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On Quantified Analysis and Evaluation for Development Reading Brain Performance Using Neural Networks' Modeling

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ABSTRACT

Recently, neuroscientists, and educationalists as well have revealed some resulted educational interesting findings. Originally those findings have been derived in accordance with commonly increasing sophisticated role of Artificial Neural Networks (ANNs) modeling. Herein, performance evaluation of an observed educational field phenomenon considered via realistic ANN modeling. Briefly, realistic ANNs modeling for analysis, and evaluation of an interdisciplinary challenging phenomenon, has been adopted in this article. More specifically, that realistically modeled phenomenon based originally upon the observable children's reading brain performance in classrooms (equivalently: children's academic achievement). By more details, the adopted educational phenomenon essentially concerned with quantification of the reading children's brain performance that affected by educational physical environment as well as teaching reading methodologies. Furthermore, realistic (ANNs) simulation has been suggested in accordance with the highly specialized neurons' number while performing reading brain function's role. Consequently, realistic simulation for quantifying reading brain function is suggested by adopting (ANNs) modeling. Optimal selectivity for gain factor value, learning rate parameter value, and number of neurons are considered to improve learning reading brain function. Obviously, that function is dynamically involved by enhanced cognitive goal for reading brain process that based on dynamic synaptic interconnectivity. In this context, the presented work illustrates via ANN simulation results: How ensembles of highly specialized neurons could be dynamically involved to perform developing of reading brain's cognitive function. That function considers essentially translation of orthographic word-from into a spoken word (phonological word-form). Interestingly, the realistic ANN model presented herein has been in close resemblance functionally and structurally to biological neuronal systems.

Keywords: artificial neural network modeling ; reading brain function; synaptic plasticity; highly specialized neurons.

INTRODUCTION

The field of the learning sciences is represented by a growing community internationally. The last decade of previous century(1990-2000) named as the Decade of the brain, after referring to WHITE HOUSE OSTP REPORT (U.S.A.) which declared in 1989[1]. Therefore, educationalists, neurobiologists, and computer engineering scientists have adopted research approach associated with natural intelligence (recent computer generation), in addition to investigation of the two essential brain functions (learning and memory). Furthermore, overwhelming majority of neurobiologists, neurologists, and educationalists research efforts have revealed findings associated with the increase of commonly sophisticated role of artificial neural networks (ANN). This paper addressed the conceptual approach of (ANN) sophisticated role inspired by functioning of highly specialized biological neurons in reading brain processing. Interestingly, observed reading function is dependable upon individual differences of brain's contribution ability originated from its structures/substructures organization and even sets of neurons. More specifically, introduced models concerned with performed tasks by human brain are commonly coupled tightly to the two main brain functions. These are: learning that defined as brain's ability to modify the behavioral neural response to stored experience (inside the brain synaptic interconnections). And the memory is the capability of storing modified (information) during a time period as well as spontaneous retrieving of modified experienced (learned) patterns i.e. Pattern Recognition. Considering the modeling of neural networks, the tightly mutual relation between learning and memory brain functions has been presented at [2][3] and extended illustrations have been introduced at two more recently at two previously published pieces of researches [4][5]. All these publications and more [6][7] have motivated by a challenging educational debated issue titled: “how to learn reading?” which announced before two decades, by the great debate held in 1996, at [8], and at the two papers published during last decade [9][10].

Recently, neurological researchers as well as educationalists have revealed their interesting findings concerned with the increasingly common. And sophisticated role of Artificial Neural Networks (ANNs) to evaluate some of observed educational phenomena. More specifically, the presented research work provides a special attention to the analysis of applicable realistic models for the reading brain role. of recent interdisciplinary modeling considering That role applied for systematically realistic modeling of an interdisciplinary discipline incorporating neuroscience, education, and cognitive sciences. Therefore, the ANN Models varied in relation to nature of assigned brain functioning to be modeled. For example, as human learning takes place according to received stimuli that is simulated realistically through self-organization paradigm by artificial neural networks modeling. Additionally, in accordance with the prevailing concept of individual intrinsic characterized properties of highly specialized neurons, presented models closely correspond to performance of these neurons for developing reading brain in a significant way. More specifically, introduced models concerned with their important role played in carrying out cognitive brain function' outcomes. The cognitive goal for reading brain is to translate that orthographic word-from into a spoken word (phonological word-form)[11]. In this context herein, the presented work illustrates via ANN simulation results: How ensembles of highly specialized neurons could be dynamically involved in performing the cognitive function of developing reading brain. The ensembles of highly specialized neurons (neural networks) in human play the dominant dynamical role in the functioning for developing of reading brain[12]. In accordance with referring to contemporary neuroscience evaluation, there are possibly great implications for learners, tutors, and educationalists. Modeling of the popular and sophisticated type of complex system named "Artificial Neural Network"(ANN) has been adopted. Where collection of artificial neurons (nodes) are linked up in various ways, and the network then processes "synapses" according to a distribution of weights for the connections between the neurons and transfer functions for each individual neuron [13]. The synaptic connectivity patterns among artificial neurons has implication on learning ability [14], and also on the human learning creativity [13]. More specifically, modeling of complex neural network could be considered as a series of highly specialized interconnected nodes (artificial neurons) contributing to spoken words for reading brain. Obviously, children's individual differences which characterized by various gain factor values of (highly specialized artificial neurons), are relevant for realistic quantification the *Development of Reading Brain Performance* (children's academic achievement). Interestingly, it is noticed that realistically modeled neural networks presented herein has been in close resemblance functionally and structurally as well to the natural biological neuronal systems.[15][16]. Recently, some more interesting findings have been announced considering the relation to educational physical environment's effects on the observable academic performance (achievement) quality in classrooms. These findings introduced at the two published papers at two specific educational journals: [17] and [18].

