic steps are shown at Fig.5.

1- At Table VI. ,the effect of increasing of neurons' number on SOLO is presented. The two diverse cognitive styles (field dependant and independent) at various introversion attitudes (gain factor λ= 0.5, 1, 1.5) are introduced. That's corresponding respectively to three students' approaches to learning (surface, deep, and strategic).

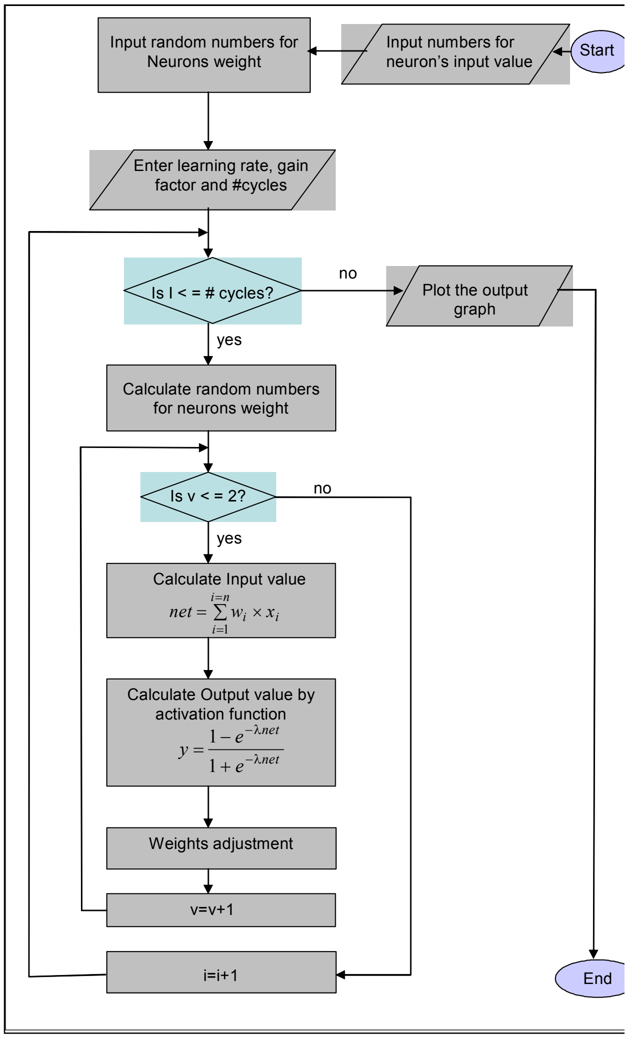

Fig. 5. A simplified macro level flowchart describing algorithmic steps for Artificial Neural Networks modeling considering various neurons' number.

TABLE V. EFFECT OF INCREASE OF NEURONS' NUMBER ON LEARNING (SOLO)

# Neu.	Gain Factor λ =0.5		Gain Factor λ = 1		Gain Factor λ = 1.5	
	Hebb Rule	Error Corr.	Hebb Rule	Error Corr.	Hebb Rule	Error Corr.
2	18.2	19.2	35.5	35.9	50.3	49.3
3	25.7	25.8	48.5	47.8	63.4	62.8
4	30.7	31	56.6	56.1	74.5	71.5
5	36.8	36.7	62.5	62.9	79.9	78.5
6	43.5	43.7	73.1	72.1	87	86.7
7	50	49.7	79.7	77.8	92.1	90.9
8	55.3	53.9	84.2	83.4	94.5	93.3
9	63.3	62	90	87.9	96.6	95.9
10	65.6	64.8	91.3	89.3	97.4	96.8
11	70.9	69.6	93.6	92.4	98.3	97.8
12	76.1	74.6	95.9	94.9	98.8	98.5
13	77.9	76.7	96.5	95.3	98.8	98.7
14	79.2	77.8	97	96.2	98.9	98.8

2- At Fig.6., the student's diversity for intrinsic attitudes (introversion) -as number of neurons increases- is given for (Gain factor values: 0.5, 1, and 2). That is corresponding respectively to three students' approaches to learning (surface, deep, and strategic).

