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ANALOGIC NON-PROPERLY PREPARED TEACHERS VERSUS NOISY CONTAMINATED OPTICAL CHARACTER RECOGNITION REGARDING STUDENTS' ACADEMIC PERFORMANCE, ADOPTING ARTIFICIAL NEURAL NETWORKS' MODELING

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ABSTRACT

This Research papers tackles an important and interestingly complex, and a challenging educational problematic phenomenon. Specifically, it addresses two analogously interrelated issues namely: the non-properly prepared teachers that characterized by undesirable impact on students' academic achievement inside classrooms. Additionally, Herein, this issue shown to be analogous to recognition process of noisy contaminated Optical Character Recognition (OCR). Briefly, this comparative study objectively illustrates analogous relationship between contaminated noisy information provided by non-properly prepared teaching process versus noisy contaminated (OCR) process.

By more details, various noisy power level values which changed in learning environment, results in considerable correspondence with different learning rate values. The unfavorable amount of teacher's improperness is mapped similar to well-known communication technology term namely signal to noise (S/N) ratio. Which quantitatively measures the clarity degree related to received desired learning / teaching signal across the educational communication channel. In other words, it illustrates simulated outcome presented as percentage of lessons' focusing degree versus # Neurons for different learning rate values. More properly. Performance of non-properly prepared teacher results in noisy information submitted to children's brain in classrooms. Accordingly. it observed annoyance of learning environment and negatively affects the quality of children's learning performance. Herein, this research work illustrates specifically the analogy between learning under noisy data environment in Artificial Neural Networks (ANN$^{\underline{S}}$) models versus the effect of physical environment on quality of education in classrooms. The observed non-properly prepared teachers' phenomenon in classrooms observed to have negatively undesired effect on the evaluated educational process performance. Analogously, the observed effect of additively contaminating noise power on any of map size made with the resolution of (3x3) pixels. These pixels were associated to diverse three English clear characters (T&L, or H) which originally written over (3x3) binary (black & white) digitized retina. Herein; obtained interesting findings shaded light over more complex challenging research directions towards in future more elaborated investigational study for such interdisciplinary observed educational phenomena.

KEYWORDS: Performance evaluation; Optical character recognition; Artificial neural networks models; Student's learning performance.

I. INTRODUCTION

This research deals with two interesting, interdisciplinary educational phenomenal issues. Both of them are associated to management of two observed instructional system's processes in children's classrooms. More specifically, it investigates systematically two analogically handed phenomenal problems impeded into real-world instructional systems. Interestingly, increased numbers of researchers are acknowledging that in nature many real-world systems are implicitly contaminated due to externally environmental noise sources. Accordingly, to solve this two-handed educational field problem, it is recommended to give attention to developing techniques that are robust in the presence of such noise sources. Briefly, at one hand, it adopted noisy contaminated Optical Character Recognition (OCR) which is a technique that belonged to the area of Pattern Recognition that has been studied (over the past some decades). On the other hand, the problem of answering two interrelated questions: how realistic simulation using ANN modeling capable to evaluate learning process convergence considering noisy environment? & how convergence of learning process could be quantitatively evaluated due to contaminated noisy information provided by a non-properly prepared teacher in children's classroom? By more details, this study tackles a multidisciplinary, fascinating, and important complex, and challenging educational phenomenal problem. That adopted two analogical phenomena. It is directly associated to the clarity of the educational environment, which influences the enhancement and illumination of learning / teaching student's performance. Specifically addresses the severe problem of non-properly prepared teachers having an impact on students' learning performance (achievement) in classrooms. The unfavorable amount of improperness is mapped into the well-known communication term signal to noise ratio. This word is abbreviated as SNR or S/N in the context of communication technology, and it evaluates the clarity of the received desired signal across the transmission channel. While bits training to recognize, three figures with (T, L, and H) forms using (3X3) retina based on OCR. The Artificial Neural Network (ANN) adopted feed forward (FF) model considering Kohonen learning law paradigm. After running the suggested realistic simulation program, several interesting results have been obtained. Such as the relationship between the value of the learning rate parameter □ and the Gaussian additive noise power (□) learning data submitted by a poorly prepared teacher. Furthermore, the impact of both parameters on students' learning achievement and learning convergence (response time). Herein, this work illustrates specifically the analogy between learning

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under noisy data environment in ANN models versus the effect of physical environment on quality of education in classrooms.