The rest of this paper is organized in six sections as follows. At next two second, and the third sections ; revising of the basic two functions of : learning performance in human brain, and investigation of an individual biological neuron are presented respectively. The mathematical modeling of a single neuronal function is introduced at the fourth section. Realistic modeling of an educational/learning process is given at the fifth section. At the sixth section, some of interestingly obtained simulation results are presented. Finally, some fruitful conclusive remarks, dissections, and suggestions for the future research work are introduced at the last seventh section.

REVISING OF LEARNERNIG BRAIN FUNCTION

This section aims to present some of detailed description about the human brain structure/substructure, and its function considering realistic modeling for biological information processing [19]. That is performed depending upon the basic processing building block (single neuron). The basic biological control component is the neuron. A full understanding of the 'architecture of brain and mind' must, ultimately, involve finding an explanation of the phenomenological observations that can be expressed in terms of the interactions between neurons [20]. By more details, biological information processing is performed via neurons' synaptic connectivity. That comprises very flexible set of basic building blocks (neurons) whose utility scales over systems covering a vast range of complexities. For examples, the very simple creatures' brains find even a small number of neurons' connectivity performs useful complex behavioral function. Honeybees find it economic to support brains comprising around ***850,000*** neurons, which give them exceptional navigational capabilities while travelling several miles from their hive. Interestingly, experts estimate that an ant brain contains about ***250,000*** brain neuronal cells [21]. That number pales in comparison to the human brain, which is believed to contain over 86 billion neurons. However, for the ant, its brain is quite powerful. Humans have evolved to carry brains comprising $\boldsymbol{10^{11}}$neurons or so and use these to support exceptional motor control and complex societal interactions. Accordingly, any human brain has about **10,000 million** so a colony of 40,000 ants has collectively the same size brain as a human.[22]. Biological neural networks are made up of real biological neurons that are physically connected or functionally-related in the human nervous system and especially in the human brain. Artificial neural networks (ANN or simply NN) on the other hand, are made up of artificial neurons interconnected with each other to form a programming structure that mimics the behavior and neural processing (organization and learning) of biological neurons. Human brain can perform tasks much faster than the fastest existing computer thanks to its special ability in massive parallel data processing. NNs try to mimic such a remarkable behavior for solving narrowly defined problems i.e., problems with an associative or cognitive tinge [23]To this effect, NNs have been extensively and successfully applied to pattern (speech/image) recognition, time-series prediction and modeling, function approximation, classification, adaptive control and other areas. As stated, a neural network consists of a pool of simple processing units, the 'neurons'. Within NNs three types of neurons are distinguished at (Fig. 1): input neurons (nodes, which receive data from outside the NN and are organized in the so called ***input*** layer, ***output*** neurons (nodes), which send data out of the NN called the output layer, and ***hidden*** neurons (nodes), whose input and output signals remain within the NN and form the so called hidden layer (or layers). The adopted neural model for simulation of reading brain performance evaluation is similarly following the most commonly known structural type of ANN. By referring to (Fig.1), it is noticed that: nine that depicted circles (4-3-2) are representing three distinct groups, or layers of biological neurons. For the four nodes represent Input layer, three nodes represent Hidden layer, and the Output two layer nodes (neurons). That is a structure of the Feed Forward Artificial Neural Network (FFANN) model consisted of three layers comprise nine nodes : an "**input**" layer of four nodes which denoted by (I_1, I_2, I_3, and I_4) is connected to a "**hidden**" layer of three nodes, which is connected to an "**output**" layer of two nodes that denoted by (O_1, and O_2). Obviously, any one of these nodes represents / simulates a single biological neuron, which illustrated schematically at (Fig.1). Generally, the activity function of that (FFANN) structure is briefly given as follows:

a) The activity of the input comprises four nodes, represents the raw information that is fed into the network.
b) The activity for each node of the hidden layer is determined by the activities provided by the four input layer's nodes and the synaptic weights' connections between the input nodes and the hidden layer's nodes.
c) The behavioral activity of the output nodes depends on the activity of the hidden nodes and the weights between the hidden and output nodes.

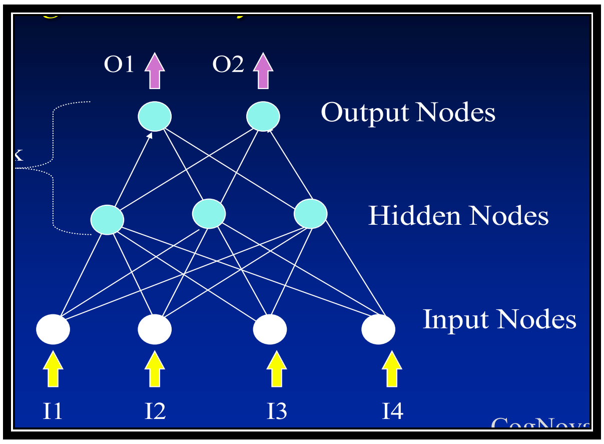


Fig. 1 A simplified schematic diagram for a (FFANN) model (adapted from, [19]).