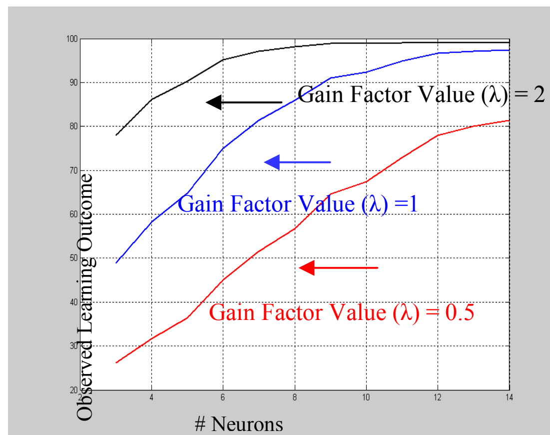

Fig. 6. Illustrates simulated SOLO learning performance obtained versus # Neurons for diversity introversion attitudes (Gain factor values: 0.5, 1, and 2). That is corresponding respectively to three students' approaches to learning (surface, deep, and strategic).

3- At Fig.7., it illustrates how learning performance of obtained student's academic achievement varies versus # Neurons For various extroversion attitudes (learning rate values: 0.01, 0.1, and 0.3). That's corresponding respectively to three students' approaches to learning (surface, deep, and strategic).

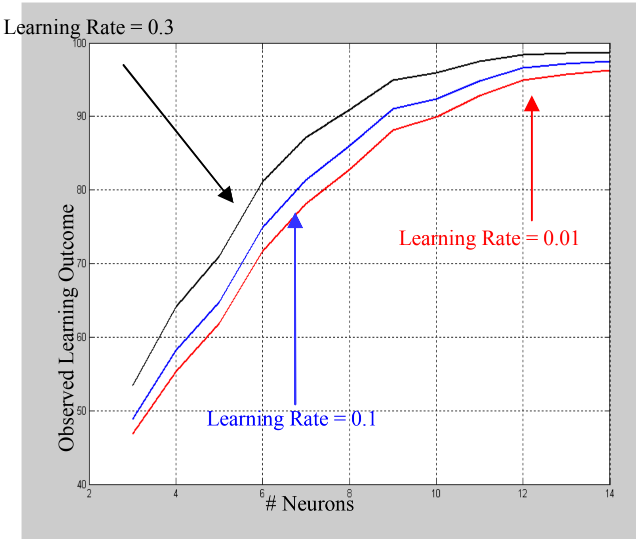

Fig. 7. Illustrates simulated SOLO learning performance versus # Neurons For various extroversion attitudes (learning rate values: 0.01, 0.1, and 0.3) corresponding respectively to three students' approaches to learning (surface, deep, and strategic).

VII. CONCLUSIONS AND DISCUSSIONS

The following are some interesting conclusion remarks deduced after analysis of obtained realistic simulation results:

1- Production of mice (or other spices) with genetically reformed brain functions, belongs to an interdisciplinary field of research. It comprises computational neurobiology (brain bioinformatics), genetic engineering, neuro microbiology, with main attention towards neurophysiology [21][43].
2- Mathematical neural networks analysis and behavioral modeling attached recently to that set of research directions [18] Consequently, reforming process of brain functions characterized by interdisciplinary costly experimental work, that inherently very complex and challenging as well.
3- Students who might wish to attain better learning performance have to follow up Data-driven decision-making in accordance with their achievements in the prerequisite courses.
4- Considering the learning style that incorporates various student characteristics can greatly improve learning outcomes. Directing learners to proper specialization in view of their achievements in the prerequisite courses is a promising trend for achieving better learning performance results.
5- ANN modeling is a realistic and relevant tool to obtain interesting results in the context of student's diversity learning styles as well as approaches.

The following are some research work directions that may be adopted in the future:

1- Genetic engineering application for improvement of NMDA receptors opening time for medical treatment of memory and learning deficiencies for elder human persons.
2- Application of improved synaptic connectivity with random weight values in order to perform medically promising treatment of mentally disable students [43]
3- Simulation and modeling of complex educational issues such as deterioration of academic achievement levels in our schools.
4- Study of ordering of teaching curriculum simulated as input data vector to neural systems. That improved both of learning and memory for the introduced simulated ANN model.

More elaborate evaluation and assessment of student's individual differences phenomena is expected as urgently requested for field educational process. That's is could be carried out by considering the effect of introversion brain state of student as well as extroversion environmental factors upon convergence of learning / training student's approaches (surface, deep, and strategic)

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