An Overview on Classrooms' Academic Performance Considering: Non-Properly Prepared Instructors, Noisy Learning Environment, and Overcrowded Classes (Neural Networks' Approach)

Hassan. M. Mustafa
Computer Eng. Department, Faculty of Engineering. Al-Baha University (K.S.A)
Email: prof.dr.hassanmoustafa@gmail.com

Ayoub Al-Hamadi
Institute for Electronics, Signal Processing and Communications (IESK), Otto-von-Guericke-University Magdeburg Germany
Email: Ayoub.Al-Hamadi@ovgu.de

***Abstract*—This piece of research considers an interdisciplinary challenging educational phenomenon associated to students' academic performance at educational field practice (classrooms). By more details, it presents specifically an educational study regarding with three challenging phenomenal problems observed in classrooms. Firstly, problem faced by teachers' relation to accessible classroom activity. Such as the relation between value of learning rate parameter η and the Gaussian additive noise power σ to learning data submitted by a non-properly prepared instructor. Secondly, noisy data which considered as main cause of environmental annoyance and it negatively affects the quality of academic performance. That presented problem motivated by "Evans' research reveals significant reading delays for children living near airports and exposed to airport noise". Finally, the problem deals with an auditory perception phenomenon, namely known as Cocktail Party Problem (CPP). This process practically experienced by the presence of overcrowded classroom noisy phenomenon considering only one speaker (instructor's speech).**

***Index Terms*—artificial neural networks models, academic performance, noisy crowded environment, signal to noise ratio, cocktail party effect**

I. Introduction

The field of the learning sciences is represented by a growing community internationally. Many educational experts now recognize that conventional ways of conceiving learning are facing increasing challenges in this time of rapid Technological, and social changes[1]-[3]. Recently, that increasing challenges have adopted a novel trend which supported by what had been announced last decade (1990-2000) (in U.S.A.) that called as Decade of the brain [4]-[6].

In this context, recent interdisciplinary educational trend has been adopted for building up realistic modeling and simulation of various human brain learning functions. This trend has been adopted by most of educational experts as an evolutionary recent interdisciplinary and realistic approach. Furthermore, this adopted trend includes analysis and evaluation of interesting and challenging educational issues associated with observed learning phenomena [7]-[9].

Interestingly, that recent trend originated by incorporating learning sciences with Nero-physiology, Psychology, and Cognitive science in order to investigate systematically some increasing challenging interdisciplinary educational issues [10], [11]. Consequently, Neural Networks theorists as well as educationalists and neurobiologists have focused their attention on making contributions for investigating the critical problematic question: how student's brain can perform well learning function considering noisy environmental conditions? In the context of Artificial Neural Networks (ANN^{s}), that educational field critical question has to be mapped into two interrelated questions: how realistic simulation using ANN modeling capable to evaluate learning process convergence considering noisy environment? [2] [3] & how this process may be quantitatively affected by contaminated noisy information provided to students by a non-properly prepared teacher? [1]. as recent interdisciplinary evolutionary trend, modeling of human brain functions considered by educationalists in learning science incorporating Nero-physiology, psychology, and cognitive sciences [12],

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[13]. Additionally, students' educational performance problem agrees (analogously) with the observed phenomenon in the context of communication field engineering. Therein, the ratio of the power or volume (amplitude) of a desired signal to the amount of mixed disturbances (the noise) contaminating in with it. This ratio is defined as signal-to-noise ratio abbreviated as SNR or S/N which measures the clarity of the received desired signal through transmission channel. Furthermore, in analog and digital communications, ratio, often SNR is a measure of signal strength relative to background noise [14].

The rest of this paper is organized as follows. At the next second section revising of the interactive educational process is introduced via its two subsections *(A&B)*. At subsection *(A)* General conceptual view of modeling of interactive learning process is presented. Additionally, detailed mathematical formulation of interactive learning is given at subsection *(B)*.

