On Enhancement of Reading Brain Performance Using Artificial Neural Networks' Modeling

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Abstract—**This piece of research addresses an interdisciplinary and challenging issue which originated by a discipline incorporating neuroscience, education, and cognitive sciences. More specifically, this work concerned with developing reading brain in a significant way, which based upon recent increase of sophisticated realistic artificial neural networks (ANNs) modeling. Interestingly, the role of (ANNs) modeling has been recognized by both neurological researcher as well as educationalists. In more details, this paper adopts the conceptual approach of (ANN) models inspired by functioning of highly specialized biological reading brain's neurons. The cognitive goal for reading brain is to translate visualized (orthographic word-from) into a spoken voiced word (phonological word-form). In this context, by end of presented work, obtained ANN simulation results illustrated, how ensembles of highly specialized neurons could be dynamically involved in performing the cognitive function for developing reading brain.**

Index Terms—**brain reading function, phonological and orthographic processing, artificial neural networks' modeling, and pattern recognition**

I. Introduction

Overwhelming majority of neuroscientists have adopted the concept suggests that huge number of neurons besides their interconnections constituting the central nervous system and synaptic connectivity performing behavioral learning in mammals such as: cats, dogs, ants, and rats [1], [2]. In this context, ensembles of highly specialized neurons (neural networks) in human play the dominant dynamical role in the functioning for developing of reading brain [3]. 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 [4]. The synaptic connectivity patterns among artificial neurons have implication on learning ability [5], and also on the human learning creativity [6].

More specifically, modeling of complex neural network may be considered as a series of highly interconnected nodes (artificial neurons) contributing spoken words for reading brain. Interestingly, it is noticeable that adopted neural networks' models correspond closely to biological neuronal systems functionally as well as structurally [7]-[9].

In nature, the working memory components contribute to development of a functional system for a reading brain. Accordingly, reading process in human brain performed as transferring of written (seen) word-form into pronounced (spoken) word-form. This reading brain process viewed to be performed by brain moment our eyes fall on depicted written word-form, a complex set of physical, neurological, and cognitive processes is originated. That enabling reading brain (via highly specialized neurons) to carry out conversion coding process of a written (orthographic word-from) into a spoken word (phonological word-form). Accordingly, number of highly specialized neurons at corresponding visual brain area contribute to the perceived sight (seen) signal. The increase of this number proved to be 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. So, the reader may also code morphological structure (base word plus prefix and/or suffix/es) of both the orthographic and phonological word-form [3]. Furthermore, individual intrinsic characteristics of such highly specialized neurons (in visual brain area) influence directly on the

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correctness of identified images associated with orthographic word-from [10].

The extremely composite biological structure of human brain results in everyday behavioral brain functions. At the educational field, it is observable that learning process performed by human brain is affected with the simple neuronal performance mechanism [11]. Accordingly, in general sense, the human ability to speak (read) English language is motivated by associative features of human brain. That association considered between two stimulating signals (heard voice and seen written words) via brain receptor neurons. In brief, artificial neural networks were originally conceived of in relation to how systems according to the stimuli they receive [12], [13]. Moreover a recently published research work revealed that using some pauses while talking, may enhance the teaching methodology of children how to read English language [14], [15]. Recently, a related research work has been published. That addressed the issue of how ensembles of highly specialized neurons could be dynamically involved in performing the cognitive function of recognizing words' vocabulary during early infancy development of human reading brain [16].

Finally, it is worthy to note that presented study motivated by some recently other published interdisciplinary work dealing with the intrinsic properties of neurons associated with learning creativity [17]-[19], and brain-based learning [20].

The rest of this paper is organized as follows. At the next section, the basic concepts of reading brain process are revised. A review of reading process modeling is presented at the third section. At the fourth section, graphical simulation results are introduced. Interesting conclusive remarks are given at the final fifth section.