Optical Character Recognition (OCR) which is a technique that belonged to the area of Pattern is technique of automatic identification of different character from alphanumeric recognition of printed or handwritten characters, text numerical, letters, and symbols [1]. More recently, by referring to [2], the authors have been interesting in reviewing OCR and the study belongs to both typed characters and handwritten character recognition (OCR). That is based on the three operations to detect the text/character namely, text location, feature extraction, and recognition.

On the other hand, an educational technology specific, topic that tightly coupled by the Decade of the Brain, which was announced previously at decade (1990-2000) in the United States of America [3,4,5,6]. As a result, educationalists have embraced the realistic developmental human brain simulations for modeling various activities considering Artificial Neural Networks (ANN[s]), as a relevant interdisciplinary evolutionary trend. This is accomplished by combining learning sciences with neurophysiology, psychology, and cognitive science in order to investigate some increasingly difficult interdisciplinary issues in a systematic approach. 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 academic learning achievement learning. Even though while regarding either noisy classroom environmental conditions or when considering Non-Properly Prepared Teachers in classrooms. In the context of Artificial Neural Networks (ANN[s]), educationalists were searching for replying the challenging and critical problematic question by mapping it into two interrelated questions: how realistic simulation using ANN modeling capable to evaluate learning process convergence considering noisy environment? & How this process may be evaluated quantitatively while affecting with contaminated noisy information provided to students by a non-properly prepared teacher? Remarkably, ANN approach has been receiving wide attention for educational research purposes. [7] applied ANN to model and perform data training based on students' course selection behavior, and further identified the best strategy and configuration to meet students' demands for every course for optimal course scheduling within a university [8,9,10]. Interestingly, 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 quantity 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 [11].

Herein, a self-organized unsupervised ANN model has been suggested, for measuring selective performance which focused on attention and recognition for visual signal specifically optical character recognition (OCR) that contaminated by intended various noisy power levels (signal to noise ratios). Additionally, suggested ANN simulation obeys the brain targeted teaching model [12] and it agrees with the competitive learning law introduced by Kohonen [13,14]. By more details, this research work has an interdisciplinary characteristic that specifically addresses a study of an educational challenging issue facing students in classrooms. In the context of solving of Pattern recognition problem concerned with educational field. The presented study gives a special attention of how machines (such as computers) can observe the environment, learn to distinguish patterns of interest (Characters) from their natural noisy background [15]. That observations resulted in a sound evaluation, and reasonable decisions about patterns (data) provided by non-properly prepared teachers in classrooms. Furthermore, this study associated with evaluation and analysis of learning performance considering noisy environmental conditions [16,17]. Generally, in classrooms noisy data considered as main cause of environmental annoyance and it negatively affects the quality of life of a large proportion of the population (students in classroom). More specifically, in our schools, these noisy conditions contaminate information/data which vulnerable to two types of contaminating noise: either external or internal (inherent). This paper pays a special attention to the internal (inherently) contaminated information/data that resulted by acquired noise via non-properly prepared lessons. Accordingly, this inherently environmental noise results in deteriorated learning achievements (outcomes) of students facing non-properly prepared teachers in their classes. In more precise words, this research work adopted Artificial Neural Networks (ANN^s) for systematic approach towards evaluation of an interdisciplinary educational challenging phenomenon observed in classrooms. Suggested phenomenon is associated with the effect of one physical educational environment issue on students' learning performance in classrooms. Specifically, it describes a serious problematic issue of non-properly prepared teacher (before going into a classroom), on students' performance. In other words, in the educational field practice, one challenging and critical question arises which concerned with students' performance: How a student could focus his attention while an interactive teacher lecture transferring informative lessons in case if that teacher has not properly prepared his lesson? Obviously, students' interaction with such teacher will inevitably results in some level of confusion for understanding focused on lessons. In the context of OCR which interrelated with ANN application, Online and offline character recognition are two modes of data acquisition in the field of OCR and are also studied. As deep learning is the emerging machine learning method in the field of image processing, the authors have described the method and its application of earlier works. From the study of the recurrent neural network (RNN), a special class of deep neural network is proposed for the recognition purpose. Further, convolution neural network (CNN) is combined with RNN to check its performance [2]. In this work, specifically, a generic iterative neural network model is suggested for acceptance of input noisy detectors. The ideal input vector is one out of three original clear English characters (T& L or H) which are written over (3x3) retina. The model is arranged as a feed forward neural network with two layers: the first is a sensory layer, while the second considered for having output decisions. Interestingly, obtained results revealed that convergence response time of learning process is reached after 47, 62, 85 training cycles when the values of noise power are: 0.05, 0.1 and 0.2, respectively. Conclusively, for any learning process: observed numbers of training cycles (convergence times) are directly proportional to noise power value (s). Furthermore, an interesting inter4relation between the two ANN parameters: learning rate value (□) and noise power value (□) has been derived.