At the third section, a brief description of unsupervised ANN model has been suggested, for analysis of selective performance which focused on attention and recognition for visual signal specifically Optical Character Recognition (OCR).That recognition process has been contaminated by intended various noisy power levels (signal to noise ratios). That reflects mapping the analogy of the influence of not well prepared instructor on academic learning performance in classrooms. This section motivated by recently published work which concerned with non-properly prepared instructors' implication on students' academic performance [1]. The noisy data impact on students' academic performance is briefly introduced at the fourth section including the detailed description of relation between Learning Rate Parameter η to Noise Power σ . Additionally, some interesting realistic simulation obtained results are presented [2]. At the fifth section, brief conceptual views about observed Optical Character Recognition (OCR) as well as pattern recognition processes have been introduced. Both have been carried out under non ideal environmental learning condition (under effect of noisy data). Furthermore, introduced proposal for active audition modeling is motivated by analogous active vision processes, such as that observed (OCR) [3]. The obtained simulation results after running the adopted (ANN^{S}) model are introduced at the sixth section. Finally, some interesting conclusive remarks are given at the last seventh section.

II. Revising of Educational Process Modeling

This revising section introduces the conceptual basis of teaching/learning process and illustrates its realistic interactive modeling via four subsections as follows.

At the subsection *A*, a generalized brief overview of the block diagram describing interactive teaching/learning process is given. A detailed mathematical formulation considering either bidirectional communication between a teacher and his learners (supervised) or self-organized (unsupervised) Kohonen learning by interaction with environment is introduced at subsection *B*. In subsection *C*, the expected behavioral implication of non-proper prepared teacher on students' learning convergence (response time) is presented briefly. The interesting interrelation between noise power value (σ) and learning rate parameter η is given at the fourth subsection *D*.

A. Modeling of 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 instruction learning. Consequently, he provides the model with non-redundant cleared data maximizing its signal to noise ratio in according to tutor's experience [15], [16]. Conversely, in the case of unsupervised/self-organized learning, this is based upon either Hebbian rule [17], or interaction with environment [18]. Both are implicitly formulated mathematically by above equation (7).

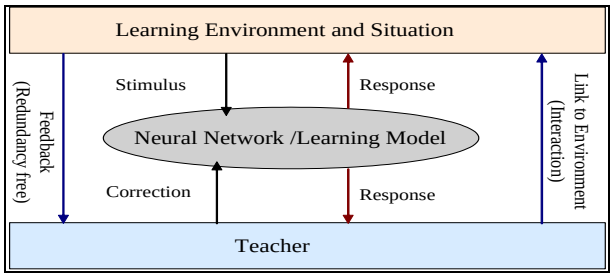

Figure 1. Illustrates generalized simple block diagram for interactive learning process

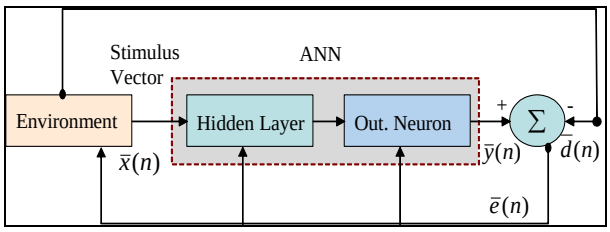

Figure 2. Generalized ANN block diagram simulating two diverse learning paradigms adapted from [19]

B. Mathematical Formulation of Interactive Learning

The presented model given in Fig. 2 simulates simply 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 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) [17].

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

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

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 equation (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 equation (5).

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

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

$$e_k(n) = |d_k(n) - y_k(n)| \quad (4)$$

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

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:

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

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:

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

Noting that e_k(n) equation (6) is substituted by y_k(n) at any arbitrary time instant (n)during the learning process. Instructor designs the learning environment.