II. Revising Reading Brain Concepts

A. Basic Brain Functions Modeling

Referring to [21], [22] the development of neural network technology is originally motivated by the strong desire to implement systems contributing tasks similar to human brain performance. Accordingly, adopting this technology is well relevant for modeling systems performing similar tasks to human brain functions. Basically such systems are characterized by their smartness and capability to perform intelligent tasks resembling human. Objectively, after a completing of training of well-designed neural system models it is expected to respond correctly (in smart manner) and spontaneously towards input external stimuli. In brief, these systems well resemble human brain functionally in two ways:

1) Acquiring knowledge and experience through training/learning through adaptive weights neurodynamic.
2) Strong memorizing of acquired knowledge/stored experience within interconnectivities of neuronal synaptic weights.

Consequently, adopting of neural network modeling seems to be very relevant tool to perform simulation of educational activity phenomena. To implement realistically some simulated educational activities we should follow the advice that such models needed to be with close resemblance to biological neural systems. That resemblance ought to be not only from structural analysis but also from functional characterization. In other words understanding learning/training process carried out by ANN is highly recommended for increasing efficiency and effectiveness of any simulated educational activity [23]. The statistical nature of training/learning time of convergence for a collection group (of ANN models) observed to be nearly Gaussian. This simulates a group of students under supervised learning. Additionally, the parameters of such Gaussian distribution (mean and variance) shown to be influenced by brain states of student groups as well as educational instrumental means. The well application of educational instrumentation during proceeding of learning/training processes improves the quality of learning performance (learning rate factor). Such improvements are obtained in two folds. By better neurodynamic response of synaptic weights and by maximizing signal to noise ratio of input external learning data (input stimuli). So, any assigned learning output level is accomplished if and only if connectivity pattern dynamics (inside learner's brain) reaches a stable convergence state. I.e. following Hebbian learning rule, connectivity vector pattern associated to biological neuronal network performs coincidence detection to input stimulating vector [24].

B. Simplified Interactive Learning Process

Referring to Fig. 1, 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 the noise and redundancy of model pattern input. That is in accordance with tutor's experience while performing either conventional (classical) learning or Computer Aided Learning (CAL). Consequently, he provides the model with clear data by maximizing its signal to noise ratio [25]. It is mathematically formulated by equation (6) given at the next subsection. Conversely, in the case of unsupervised/self-organized learning, which is based upon Hebbian rule [26], it is mathematically formulated by equation (7) given at the next subsection. For more details about mathematical formulation describing a memory association between auditory and visual signals, for more details the reader is referred to [27].

The presented model given in Fig. 2 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 learners (supervised learning) [25].

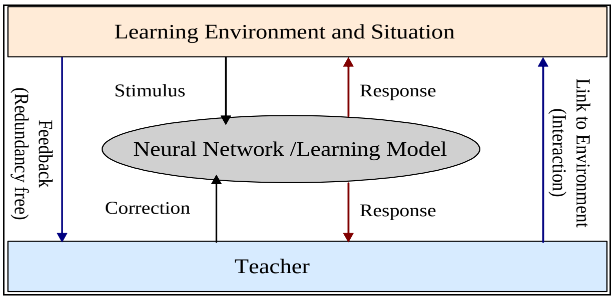

Figure 1. Simplified view for interactive learning process.

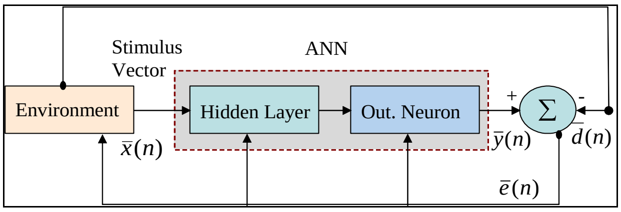

Figure 2. Generalized ANN block diagram simulating two diverse learning paradigms adapted from [25].

C. *Interactive Mathematical Formulation of Learning Models*

The presented model given in Fig. 2 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 learning model paradigm proceeds interactively via bidirectional communication process between a teacher and his learners (supervised learning) [25]. However, the second other learning paradigm performs self-organized (autonomously unsupervised) tutoring process.