Artificial neural networks (ANN$^{\underline{S}}$) are mathematical models inspired by the organization and functioning of biological neurons. There are numerous artificial neural network variations that are related to the nature of the task assigned to the network. There are also numerous variations in how the neuron is modeled. In some cases, these models correspond closely to biological neurons [24][25] in other cases the models depart from biological functioning in significant ways. Moreover, (ANN$^{\underline{S}}$), considered as computational systems which are increasingly common and sophisticated. Computational scientists who were adopted to work with such systems however, often assume that they are simplistic versions of the neural systems within our brains and Cilliers (1998)[26] has gone further in proposing that human learning takes place through the self-organization of such however, (ANN$^{\underline{S}}$), were originally conceived of in relation to how systems according to the stimuli they receive. Additionally, by referring to the previously White House report namely: the Decade of the brain [1], neural network theorists and neurobiologists as well, have focused their attention on making a systematical contribution for investigating mystery of human biological neural system (mainly, the brain), functions. There is a strong belief that making such contribution could be accomplished by adopting recent interdisciplinary research work direction, via combining ANN$^{\underline{S}}$ realistic modeling with neuroscience. Therefore, it is interestingly relevant to consider that modeling of the biologically inspired natural neural models it might have become possible to shed lighting on behavioral learning principles and functions concerned mysterious human biological neural systems. By some more details about the learning brain function, it is noticed they have been tightly coupled with the two following mainly sub-functions [2]:

a) Learning: is that ability to modify behavioral brain's response in accordance with the stored experience. That is consequently corresponds to modified synapses' interconnections (inside brain).
b) Memory: is that ability to restore the modified behavioral information over a period of time. As well as the ability to retrieve spontaneously the modified experienced (learned information) patterns distributed inside brain synaptic connections.

REVISING A BIOLOGICAL NEURON FUNCTION

A single biological neuron cell is represented as a node depicted circle at the FFANN diagram at Fig.1. By referring details at Fig.2, that neuron node (circle) viewed as comprising four basic neuronal (primary) structures. These structures coupled functionally among themselves as : inputs collected through dendrites and passed to the soma, the main body of the cell. The action potential (spike) generated in the soma propagates along the axon, where it passed through synapses to the dendrites of other neurons. The synapse is the primary location of adaptation in the neural system: the strength of the coupling between two neurons self-adjusts over time in response to factors such as the correlation between the activities of the two neurons that are coupled through the synapse. **By** more details, the four structures of any single node could be functionally described as follows:

a) Dendrites are the tree-like structures that gather the inputs to the neuron from other neurons or sensory inputs and couple them to the soma.
b) The soma is the central body of the neuron where the inputs are processed and the output is generated.
c) The axon carries the output of the neuron through another tree-like structure to couple it to other neurons or physical actuators, incurring a signal-propagation delay that depends on the length of the axon.
d) Synapses form the coupling between neurons. These can develop wherever the axon from one neuron is physically proximate to a dendrite of another. The coupling process incurs some time delay, but this can generally be added into the axonal delay for modeling purposes.

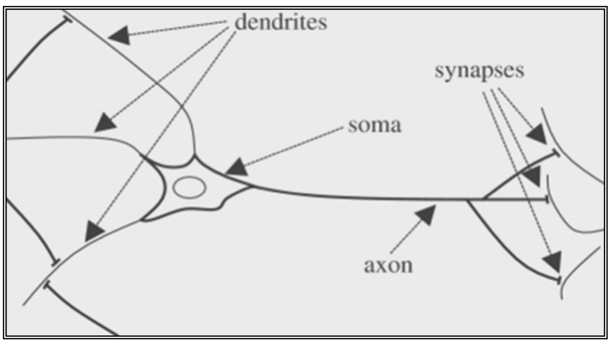


Fig.2 A simplified schematic structure of a single biological neuron adapted from [27]

A. From Biological to Artificial Neuron

The fundamental building block of every nervous system is the single neuron. Understanding how these exquisitely structured elements operate is an integral part of the quest to solve the mysteries of the brain. Quantitative mathematical models have proved to be an indispensable tool in pursuing this goal. We review recent advances and examine how single-cell modeled by distinct five levels of presentation complexity[28] . The simplest presentation of modeling levels is the black-box approaches to detailed compartmental simulations. At Fig.3, a single neuron cell Input / Output relation is represents as a *Black-Box* model. That is after neglecting of biophysical mechanisms and considering the conditional probabilities p(R|S) describe responses R for given stimuli S.

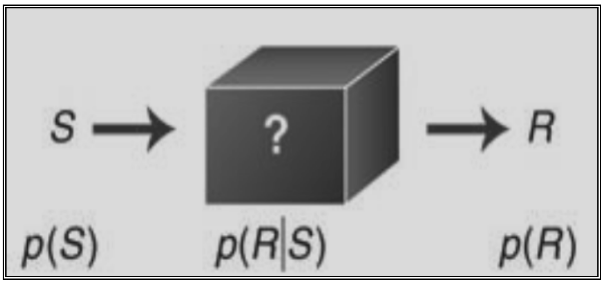


Fig. 3 Illustrates the global single neuron computational function as a Black-Box Model {Adapted from[28]}

Basic function of neuron is to sum inputs, and produce output given sum is greater than threshold of the ANN node which produces an output as follows:

1. Multiplies each component of the input pattern by the weight of its connection
2. Sums all weighted inputs and subtracts the threshold value => *total weighted input*
3. Transforms the total weighted input into the output using the activation function.

The detailed model structure of a single neuron cell in addition to brief mathematical formulation is given at the next subsection. Furthermore, the next section introduces the mathematical formulation model of a single neuronal cell with the sufficient details to account for the dynamics of a single-cell complexity and reducing it to the very essential characteristics for making the given the mathematical model well tractable.

B. A Simplified Model For A Single Artificial Neuron

A single artificial neuron model considered as an information processing unit that is the fundamental of ANN[s] operation, three basic elements of that model are given (by referring to the graphical presentation shown at Fig. 4. in below) as follows :

1. A set of weights, each of which is characterized by a strength of its own. A signal x_i connected to neuron k is multiplied by the weight w_{ki}. The weight of an artificial neuron may lie in a range that includes negative as well as positive values.
2. An adder for summing the input signals, weighted by the respective weights of the neuron.
3. An activation function for limiting the amplitude of the output of a neuron. It is also referred to as transfer function which squashes the amplitude range of the output signal to some finite value. Two types of the sigmoid transfer (activation)functions are commonly used in ANN applications. First one is the logistic sigmoid and the second other function is the odd sigmoid. There values are given at any arbitrary time instant (n) by equations (3) & (4) respectively.