Since beginning of last decade, (ANN^S) models have been adopted to investigate systematically mysteries of human brain, the most complex biological neural system, [3,18]. In this context, there is strong evidence in modern neuroscience that networks of neurons perform a dominant role in performing cognitive brain functioning such as selectivity. Consequently, ensembles of highly specialized neurons (neural networks) in human play the dominant dynamical role in the functioning of developing selectivity function by brain [19, 20, 21]. Interestingly, modeling of human brain functions considered as recent interdisciplinary evaluation trend by educationalists in learning science incorporated Nero-physiology, psychology, and cognitive science [21, 22]. The rest of this paper is organized as follows. At the next section revising of the interactive educational process is introduced via its four subsections. It included some simulation obtained results published during last decade. A brief description of adopted ANN model is presented at the third section. At the fourth section they obtained simulation results after running the adopted model is introduced. Finally, some interesting conclusive remarks are given at the fifth section.

1 REVISING OF EDUCATIONAL PROCESS

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 2.1 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 2.2. In subsection 2.3, the expected behavioral implication of non-proper prepared teacher on students' learning convergence (response time) is presented briefly. The interesting inter-relation between noise power value (□) and learning rate parameter (□□□ is given at the fourth subsection 2.4.

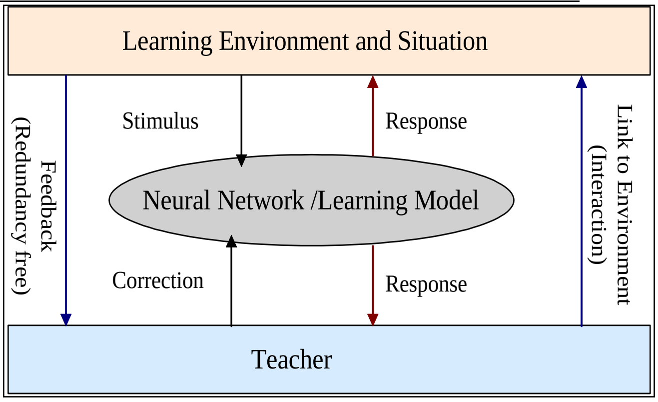

Fig. 1. Illustrates generalized simple block diagram for interactive learning process.

1.1 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 [23, 24]. Conversely, in the case of unsupervised/self-organized learning, this is based upon either Hebbian rule [15] or interaction with environment [23]. Both are implicitly formulated mathematically in below.

1.2 Mathematical Formulation of Interactive learning Prediction and Learning.

To use the neural network, we need to teach the neural network in order to choose the weight parameter. Prediction of result using neural network is simple but the difficult part is teaching the neuron the right value of weight. Learning is a process by which free parameters of a neural network are adapted through a process of stimulation by the environment through which it is embedded. There are different types of algorithms are used in different learning types. Different types of learning are:

Error-Correction Learning**:** It is a learning in which synaptic weights are correct according to the error of the neuron output. Here the output generated is compared with target output and desired response.