Referring to above Fig. 2, the error vector $\bar{e}(n)$ at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \tag{1}$$

where $\bar{e}(n)$ …… is the error correcting signal that adaptively controls the learning process, $\bar{y}(n)$ …… is the output obtained signal from ANN model, and $\bar{d}(n)$ …… is the desired numeric value(s).

Moreover, the following four equations are deduced to illustrate generalized interactive learning process. These equations are commonly well valid for either guided with a teacher (supervised) or self-learning without a teacher (unsupervised):

Equation (2) considers the scalar product of two vectors the input vector (X) and internal weight vector (W) computed at the time instant (n). It is noticed that both are associated to neuron (k), and each has the same dimension (number of vector's components). The output of this neuron is given by (3), which originated from the hyperbolic tangent function deduced from classical sigmoid function.

Equation (4) computes the error value which controls the guided learning process (supervised with a teacher) and so it does not valid in case of unsupervised (learning without a teacher).

The dynamic learning law at two subsequent time instances (n) & (n+1) is shown by (5).

$$V_k(n) = X_j(n) W_{kj}^T(n) \tag{2}$$

$$Y_k(n) = \varphi(V_k(n)) = (1\text{-}e^{-\lambda V_k(n)}) / (1 + e^{-\lambda V_k(n)}) \tag{3}$$

$$e_k(n) = \left| d_k(n) \text{-} y_k(n) \right| \tag{4}$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \tag{5}$$

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. Note that $\Delta W_{kj}(n)$ 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 student's self-study). The dynamical changes of weight vector value specifically for supervised phase is given by:

$$\Delta W_{kj}(n) = \eta\, e_k(n) X_j(n) \tag{6}$$

where η is the learning rate value during the learning process for both learning paradigms. At this case of supervised learning, instructor shapes child's behavior by positive/negative reinforcement Also, Teacher presents the information and then students demonstrate that they understand the material. At the end of this learning paradigm, assessment of students' achievement is obtained primarily through testing results. However, for unsupervised paradigm, dynamical change of weight vector value is given by:

$$\Delta W_{kj}(n) = \eta\, Y_k(n) X_j(n) \tag{7}$$

Noting that $ek(n)$ (6) is substituted by $yk(n)$ at any arbitrary time instant (n) during the learning process. Instructor designs the learning environment.

III. Reading Process Modeling

A. *Functional and Structural Neuroimaging Studies*

Application of recent biomedical engineering technology such as Neuroimaging has revealed that adult readers could provide neuroscientists as well as educationalists with a deeper understanding of the neural basis of reading. Yet such findings also open new challenging questions about how developing neural systems come to support learned ability. A developmental cognitive neuroscience approach provides insights into how skilled reading emerges in the developing brain, yet also raises new methodological challenges. This review focuses on functional changes that occur during reading acquisition in cortical regions associated with both the perception of visual words and spoken language, and examines how such functional changes differ within developmental reading disabilities. We integrate these findings within an interactive specialization framework of functional development, and propose that such a framework may provide insights into how individual differences at several levels of observation (genetics, white matter tract structure, functional organization of language, cultural organization of writing systems) impact the emergence of neural systems involved in reading ability and disability [28].

B. Associative Memory Function (Mathematical Formulation)

Reading brain process originated through associative memory function between audible pathway via cochlea sensory area, and visual pathway via retina sensory area. In mathematical formulation context, consider $X_k^{'}$ and $X_k^{''}$ are the two vectors simulating heard and seen by input stimuli patterns respectively. Similarly output responses respectively $Y_k^{'}$ and $Y_k^{''}$ are the two vectors simulating phonological word-form (pronouncing) and orthographic word-form (visual recognizing). The two expected unconditioned responses are described in matrix form as follows:

$$Y_k^{'} = W(k) \cdot X_k^{'}, k = 1, 2, 3, ..., q \tag{8}$$

where $W(k)$ is a weight matrix determined solely by the input-output pair $(X_k^{'}, Y_k^{'})$

$$y_{ki} = \sum_{j=1}^{r} w_{ij}(k) \cdot x_{kj} \quad , i = 1, 2, ..., r \tag{9}$$

where $w_{ij}(k),\ j = 1,2,\dots,r$ are the synaptic weights of neuron i corresponding to the k^{th} pair of associated patterns of input -output pair $(\mathrm{X}_k^{'}, \mathrm{Y}_k^{'})$. We may express y_{ki} in equivalent form.