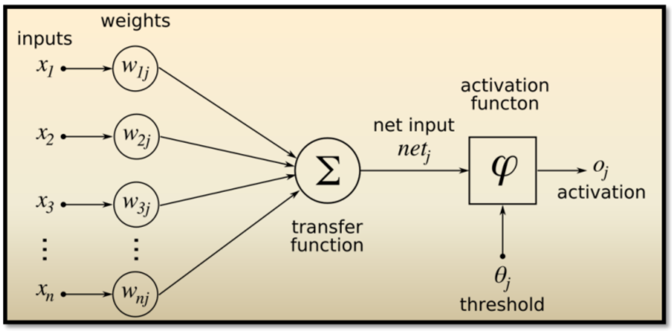


Fig. 4 . A single neuron (k) model coupled with synaptic weights from other neurons w_{ki} (i,……,p)

$$V_k = \sum_{i=1}^{p} w_{ki} x_i \quad (1)$$

$$y_k = \varphi(V_k + \theta_k) \quad (2)$$

The odd sigmoid function seemed to be well relevant for realistic simulation of learning brain performance as if this function input stimulus equals zero results in obtaining no output (zero).

$$y_k(n) = \varphi(V_k(n)) = 1 / (1+e^{-\lambda v_k(n)}) \quad (3)$$

$$y_k(n)=\varphi(V_k(n))=(1-e^{-\lambda v_k(n)})/(1+e^{-\lambda v_k(n)}) \quad (4)$$

MATHEMATICAL MODELING OF AN INDIVIDUAL NEURON FUNCTION

Referring to T.Kohenen's work [29][30], the output neuronal response signal observed to be developed following what so called membrane triggering time dependent equation. This equation is classified as a complex non-linear partial deferential. Its solution works to provide us with the physical description of a single cell (neuron) membrane activity. However, considering its simplified formula, which equation may contain about 24 process variable and 15 non-linear parameters. Following some more simplification of any neuron cell arguments, that differential equation describing electrical neural activity has been suggested, as follows:

$$\frac{dz_i}{dt} = \sum_{j=1}^{n} f(y_{ij}) \quad j(z_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where, y_{ij} .... represents the activity at the input (j) of neuron (i), and

$f(y_{ij})$ ....indicates the effect of input on membrane potential,

$j(z_i)$.....................represents the nonlinear loss term combining leakage signals, saturation effects occurring at membrane in addition to the dead time till observing output activity signal. The steady state solution of the above simplified differential equation (5), proved to be presented as transfer functions. Assuming, the linearity of synaptic control effect, the output response signal is given by the equation:

$$Z_i = \sum_{j=1}^{n} w_{ij} y_{ij} \quad {}_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where, ϕ...is the activation function that has two saturation limits.

That ϕ may be linear above a threshold and zero below or linear within a range but flat above,

θ.......................................is the threshold (offset) parameter, and

w_{ij} ....is the synaptic weight coupling between two neurons *(i)* and *(j).*

Considering realistic nonlinearity NL of neuron's signal activation function *(ϕ_i), it* has been recommended specifically to obey +ive behavioral segment of tangent sigmoid function. It is presented for any arbitrary neuron by the following equation :

$$Y(v) = (1 \quad e^{\quad v}) / \ (1 + e^{\quad v}) \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where

$$V = \sum_{i=1}^{m} w_i x_i - \theta$$

…………………………………… is the gain factor value, θ……………………………… is the threshold value, and m……………………………………is the number of synaptic inputs (from other neurons) to assigned neuron.

By referring, to the weight dynamics described by the famous Hebbian learning rule [19][31], the adaptation process for synaptic interconnections is given by the following modified equation:

$$\frac{d \quad_{ij}}{dt} = \quad z_i y_{ij} \quad a(z_i) \quad_{ij} \text{ .... } (8)$$

Where, the first right term corresponds to the unmodified learning (Hebb's rule) [31], and η is the *a* positive constant representing learning rate value. The second term represents the active forgetting factor, $a\,(z_i)$ is a scalar function of the output response (z_i). The adaptation equation of the single stage model is as follows :

$$\dot{w}_{ij} = \quad aw_{ij} + \quad z_i y_{ij} \text{ ....} (9)$$

Where, the values of η, z_i and y_{ij} are assumed all to be non-negative quantities. The constant of proportionality η is less than one represents learning rate value, However, a is a constant factor indicates forgetting of learnt output; (it is also a less than one) [32].

REALISTIC MODELING OF LEARNING PROCESSES

The extremely composite biological structure of Human brain results in everyday observed behavioral learning brain processes (functions). Specifically, at the educational field, it is observable that learning process performed by human brain is affected with a simple Neuronal performance mechanism [16][33]. At the educational field, such learning processes generally performed in agreement with the neuronal self-organized learning principle. This learning principle could be modeled relevantly by the interactive relation among input stimuli and output responses signals. That is shown schematically by a diagram structure at Fig.5 , a diagram decomposed into two level brain neural networks model schematically represents the autonomous learning by interaction with learning environment [16][34].

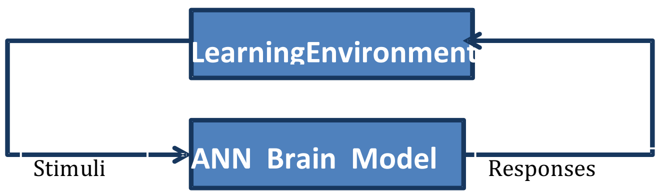


Fig. 5. A generalized schematic diagram of an ANN brain model interacts with learning environment considering input stimuli and outputs response signals.