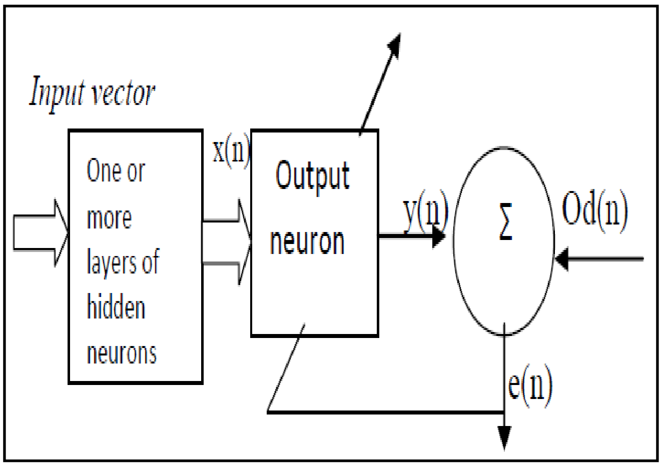

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Fig. 2. Block Diagram of neural network with error correction learning, noting the mathematical relation as, (Error= Desired Response-Actual output) Adapted from [25].

Artificial Neural Network can be best represented as a weighted directed graph, where the artificial neurons form the nodes. The association between the neurons outputs and neuron inputs can be viewed as the directed edges with weights. The ANN receives the input signal from the external source in the form of a pattern and image in the form of a vector. These inputs are then mathematically assigned by the notations x(n) for every n number of inputs. Afterward, each of the input is multiplied by its corresponding weights (these weights are the details utilized by the (ANN[S]) to solve a specific problem). In general terms, these weights normally represent the strength of the interconnection between neurons inside the artificial neural network. All the weighted inputs are summarized inside the computing unit.

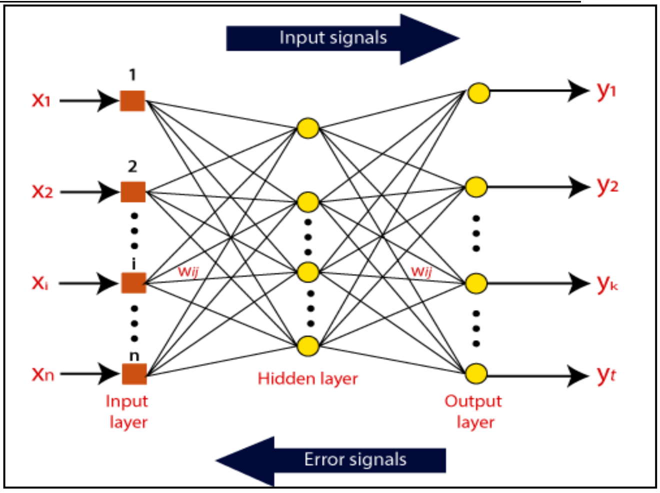

Fig. 3. Illustrates Artificial Neural Network modeled while considering feed forward learning paradigm

The presented model given in Fig. 4 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 hislearners (supervised learning) [14].