$$y_{ki} = \left[w_{i1}(k), w_{i2}(k), ..., w_{ir}(k)\right] \begin{bmatrix} x_{k1} \\ x_{k2} \\ ..... \\ x_{kr} \end{bmatrix} \quad ; i = 1, 2, ..., s \tag{10}$$

Similarly, for visual input stimulus $X_k^{''}$ and recognizing (of seen letter/ word) output response $Y_k^{''}$

$$y_{ki} = \left[w_{ir+1}(k), w_{ir+2}(k), ..., w_{im-r}(k)\right] \begin{bmatrix} x_{kr+1} \\ x_{kr+2} \\ ..... \\ x_{km-r} \end{bmatrix} \tag{11}$$

$$i = s+1, 2, 3, ..., l$$

For conditioned response, the input hearing stimulus $X_k^{'}$ results in recognizing visual signal $Y_k^{''}$. However, input seen letter/word stimulus $X_k^{''}$ results in pronouncing that letter/ word as conditioned response vector $Y_k^{'}$ which expresses the reading activity given by the equation:

$$y_{ki}^{'} = \left[w_{ir+1}(k), w_{ir+2}(k), \dots, w_{im-r}(k)\right] \begin{bmatrix} x_{kr+1}^{''} \\ x_{kr+2}^{''} \\ ..... \\ x_{km-r}^{''} \end{bmatrix} \tag{12}$$

$$i = 1,2,3,\dots,s$$

In a similar manner, the other conditioned response for recognizing heard phoneme is described by the equation:

$$y_{ki}^{''} = \left[w_1(k), w_2(k), \dots, w_r(k)\right] \begin{bmatrix} x_{kr+1}^{'} \\ x_{kr+2}^{'} \\ ..... \\ x_{km-r}^{'} \end{bmatrix} \quad ; i = 1,2,\dots,s \tag{13}$$

As a result of the above equation, the memory matrix that represents all q- pairs of pattern associations is given by $m*l$ memory correlation matrix as follows:

$M = \sum_{k=1}^{q} W(k)$, where $W(k)$ weight matrix is defined by the equation:

$$W(k) = \begin{bmatrix} w_{11}(k) & w_{12}(k) & \dots & w_{1m}(k) \\ w_{21}(k) & w_{22}(k) & \dots & w_{11}(k) \\ \dots & \dots & \dots & \dots \\ w_{l1}(k) & w_{l2}(k) & \dots & w_{lm}(k) \end{bmatrix} \tag{14}$$

This weight matrix relating input stimulus vector with m-dimensionality X_k connected by synaptic with output response vector Y_k with l-dimensionality.

The complete relation for input/ output relation is given by the following equation.

$$\begin{bmatrix} y_{k1} \\ y_{k2} \\ .... \\ y_{kl} \end{bmatrix} = \begin{bmatrix} w_{11}(k) & w_{12}(k) & \dots & w_{1m}(k) \\ w_{21}(k) & w_{22}(k) & \dots & w_{11}(k) \\ \dots & \dots & \dots & \dots \\ w_{l1}(k) & w_{l2}(k) & \dots & w_{lm}(k) \end{bmatrix} . \begin{bmatrix} x_{k1} \\ x_{k2} \\ .... \\ x_{km} \end{bmatrix} \tag{15}$$

It is worthy to note that the above equation represents memory correlation matrix after learning convergence. So, this matrix is given in other way as:

$$M = Y \cdot X^T \tag{16}$$

C. Description of Associative Memory

By more details, the associative memory function originated brain working memory. The objective of associative function implies that children must code written words and letters; this code is called orthographic word-form. The reading goal is carried out by association (translation) of orthographic word-from code into a spoken word (phonological word-form code) [1]. 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 [26].