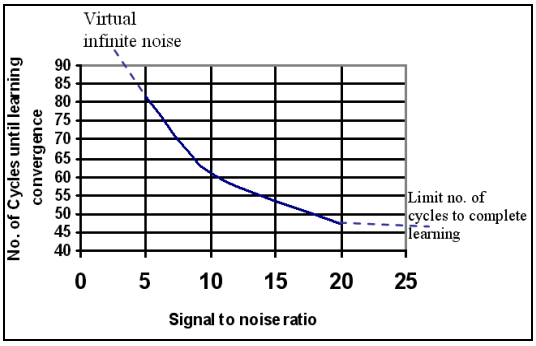

Figure 3 Graphical presentation of learning performance considering non-properly prepared (noisy) teacher by referring to Table I.

III. Non-Properly Prepared Instructor [1]

A. *Non-Properly Prepared Instructor's Analogy to Signal to Noise (S/N) Ratio Influence on Academic Performance*

Referring to Fig. 3, the instructor's correction signal should have been erroneous in accordance with level of non-proper preparation. In other words, that non-proper preparation level quantitatively measured according to signal to noise (S/N) ratio or equivalently the additive noise power (σ) to the sensory clear (ideal) signal. Consequently, the time response measured by number of training cycles (n) {defined at the second (*B)* section at equation (6)} should have been increased until reaching learning convergence at the instant (n) when

$$\Delta W_{kj}(n) = 0 \quad (8)$$

The given condition by equation (8) could be fulfilled only if the desired output learning has been obtained after some number of training cycles (response time). Therefore, the impact of interactive non-properly prepared (noisy) teacher on learning convergence time is illustrated in Table I adapted from simulation findings published at [20]. 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 η. At the next subsection the interrelation between noise power value (σ) and learning rate parameter (η) is presented.

B. *Relation between Learning Rate Parameter η Versus Noise Power σ*

Referring to Fig. 4, the three changes of noise power values σ (0.2, 0.1, and 0.05) correspond respectively to

noisy contaminated environmental information/data having the values of S/N (5, 10, and 20). Interestingly, that by the increase of S/N ratio (more properly prepared teacher) results in improvement of learning rate parameter value η

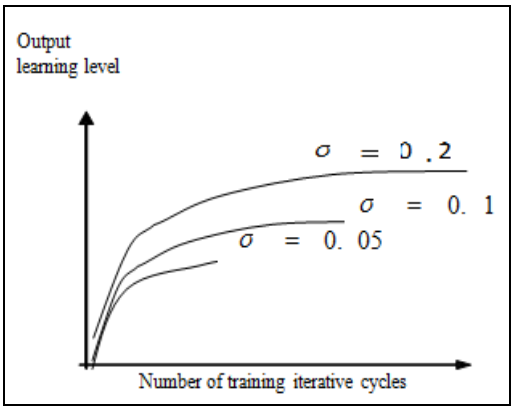

Figure 4. Relation between noise power (σ) that represents non-properly prepared (noisy) learning process convergence, adapted from [20].

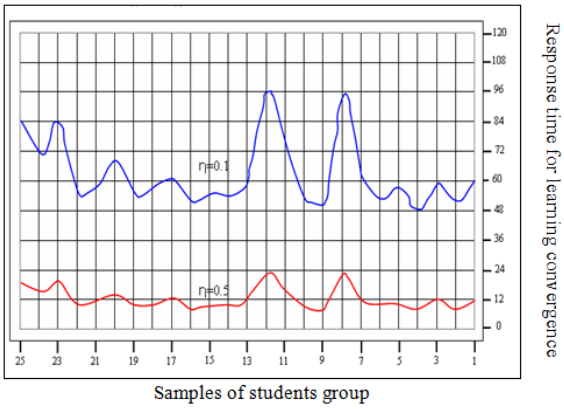

Figure 5. Illustrates the effect of learning rate parameter η on the learning convergence time for two different values 0.1(Upper curve) & 0.5(Lower curve) noting that time response obeys Gaussian distribution in an approximate manner. That is similar to bell form shape.