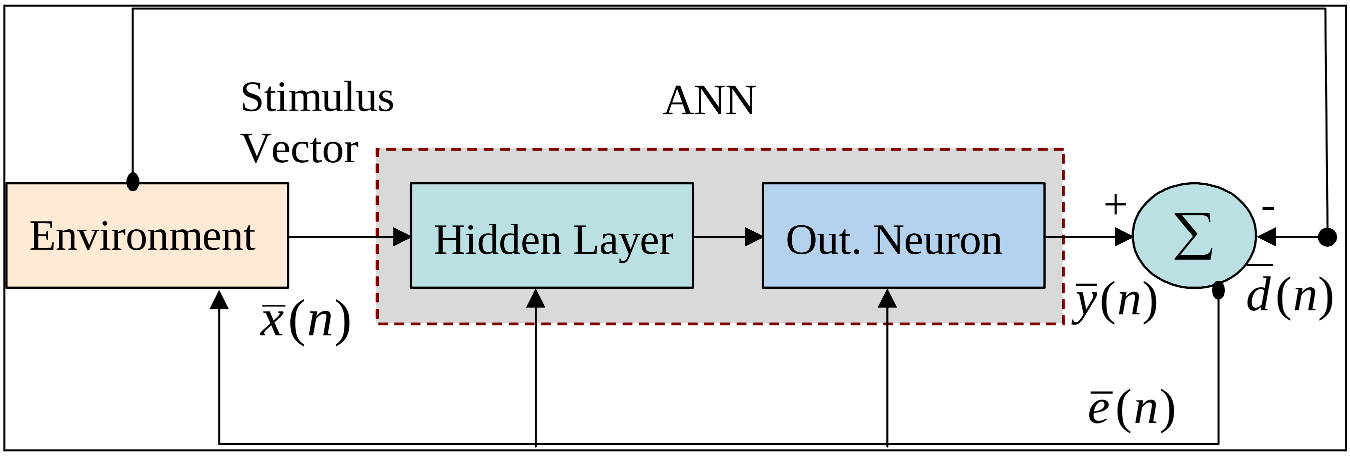

Fig. 4. Generalized ANN block diagram simulating two diverse learning paradigms adapted from [14].

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

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

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Where $e(n)$ …… is the error correcting signal that adaptively controls the learning process,

_

$y(n)$ …… is the output obtained signal from ANN model, and

_

$d\,(n)$ …… 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). This 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. □ is the activation function. Y is the output. e_k is the error value and d_k is the desired output. Note that □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 □ 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.

1.3 Non-Properly Prepared Teacher's Behavior

Non-proper prepared teacher's lessons that submitted to students in classrooms. Obviously could be considered analogously as noisy input information (data) to students' brain receptor cells. Accordingly, a challenging critical question concerned with students' performance should have been originated: How a student could be able to understand teacher's transferred informative lessons via focusing his attention, under noisy not properly prepared lesson?

Referring to Fig. 1, the teacher'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 (□) 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

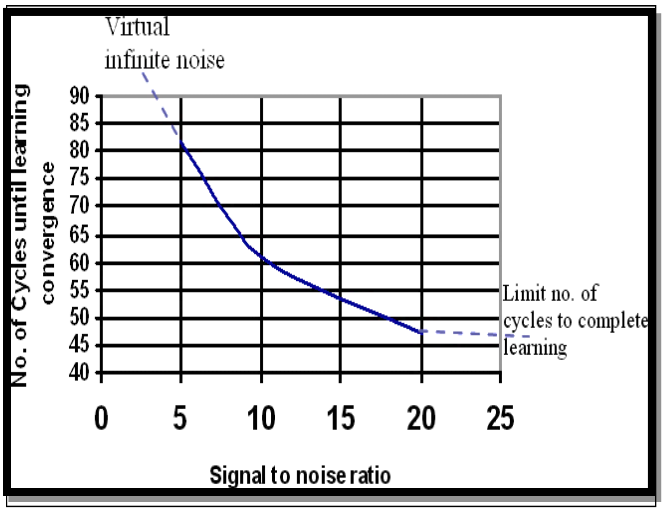
$$\Delta W_{\mathrm{kj}}(n) = 0 \quad (8)$$

The above condition given 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 1 adapted from simulation findings published at [25]. 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 □. At the next subsection the interrelation between noise power value (□) and learning rate (□) is presented.

Table 1. The effect of non-properly prepared teacher on learning convergence time, adapted from [25]

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

Referring to Fig. 4, the three changes of noise power values □ (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 □.



B Fig. 5. Graphical presentation of learning performance considering non-properly prepared (noisy) teacher by referring to above Table 1.