Referring to the two figures (Fig. 3 & Fig. 4) shown in below, suggested models obeys that concept as the two inputs I1, I2 represent sound (heard) stimulus which simulates phonological word-form and visual (sight) stimulus which simulates orthographic word-from respectively. The outputs O1, O2 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. 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 [24]. Also, the model is modified following general Hebbian algorithm (GHA) and correlation matrix memory [25], [28], [29]. The adopted model is designed basically following after simulation of the previously measured performance of classical conditioning experiments. 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.

The structure of the model following the original Hebbian learning rule in its simplified form (single neuronal output) is given in Fig. 3, where A and C represent two sensory neurons (receptors)/areas and B is nervous subsystem developing output response. The below simple structure at Fig. 4 drives an output response reading function (pronouncing) that is represented as O1. However the other output response represented as O2 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 O2. In accordance with biology, the strength of response signal is dependent upon the transfer properties of the output motor neuron stimulating salivation gland. The structure of the model following the original Hebbian learning rule in its simplified form is given in Fig. 3. That 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 sensor neurons A and C are represented by y1 and y2 respectively.

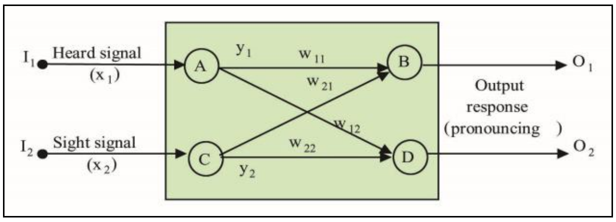

Figure 3. Generalized reading model which predented as pronouncing of some word(s) considering input stimuli and output responses.

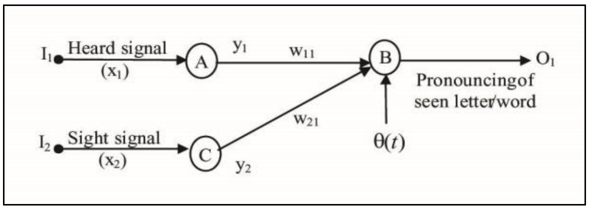

Figure 4. The structure of the first model where reading process is expressed by conditioned response for seen letter/ word (adapted from [28])

D. Reading Ability Model System

Reading ability has served as a model system within cognitive science for linking cognitive operations associated with lower level perceptual processes and higher level language function to specific brain systems [30], [31]. More recently, developmental cognitive neuroscience investigations have begun to examine the transformations in functional brain organization that support the emergence of reading skill. This work is beginning to address questions concerning how this evolutionarily recent human ability emerges from changes within and between brain systems associated with visual perception and language abilities, how learning experiences and maturation impact these neural changes, and the way in which individual differences at the genetic and neural systems level impact the emergence of this skill [32], [33]. Developmental reading studies have used ERP recordings to examine more directly the experience-dependent nature of the N170 response to visual word forms and the relationship between these signals and the rise of fast perceptual specializations for reading [31] and difficulties in reading generally (Dyslexia) [34] and specifically neural tuning for print peaks when children learn to read [35].

IV. Simulation Results

Fig. 5 introduces the flowchart for simulation program which applied for performance evaluation of behavioral learning processes. That Figure presents a simplified macro-level flowchart which briefly describes the algorithmic steps for realistic simulation program of adopted Artificial Neural Networks' model for different number of neurons.

Fig. 6 illustrates Obtained measured human results versus realistic neural network modeling results considering basic images with different images' resolution (number of pixels).

The obtained results of simulation are illustrated in graphical form at the set of five figures (Fig. 7-Fig. 11). After running of realistic simulation program following the algorithmic steps shown at Fig. 5.

Interestingly, this set of figures considers the learning performance simulated by ANN modeling is based on either the effect of environmental learning effect is considered by various learning rate values at in Fig. 7 and Fig. 8 or the intrinsic (individual differences' achievement) by gain factor effect at Fig. 9, Fig. 10, and Fig. 11.