Referring to Fig. 5, it illustrates simulation results presented by statistical distribution for students' achievements versus the frequency of occurrence for various achievements values, at different learning rate values (η = 0.1 & η = 0.5). Additionally, the graphical relation for measured values of learning convergence (response time) versus some sample group of students seems to be similar to output response results concerning some sample group of students. It is worthy to note that, the statistical data variations seen to have oscillatory performance as. These variations of most data values appeared as symmetrically positioned around the average value of time response. For example: considering, $\eta = 0.1$ approximately half of the obtained values are appeared placed in the range (39 to 71). In other words, the resulting values' distribution has a bell form shape approximately similar to normal distribution. That is convergence time(s) of learning process is directly proportional to noise power value(s) [20]. However, that convergence time is inversely proportional to the learning rate values. In other words, by less number of training cycles, desired learning response (convergence) time could be attained (as shown at Table I). Similarly, improvement of learning rate values results in better learning performance indicated by decreased learning response (convergence) time. Furthermore, it is noticed that teacher' experience observed to be transferred via a link to brain model (Artificial Neural Network) as a corrective reacting signal. So, that experience probably capable of increasing number of neurons contributing to learning process convergence. Conversely, in case of non-properly prepared teacher results in worst learning rate ratio value and increased learning response (convergence) time

TABLE I. THE EFFECT OF NON-PROPERLY PREPARED INSTRUCTOR ON LEARNING CONVERGENCE TIME. ADAPTED FROM [19]

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

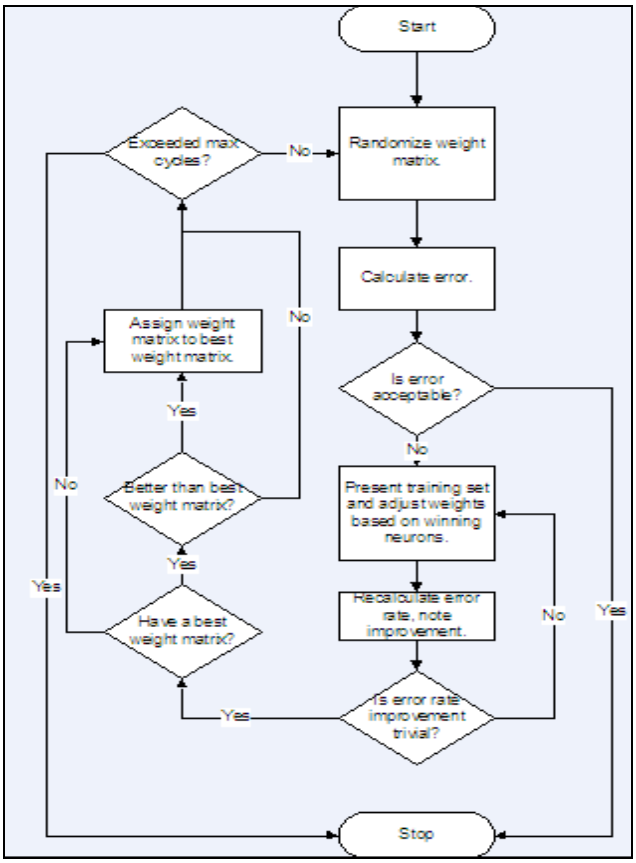

Figure 6. Flowchart of learning Kohonen neural network (algorithmic steps), adapted from [22]

C. How a Kohonen Network Recognizes

How the Kohonen neural network recognizes a pattern? We will begin by examining the structure of the Kohonen neural network. Once you understand the structure of the Kohonen neural network, and how it recognizes patterns,

you will be shown how to train the Kohonen neural network to properly recognize the patterns you desire. We will begin by examining the structure of the Kohonen neural network. Herein, adopted ANN model supposed to perform the of OCR process considering the effect of additive Gaussian noise superimposed over an ideal input vector. That model obeys Feed Forward (FF) neural network's structure which has been trained to recognize patterns of three original clear English characters (T&L or H) those have been written over (3x3) retina. The training algorithm obeys the recognition process (algorithmic steps) of Kohonen's self-organized paradigm for OCR presented by given flowchart at Fig. 6. The following subsection illustrates some detailed analysis concerned with learning performed during OCR process.