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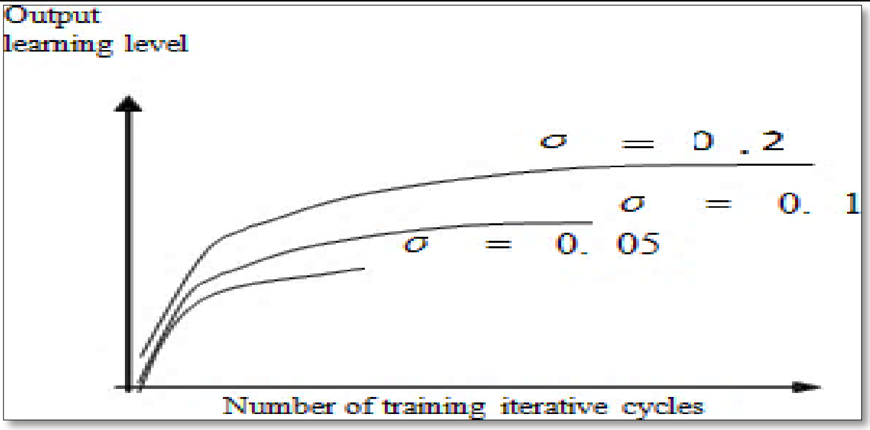

Fig. 6. Relation between noise powers (□) that represents non- properly prepared (noisy) learning process convergence, adapted from [30].

1.4 Relation between Learning Rate Parameter *(*□□ versus Noise Power *(*□□ Referring to Fig. 5, it illustrates simulation results presented

Regarding the statistical distribution for students' achievements versus the frequency of occurrence for various achievements values given at Fig. 7 & Fig.8., 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, □□□□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) [30]. However, that convergence time is inversely proportional to the learning rate values. In other words, considering little number of training cycles, desired learning response (convergence) time could be attained (as shown at Table 1). 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.

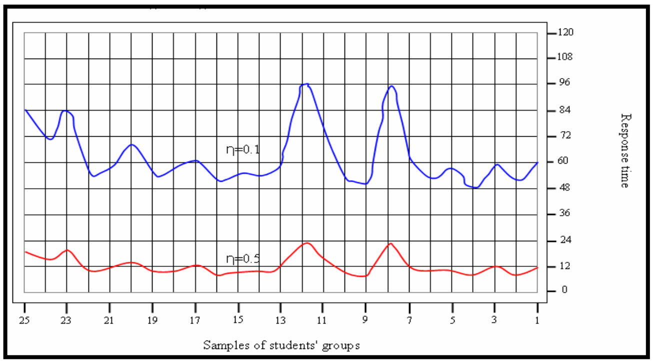

Fig. 7. Illustrates the effect of two different learning rate parameter values (0.1& 0.5) on the learning convergence (response) time presented by upper and lower curves respectively.

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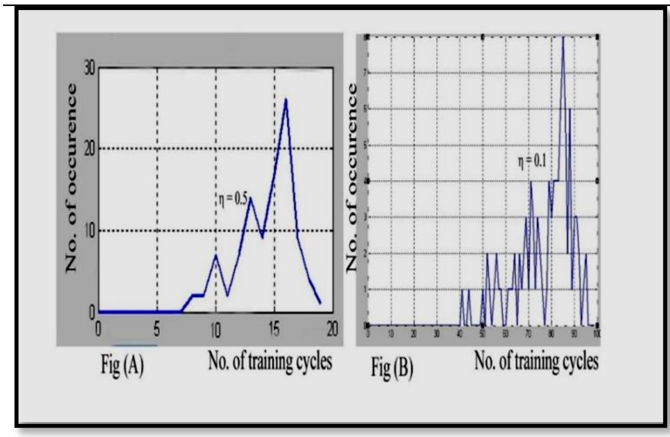

Fig. 8. Illustrates the statistical distribution for the relation between two values of learning rate parameter and learning response (convergence) time at Fig (A) & Fig (B) corresponding to two different values of learning rates 0.5& 0.1 shown at Fig.7 respectively.