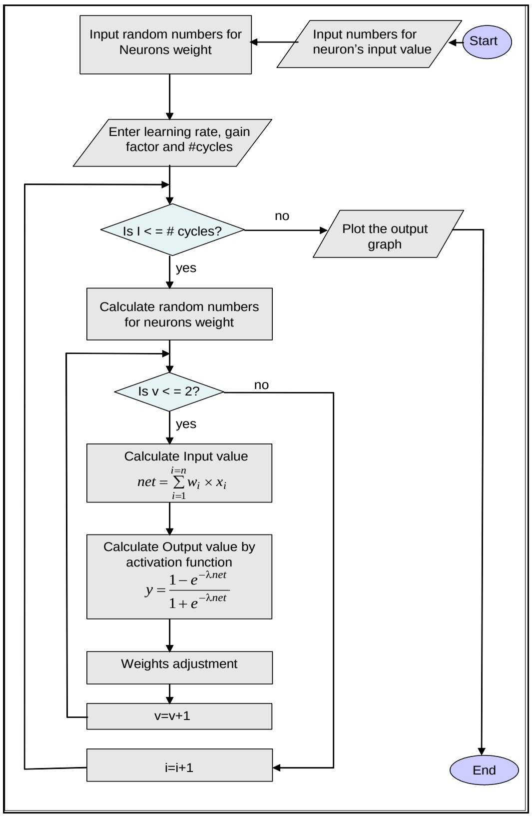

Figure 5. A simplified macro level flowchart that describing algorithmic steps for Artificial Neural Networks modeling considering various neurons' number.

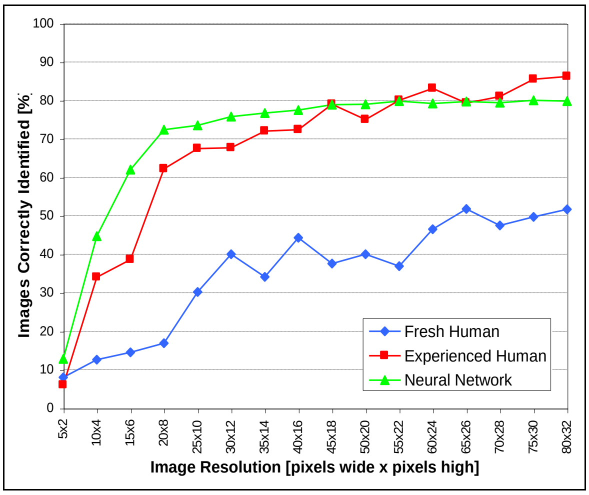

Figure 6. Simulation results obtained after running of neural network model compared versus measured human results considering basic images with different images' resolution (number of pixels) {adapted from [10]}

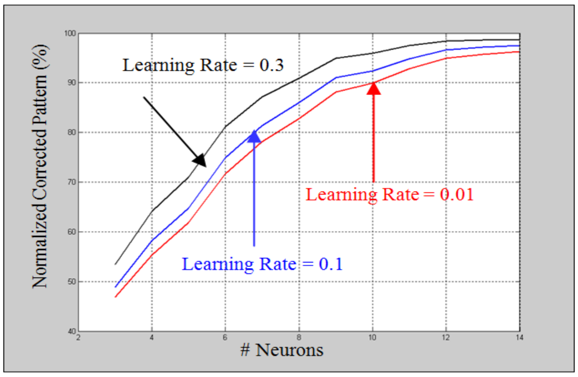

Figure 7. Illustrates outcome learning reading performance versus # Neurons For different learning rate values (0.3, 0.1, and 0.01)