A. Modeling of Interactive Learning Processes

This revising section introduces the conceptual basis of teaching/learning process and illustrates its realistic interactive modeling via two figures (Fig.6 & Fig.7). At Fig. 6, a generalized brief overview of the block diagram describing interactive teaching/learning process is given. It introduces either both bidirectional communicative learning between a teacher and his learners (supervised) or self-organized (unsupervised). That self-organized could be considered as learning by interaction with environment; either Hebbian or Kohonen interactive learning paradigms [19][29].

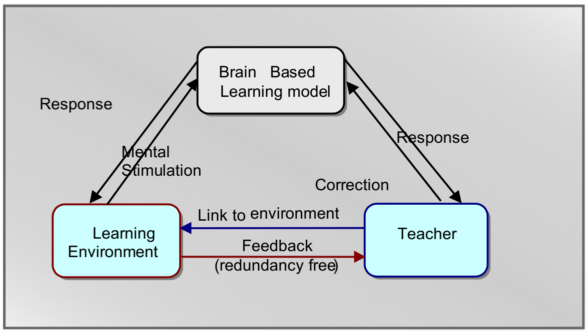


Fig.6 Illustrates a view for interactive brain based learning/teaching interactive reading process (Adapted from[7]).

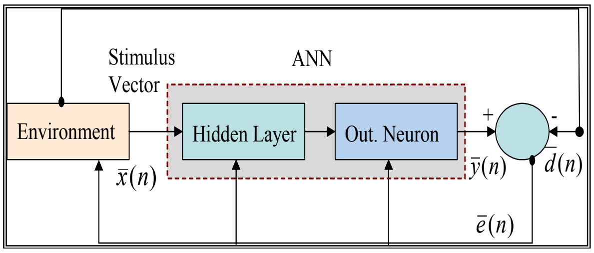


Fig. 7 : Generalized ANN block diagram simulating two diverse learning paradigms {Adapted from [19]}

At Fig.7, an interactive learning model through stimulating signals is well qualified in performing realistic simulation for evaluating learner's performance. This Figure illustrates inputs to the neural network learning model which provided by stimuli unsupervised learning environment[19]. The correction signal for the case of learning with a teacher is given by responses outputs of the model will be evaluated by either the environmental conditions (unsupervised learning) [34] or by the instructor. The instructor plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of learning model pattern input [35]. In accordance with instructor's experience, he provides illustrated model with clear data by maximizing learning environmental signal to noise ratio [34]. In brief, the reading goal is carried out by association (translation) of orthographic word-from code into a spoken word (phonological word-form code) [11][36]. In other words, the visually recognized written (code) pattern should be transferred and pronounced in accordance with its associated code as correspondingly correlated auditory code pattern which has been stored previously into working memory [12].

B. Phonics Reading Model Based On Pavlovian Concept

The structure of the model given in Fig.8, is following the Hebbian learning rule in its simplified form. This figure represents the classical conditioning learning process where each of lettered circles A, B, and C represents a neuron cell body. The line connecting cell bodies are the axons that terminate synaptic junctions. The signals released out from sound and sight sensory neurons A and C are represented by y_1 and y_2 respectively. The output of Hebbian structure after Pavlov's conditioning experimental process, is given by the function : Z = (ϕ_i). The obtained measurements' values are shown at Fig. 8.

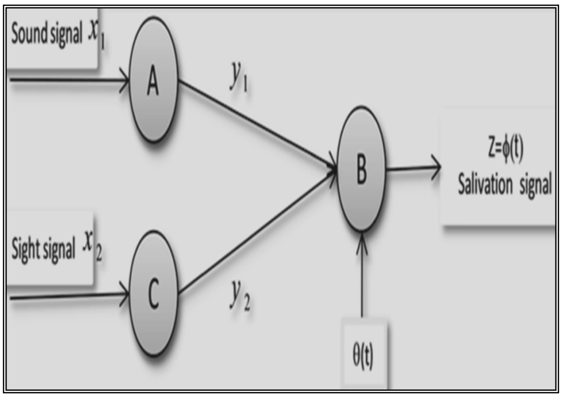


Fig.8 The structure of the Hebbian learning rule model representing Pavlov's psycho-experimental work form {adapted from [40]}.

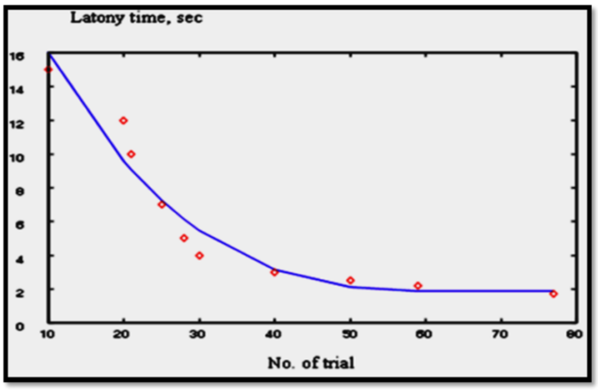


Fig.9. Fitting curve for latency time results observed by Pavlov's experimental work.{Adapted from[38]}.