2 DESCRIPTION OF ADOPTED ANN MODEL

Herein, adopted ANN model supposed to perform the of OCR process considering the effect of additive Gaussian noise superimposed over an ideal input vector. The model has feed forward (FF) structure which obeys Kohonen learning law. The pattern is one out of three original clear English characters (T& L or H) which are written over (3x3) retina. That model has been trained according to given flowchart at Fig. 6. More precisely, that adopted training algorithm obeys the recognition process (algorithmic steps) of Kohonen's self-organized paradigm for OCR presented at Fig. 6. The two following subsections illustrate some detailed analysis for performing the of OCR process.

2.1 How a Kohonen Network Recognize 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.

2.2 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. 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. We will first examine the overall process involving training the Kohonen neural network. These individual steps are summarized in Fig. 6.

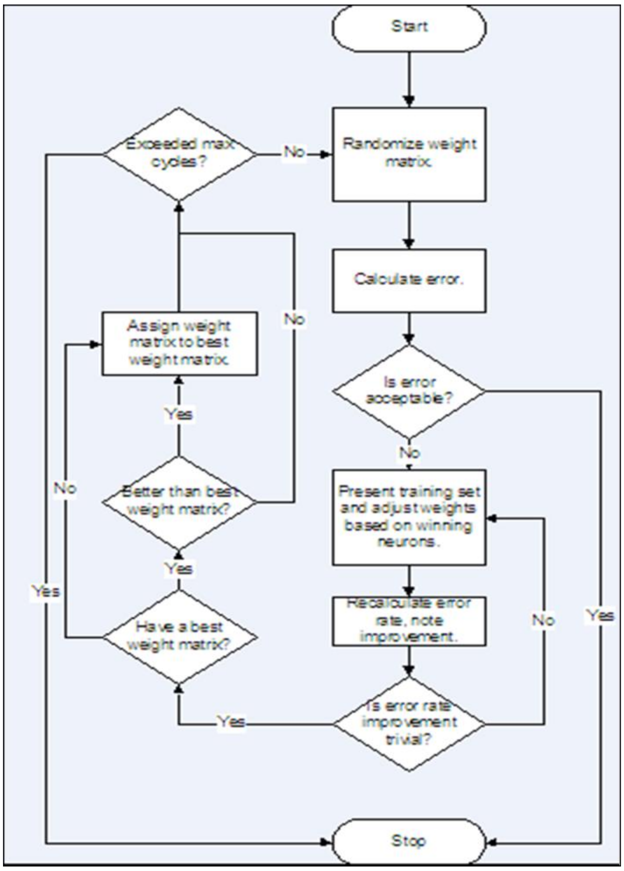

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Fig. 9. Flowchart of learning Kohonen neural network (algorithmic steps), adapted from [28]

3 SIMULATION RESULTS

After running of realistic simulation program for ANN model adopting the competitive learning law of Kohonen [29]. It results in the set of three distribution curves at Fig. 6 the three changes of Noise power values (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. Noting that the nearness of balance point (at the x-axis) is a suggested measure for degree of exact tuning to understand the speech. Furthermore, after running of the suggested realistic simulation program, it results in the set of three distribution curves depicted at Fig. 9.

Referring to Fig. 8, 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, [24,25].

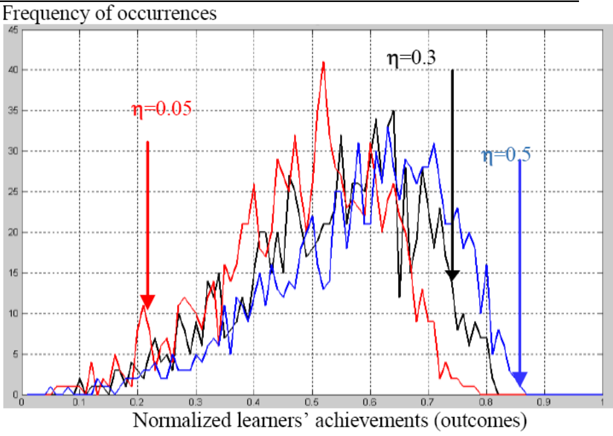

Fig. 10. the three changes of Noise power values (0.2, 0.1, and 0.05) in noisy environment considered to be in correspondence with three learning rate values(0.05, 0.3, and 0.5)