D. *How a Kohonen Network Learns*

In this subsection, learning to train a Kohonen neural network is introduced. There several steps involved in this training process in Fig. 6. Overall the process for training a Kohonen neural network involves stepping through several epochs until the error of the Kohonen neural network is below acceptable level. In this section we will learn these individual processes. You'll learn how to calculate the error rate for Koenig neural network; you'll learn how to adjust the weights for each epoch. You will also learn to determine when no more epochs are necessary to further train the neural network. The training process for the Kohonen neural network is competitive [17], [21]. For each training set one neuron will "win". This winning neuron will have its weight adjusted so that it will react even more strongly to the input the next time. As different neurons win for different patterns, their ability to recognize that particular pattern will be increased [21].

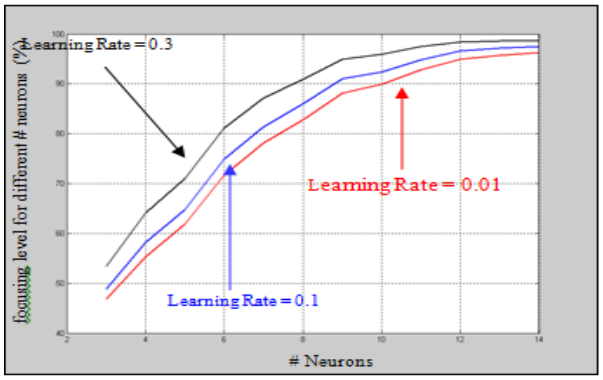

Figure 7. Illustrate simulated outcome presented as percentage degree of lesson focusing versus # Neurons for different learning rate values η (0.3, 0, 1, and 0.01).

IV. Noisy Learning Environment [2]

Noisy data at educational field classrooms considered as the main cause of environmental annoyance. In addition to observed negatively influences on quality of academic performance. Therefore, noisy learning environment results in observations of worst learning/teaching process and less students' focusing on lessons in classrooms.

A. *Effect of Neuron's Number on Lessons' Focusing*

At Fig. 7, the three changes of Noise power σ (0.2, 0.1, and 0.05) in noisy environment considered to be in correspondence with three learning rate values η (0.01, 0.1, and 0.3), respectively. The obtained three curves are derived after running of simulation program for different neurons' number. Additionally, the statistical distribution of learning convergence time for different learning rate values is given at Fig. 8 and also illustrated at Table II. In Fig. 9 a simplified macro-level flowchart for simulation program is introduced. It briefly describes the algorithmic steps for realistic simulation program of adopted Artificial Neural Networks' model for different number of neurons

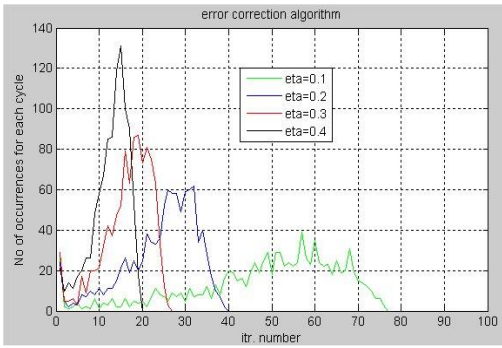

Figure 8. Illustrates the statistical distribution of learning convergence time for different learning rate values (eta) adapted from [10]