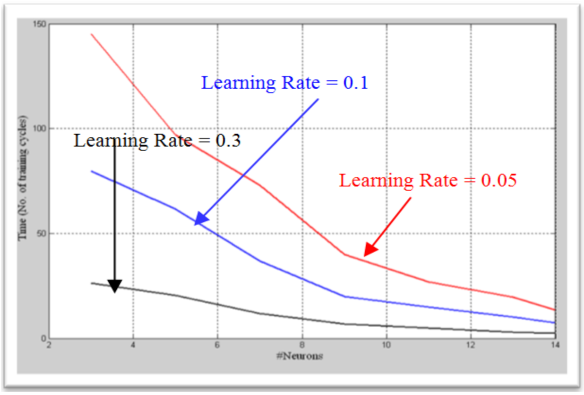

Figure 8. Illustrates the reading learning performance via convergence time (number of cycles) versus different learning rate values (0.05, 0.1, and 0.3)

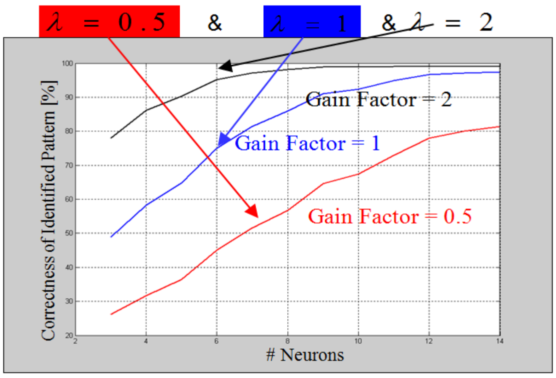

Figure 9. Illustrate students' learning achievement for different gain factors and intrinsically various number of highly specialized reading neurons which measured for constant learning rate value = 0.3.

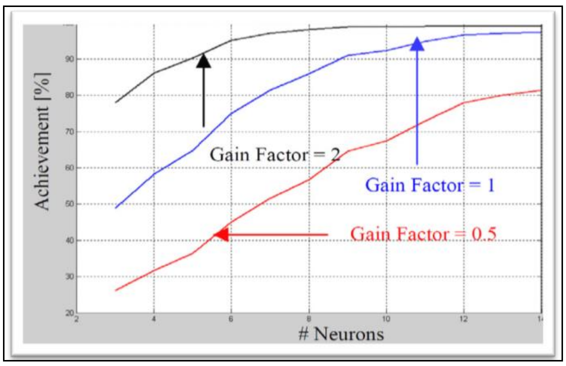

Figure 10. Illustrates the performance of error correction algorithm versus learning convergence time for different gain factor values.

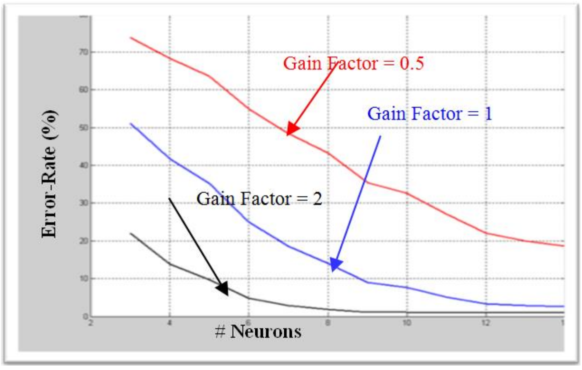

Figure 11. Illustrate reading learning performance to get accurate solution with different gain factors 0.05, 1, and 2, while #cycles = 300 and Learning rate = 0.3

V. CONCLUSIONS

Herein, the presented issue of reading brain performance is tightly related to neuronal mechanism in human brain for speech language process. Therefore, this work proposes an intelligent classification technique based on realistic ANN modeling based on either intrinsic students' individual differences or external environmental learning conditions. Interestingly interdisciplinary research learning issue "how reading should be taught?" [3], [36]. That's an interdisciplinary issue associated with neuronal coding of speech formant in the reading process responding to stimulating student's brain. Additionally, the reader may also consider morphological code structure (base word plus prefix and/or suffix/es) of both the orthographic and phonological word-form [11]. In the future, expected extended research work of presented paper highly recommends more elaborate investigational and systematic analysis for other cognitive behavioral learning phenomena such as learning creativity. Furthermore, by application of realistic ANNs modeling, enhancement of learning performance quality could be carried out effectively considering learning and teaching styles, etc.

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