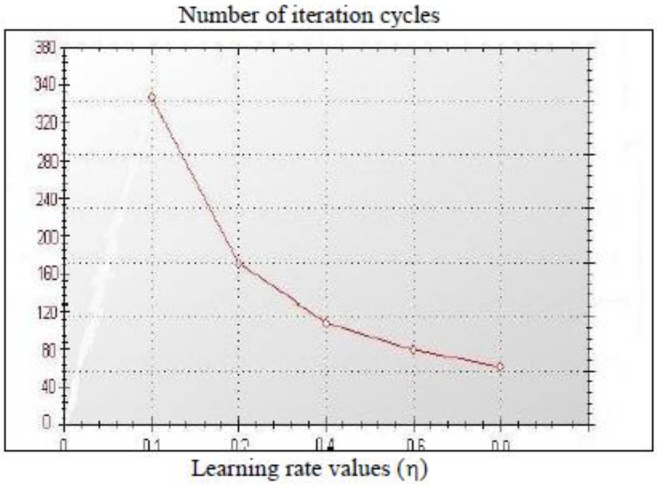

Fig. 11. Illustrates the average of statistical distribution for learning response time (number of iteration cycles) for different learning rate values

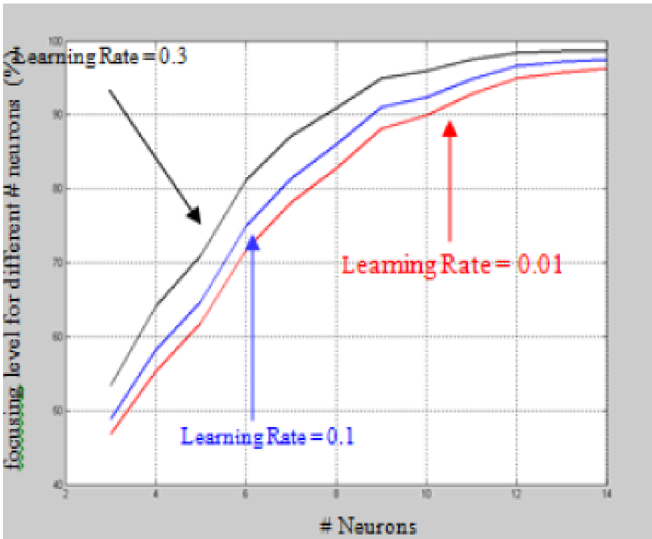

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Fig. 12. Illustrate simulated outcome presented as percentage degree of lesson focusing versus # Neurons for different learning rate values (0.3, 0, 1, and 0.01)

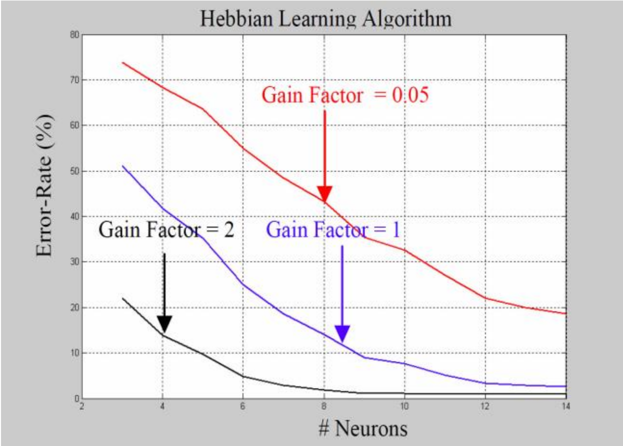

Fig. 13. Hebbian learning performance error-rate with different gain factors: 0.05, 1, and 2, while #cycles = 300 and Learning rate = 0.3.

4 CONCLUSIONS

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 [30]. Herein; obtained results opened an Interesting challenging research area for more elaborate future investigations of observed educational phenomena.

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