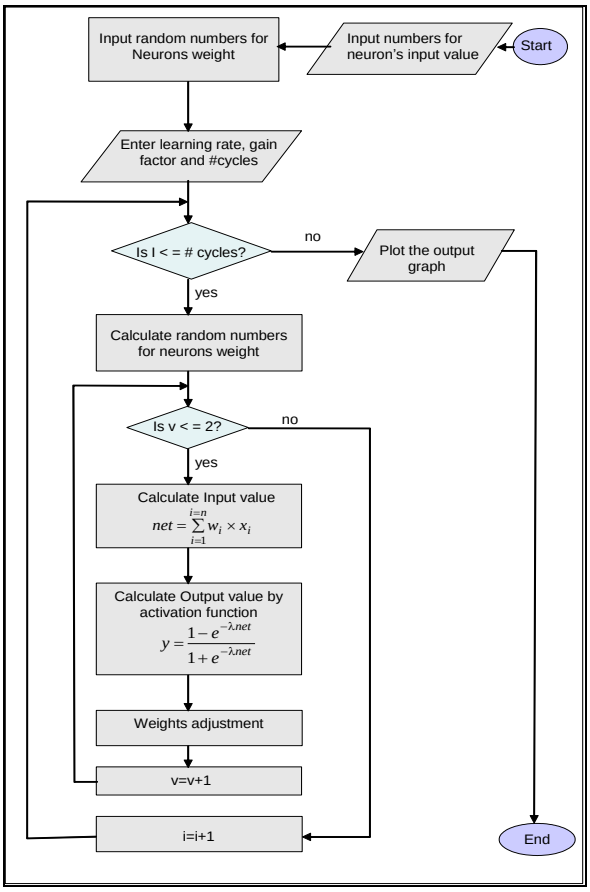

Figure 9. A simplified macro level flowchart that describing algorithmic steps for Artificial Neural Networks modeling considering various number of neurons.

TABLE II. THE RELATION BETWEEN LEARNING RATE VALUES AND CONVERGENCE LEARNING TIME

Learning rate Value (η)	0.1	0.2	0.3	0.4
Average Response time	55	27	17	13

V. OVERCROWDED CLASSROOMS' ENVIRONMENT [3]

The effects of the physical learning environment in classrooms include three distinct effective factors namely: noisy level in classes, overcrowded classroom space, and housing and neighborhood quality [23]. Specifically, this work explores pupils' ability to listen to, and follow, one speaker in the presence of others. More precisely, it considers investigational answer for a challenging question: How students could focus on teachers' interactive speaking in noisy crowd environment? When discussing the auditory system it is important to understand the difference between the physical mechanism of the ear and the central auditory nervous system in the brain responsible for processing auditory information [24]. Commonly, this process experienced as following one speaker in the presence of another. Such common experience, we may take it for granted as called: "the cocktail party problem" CPP. It can be trivial experienced process for a normal human (student) listener. From a neurological P.O.V., sounds all enter the ear as one cacophonous roar, but the brain processes all the information and tunes into one sound, such as a person's voice, and filters out the rest [25]. Interestingly, referring to brain functions and anatomical structure, sound and light are processed by different receptors and neural pathways in the brain. However, by considering current knowledge of how auditory and visual stimuli sensations are responding to sound and light respectively. They are represented in the nervous system in similar complexity and that undergo with similar initial processing by the nervous system [26]. Furthermore, by referring to findings announced after some experimental work, the results published therein at [26] have implicitly declared that auditory and visual short term memory employ similar mechanisms. Consequently, modeling of Artificial Neural Networks (ANN^S) has been adopted for realistic simulation for students' selective attention in overcrowded classrooms. Therefore, an ANN unsupervised model has been suggested herein, to measure performance of selective attention and recognition for visual signal specifically optical character recognition (OCR) subjected to various contaminating noisy levels (Signal to noise ratios) [14]. Finally, obtained simulation results declared the effect of Neural Network's parameters' relation between extrinsic {various noisy levels (corresponding learning rate values)} and intrinsic {individual students' differences (corresponding to various gain factor values)} factors on recognition and selective attention performances. Additionally, presented obtained findings proved to be in well agreement with recently published results considering the dealing with noisy environmental learning problem [27].