Referring to the two figures shown in below, an interesting application given for reading model which obeys Pavlov' learning concept. By more details, considering at Fig. , the two inputs I_1 and I_2 represent sound (heard) stimulus and visual (sight) stimulus respectively. The outputs O_1 and O_2 are representing pronouncing and image recognition processes respectively. In order to justify the superiority and optimality of phonic approach over other teaching to read methods, an elaborated mathematical representation is introduced for two different neuro-biologically based models. Any of models needs to learn how to behave (to perform reading tasks). Somebody has to teach (for supervised learning)- not in our case – or rather for our learning process is carried out on the base of former knowledge of environment problem (learning without a teacher). The model obeys the original Hebbian learning rule given at [19][31]. The reading process is simulated at that model in analogues manner to the previous simulation for Pavlovian conditioning learning. The input stimuli to the model are considered as either conditioned or unconditioned stimuli. Visual and audible signals are considered interchangeably for training the model to get desired responses at the output of the model. Moreover the model obeys more elaborate mathematical analysis for Pavlovian learning process [37] referring to Fig.8. The input/ output relation of the Pavlov's classical conditioning model is presented at Fig.9. Furthermore, that model is modified following general Hebbian algorithm and correlation matrix memory [31]. The adopted model is designed basically after simulation of the previously experimentally measured performance of classical conditioning . The model design concept is presented after the mathematical transformation of some biological hypotheses. In fact, these hypotheses are derived according to cognitive/ behavioral tasks observed during the experimental learning process. Generally, the output response signal varies as shown in the original Pavlov experimental work [38][39], and its mathematical modeling presented at [40]. Therein, the output response signal is measured quantitatively in the exactness of pronouncing letter/ word. In accordance with biology, the output of response signal is dependent upon the transfer properties of the output motor neuron stimulating pronouncing as unconditioned response (UCR) for heard phoneme (sound signal). However, this pronouncing output is considered as conditioned response (CR) when input stimulus is given by only sight (seen letter/ word). The structure of the model following the original Hebbian learning rule in its simplified form (single neuronal output) is given in Fig.8, where A and C represent two sensory neurons (receptors)/ areas and B is nervous subsystem developing output response. The below simple structure drives an output (Writing) response that is represented at Fig.10 as O_1. However, the other output (Pronouncing) response represented at Fig.11 as O_2. That is obtained when input sound is considered as conditioned stimulus. Hence visual recognition as condition response of the heard letter/ word is obtained as output O_2. In accordance with biology, the strength of response signal is dependent upon the transfer properties of the output motor neuron stimulated by salivation gland output as illustrated at Fig.9.

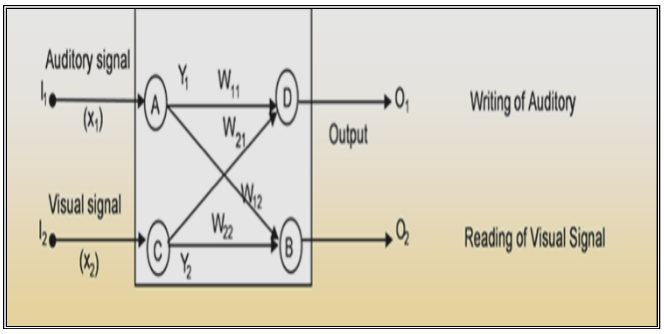


Fig. 10. Generalized reading model which pretended as pronouncing of some word (s) considering input stimuli and output responses.

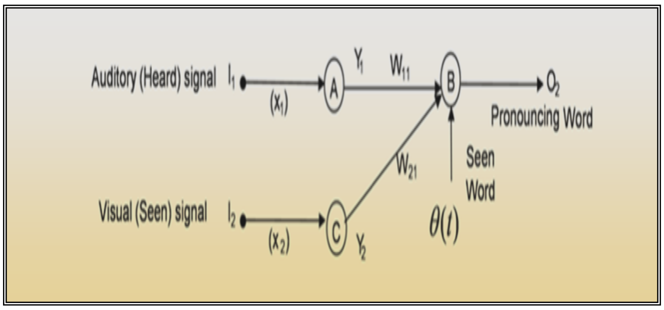


Fig. 11 The structure of the first model where reading process is expressed by conditioned response for seen letter/ word (adapted from [7]).

SIMULATION RESULTS

The algorithm for the Pavlovian learning process is given at Fig. 12. , by considering the latency time phenomenon given at Fig.9. It composed of two loops with iterative learning cycles. Referring to Fig. 13, a simplified macro-level flowchart for simulation program is introduced. It describes briefly the algorithmic steps for a suggested realistic simulation program of adopted Artificial Neural Networks' model taking into account the different number of neurons.(# neurons). The simulation results introduced in this section comprise mainly the three figures (Fig.14, Fig.15, and Fig.16). Some interesting simulation results presented after taking into account the comparative studies of two essential ANN parameters namely : learning rate and gain factor values. Versus varying neurons' number of the hidden layer associated to self-organized ANN paradigm model. These results revealed the effect of interrelations a among various learning rate values against different values of signal to noisy ratio considering student's selective responsive for focusing attention of considering the contributions of the number of neurons inside any student' brain. It represented the performance considering different learning rate values, considering Hebbian self-organized learning at different noisy environmental levels and number of contributing neurons. The individual differences of students' responsive for are represented by various gain factor values.

s
Initialize

Loop /* at this level each loop is called an iteration that completed by the end of learning process*/

Each pairing stimulus is positioned on a starting latony time cycle

Loop /* at this level each loop is called a step which completed by developing some output by the motor neuron */

Each weight is changed dynamically according to Hebbian learning law

Until developing output signal corresponding to any arbitrary latony time

A maximum salivation signal is obtained when threshold value reaches to zero // Until

End_condition

Fig.12, illustrates training process in ANN models considering latency time phenomenon having two loops with iterative learning cycles.

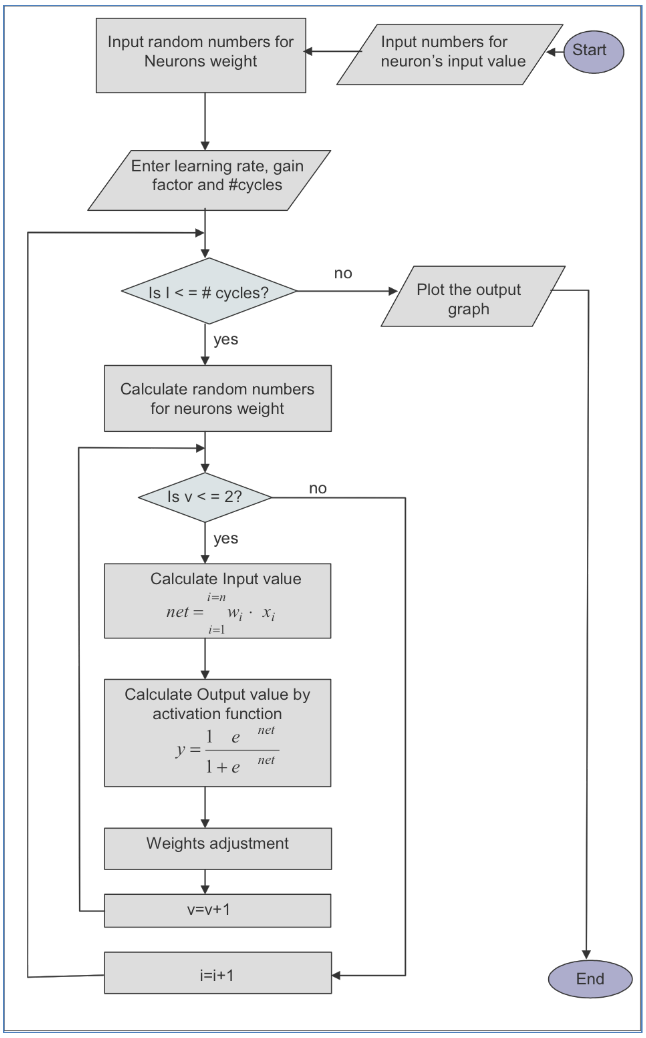


Fig. 13. A simplified macro level flowchart that describing algorithmic steps for Artificial Neural Networks modeling considering various # neurons{Adapted from [41]}.

Number of highly specialized neurons at corresponding visual brain area contribute to the perceived sight (seen) signal is in direct proportionality with the correctness of identified depicted / printed images. These images represent the orthographic word-from has to be transferred subsequently into a spoken word (phonological word-form) during reading process. Furthermore, in visual brain area individual intrinsic characteristics (Gain Factor) of such highly specialized neurons have direct influence on the correctness percentage [%] of identified images associated with orthographic word-from. Those results given at Fig.15 are analogous to obtained simulation results shown at the two figures (Fig.14, and Fig. 16). Interestingly, obtained simulation results herein are observed to be in agreement with obtained results after analytical approach adopted by recently published work at[11]. Therein, depicted graphical results observed to be in agreement with that presented two figures . It is corresponding to corrected image identification normalized values between [0 & 90] at vertical y-axis in Fig. 15.Similarly, in Fig.14,and Fig. 16, neurons' number values increasing between [1 & 10] (at the x-axis), are in correspondence with horizontal x-axis in Fig. 15, which presents image resolution started at (2x5) pixels. In other words, the improvement of image resolution (increasing number of pixels) is directly analogous to the increase of number of neurons contributing the outcomes of learning (reading) process.

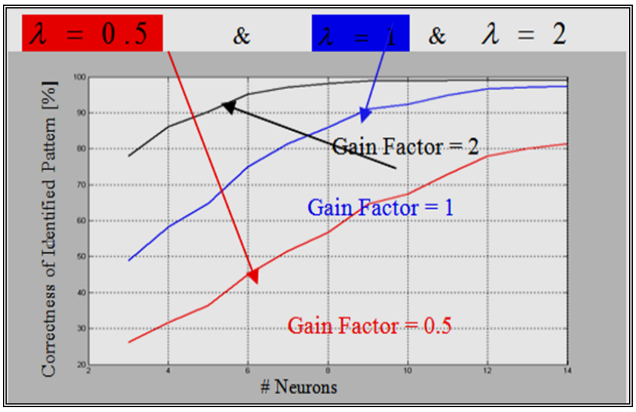


Fig. 14. Illustrate students' learning achievement for different gain factors and intrinsically various number of highly specialized reading neurons which measured for constant learning rate value = 0.3.

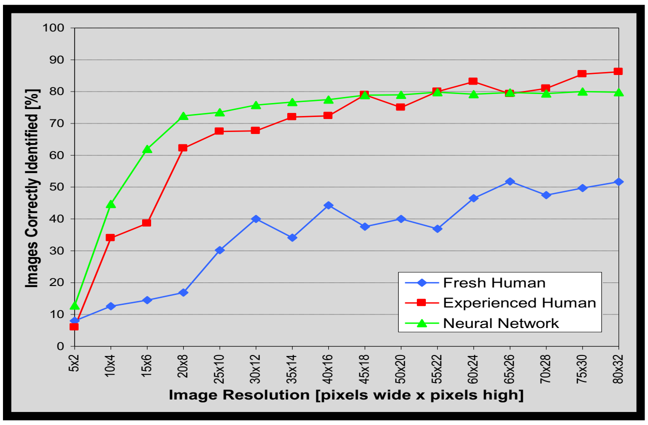


Fig.15. Obtained simulation results after running of neural network model compared versus measured human results considering basic images with different images' resolution (number of pixels). These results are illustrated in graphical form {adapted from [42]}.