VI. COMPREHENSIVE VIEW ON SIMULATION RESULTS

Referring to [1]-[3], after running of realistic simulation program that adopts the competitive learning law of Kohonen's self-organized learning [17], [21]. It results in the set of three distribution curves at Fig. 11, the three changes of Noise power values σ (0.2, 0.1, and 0.05). These values correspond to noisy environmental values of S/N (5, 10, and 20). Additionally, they observed to be in correspondence with the three learning rate values η (0.05, 0.1, and 0.3) respectively. It is noticed that nearness of balance point (at the x-axis) is a suggested for measuring for degree of the exact tuning to students' proper interaction with the environmental education conditions. Furthermore, after running of the suggested realistic simulation program, it results in the set of three distribution curves depicted at Fig. 10.

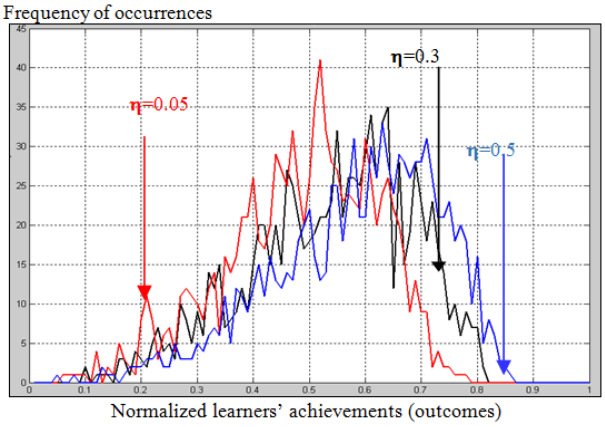

Figure 10. The three changes of Noise power values σ (0.2, 0.1, and 0.05) in noisy environment shown to be in straight correspondence with three learning rate values η (0.05, 0.3, and 0.5) respectively.

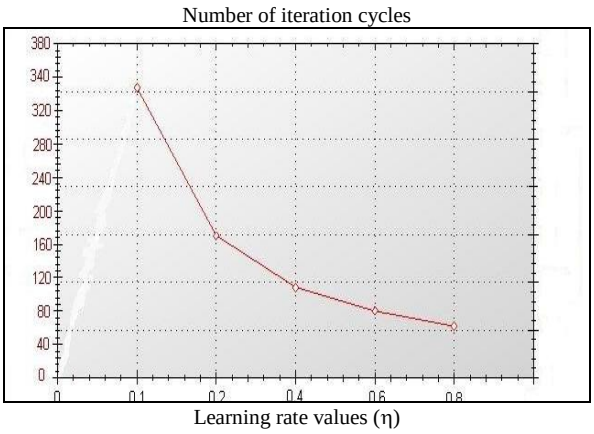

Figure 11. Illustrates the average of statistical distribution for learning response time (number of iteration cycles) for different learning rate values η.

Referring to Fig. 11, 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) iteration training cycles. Conclusively, convergence time (number of training cycles) is inversely proportional to the corresponding learning rate values. Moreover, it is an interesting remark that under more noisy environmental conditions, learning rate tends to have lower value. Conversely, creatures performing learning rate improvement by interaction with environment imply increase of their stored experience. Consequently, such creatures have become capable of responding spontaneously to input environmental stimuli in optimal manner [18]-[20].

VII. Conclusions, Discussions, and Future Work

The school bears the responsibility for creating clearly learning environment that is based on skills and knowledge of prepared teacher facilitates students' understanding of the submitted lessons. Non-properly prepared teacher results in noisy data submitted in classrooms considered as main cause of learning environmental annoyance and it negatively affects the quality of learning performance. Herein, this work illustrates specifically the analogy between learning under noisy data environment in Artificial Neural Networks models versus the effect of physical environment on quality of education in classrooms. The observed non-properly prepared teachers' phenomenon in classrooms shown to have negative effect on educational process performance. Similarly, that observed effect of additive noise power to any of pixels associated to three originally clear English characters (T&L or H) which are written over (3x3) retina. Herein; obtained results at [1], opened an interesting research area for future investigations of observed phenomenal education issues.