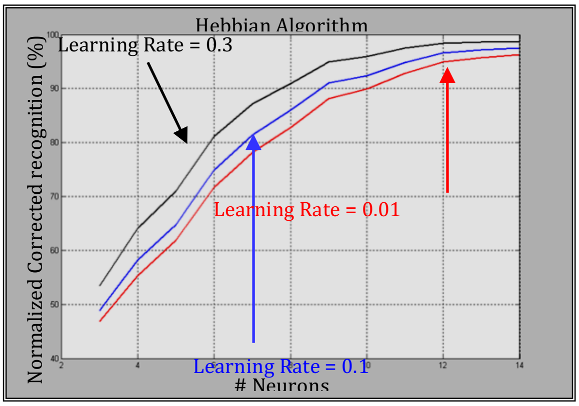


Fig. 16. Illustrates simulated outcomes of Selective Focusing Level presented as percentage degree of lesson focusing versus #
for different learning rate values (0.3, 0.1, and 0.01).

Hebbian Algorithm

In Fig.17, a set of performance curves is shown for general normalized ANN learning model, it represents considers various gain factor values (denoted by λ parameter). By changing values of this parameter, results in various response time (speeds)in reaching optimum (desired) achievements in accordance with the following equation:

$$y(n)=(1-\exp(-\lambda_i(n-1)))/(1+\exp(-\lambda i(n-1))) \quad (10)$$

Where λ_i represents one of gain factors (slopes) for odd sigmoid function given by equation (8) and n represents the learning convergence response time expressed in the number of cycles (epochs).

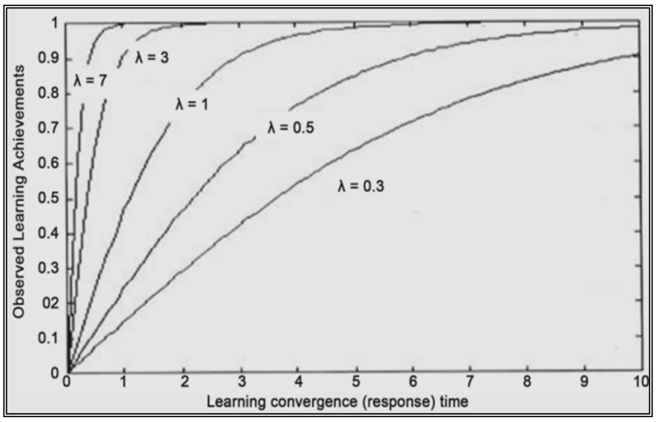


Fig. 17. Graphical representation of learning performance of model with different gain factor values (λ).

Interestingly, the learning convergence time has been presented at TABLE 1 which adapted from the simulation results findings introduced at [43]. Conclusively, it is observed during interactive learning process that: teaching/learning environment with decreasing S/N ratio results in decreasing of learning rate parameter value . That explicitly computed as noise power value ( )

TABLE I. The Effect of Noisy Environment on Learning Convergence Time, {Adapted From [22]}

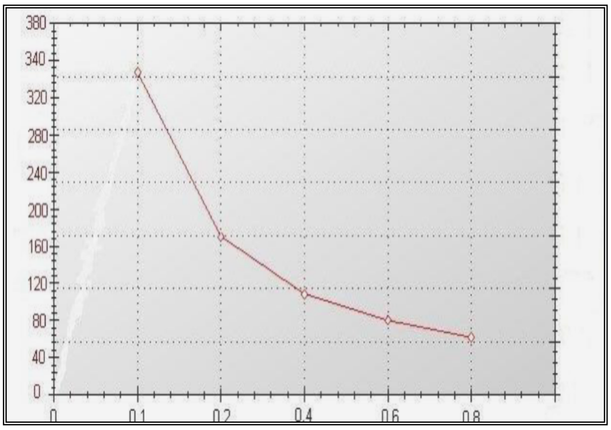
Signal to Noise Power Ratio of Input Data	5	10	20
Noise Power in Learning Environment	0.2	0.1	0.05
Convergence Learning Time (cycles)	85	62	47

Referring to Fig.18, it is worthy to note that statistical variations(on the average) relating learning rate values versus corresponding selectivity convergence (response) time. That time is measured by the number of iteration cycles., obtained output results(of response time) corresponding to the learning rate values (0.1,0.2,0.4,0.6, and 0.8), are given respectively, as (330, 170, 120, 80, and 40) number of iterative training cycles . Conclusively, convergence time (number of training cycles) is inversely proportional to the corresponding learning rate values as tabulated in TABLE II.

TABLE II. The Relation Between Learning Rate Values And Convergence Learning Time

Learning rate Value (η)	0.1	0.2	0.4	0.6	0.8
Average Response time	330	170	120	80	40

Number of iteration cycles



Learning rate values ( )

Fig. 18. Illustrates the average of statistical distribution for learning response time (number of iteration cycles) for different learning rate values .

CONCLUSIONS AND DISSCOTIONS

This piece of research comes to the following seven interesting conclusive remarks:

- The schools' responsibility have to take into account students' developed learn performance aside from noisy contaminated (undesirable) impact on created learning environment.
- The ideally noiseless learning environment supporting students' enhanced development into an independent and active learner. Considering the basic values of educational levels and the school's mental attitude, and preserves and refines the traditions of the region and the school community.
- ANN modeling is a realistic and relevant tool to obtain interesting results in the context of student's learning performance.
- Interestingly, referring to ANN modeling context, the two parameters: Learning rate and Gain factor are considered by the presented simulated comparative s
- The considered simultaneous visual and audible learning materials revealed dependency of learning/teaching effectiveness upon children's sensory cognitive systems.
- The above obtained results agree well with Lindstrom's findings that participants could only remember 20% of the total learning materials when they were presented with visual material only, 40% when they were presented with both visual and auditory material, and about 75% when the visual and auditory material were presented simultaneously [44].
- Additionally, the presented work results are in well agreement with the findings revealed at the recent research paper at [45]

Finally, referring to the above seven remarks, for the future extension of the presented research work, it is highly recommended to consider more elaborate investigational analysis and evaluations for other behavioral learning phenomena observed at educational field (such as learning creativity, improvement of learning performance, learning styles,… etc.) using ANNs modeling.

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