Noisy data which considered as main cause of environmental annoyance and it negatively affects the quality of life of a large proportion of the population. Herein, this work illustrates specifically the analogy between noisy data learning in Artificial Neural Networks models versus the effect of physical environment on quality of education in classrooms. Interestingly, it is observed that overcrowding in classrooms shown to have negative effect on educational process similar to the noise effect. Those obtained interesting results have been considered as a guiding indication for challenging research works in future for more elaborate investigation of observed educational phenomena issues [2].

Generally, at any level of education, school bears their responsibility in order to create relevant enhancing of learning environment. hat is based on modern skills and knowledge and facilitates students' understanding of the world of technology. That learning environment is regarded as the ensemble of the intellectual, social, and physical environments. Accordingly, schools' responsibility have to take into account students' developed learn performance aside from noisy contaminated (undesirable) effects on created learning environment. This work illustrates clearly the analogous undesirable effect observed by effects of both overcrowded classroom as well as Cocktail Party Problem on learning performance phenomenon. The learning environment supports the student's development into an independent and active learner, carries the basic values of basic education and the school's mental attitude, and preserves and refines the traditions of the region and the school community. Furthermore, the learning environment creates prerequisites and conditions for acquiring a subject as well as for the development of the student's personality. Interestingly, in ANN context, the two parameters: Learning rate and Gain factor are considered by the presented simulated comparative study. Accordingly, interesting simulation results have been obtained by the end conclusion of this work declaring the interrelation between learning rate values versus different noisy levels. As well as, the effect of intrinsic individual children's differences (gain factor values) on selective attention performance is presented. Furthermore, the work illustrates specifically the analogous effect between Artificial Neural Networks modelling of noisy audible data (education in classrooms), versus the noisy physical visual data such as Optical Character Recognition (OCR). The overcrowding in classrooms shown to have negative effect on educational process similar to the noisy learning environmental effect. The interesting results have been obtained indicating an extendable future challenging research. In future, this work is recommended to be extended by more elaborate practical educational field application, in order to investigate systematically both observed educational phenomena presented herein.

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Hassan M. H. Mustafa has born in Cairo, on first of October 1947. He received his B.Sc. Degree and M.Sc. Degrees in Electrical Engineering from Military Technical College Cairo-Egypt in 1970, and1983 respectively. He received his Ph.D. degree at Computer Engineering and Systems in 1996 from Ain Shams University -Faculty of Engineering Cairo–Egypt. Currently, he is Associate Professor with Computer Engineering, Department, Al-Baha University K.S.A. He is a member with a set of Scientific, En Engineering, and educational technology Societies. Such as IIIS (International Institute of Informatics and Systemics), the Society of Digital Information and Wireless Communications (SDIWC). And at the International Association of Online Engineering IAOE. He is a senior member at International Economics Development Research Center (IEDRC) organization. Furthermore, he has been appointed as a member of technical comity for Artificial Neural Networks research work at IASTED organization during the period (2009-2012). He is an advisor at ELIXIR Journal and he has been appointed as a reviewer member at WCSIT Journal. His interest fields of research are Artificial Neural Networks, Natural Inspired Computations, and their applications for simulation, modeling and evaluation of learning processes /phenomena. He is an author / coauthor for more than 90 published publication papers & technical reports & books. All articles have been published at international specialized conferences and journals during time period from 1983 till 2014. His two E-mails addresses are: prof.dr.hassanmoustafa@gmail.com & hhasan@bu.edu.sa

Ayoub Al-Hamadi was born in Yemen. He received the master's (Dipl.-Ing.) degree in electrical engineering and information technology in 1997, the Ph.D. degree in technical computer science in 2001, the Habilitation degree in artificial intelligence in 2010, and the Venia Legendi degree in pattern recognition and image processing from Otto von Guericke University Magdeburg, Magdeburg, Germany.

He became a Professor of Neuro-Information Technology with Otto von Guericke University Magdeburg in 2008. He has been a Junior Research Group Leader with the Institute for Electronics, Signal Processing and Communications, Otto von Guericke University Magdeburg, since 2002. He has authored over 280 articles in peer-reviewed international journals, conferences, and books.