Cognitive Neuroscience and qEEG for Educational Resilience

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Keywords: Stimulator App, Neurocogitive, Reading, Writing, Object-Oriented Programming.

Abstract: The Program for International Student Assessment examines educational achievement, and the results show that several countries are below average. The OECD average with a low level of competence in mathematics is 24%, for Mexico it is 56%, 45% showed growth mindsets. Mexico and the Ministry of Public Education have made every effort to make education relevant. Today the contingency of COVID-19 encourages the search for educational alternatives to strengthen teaching-learning methods. The article converges on a neurocognitive stimulator-based architecture general, protocol and tools that contributes to the functional student's regeneration nerve cells, and sensory stimulates the reinforcement of mathematical epistemic thinking in cognitive abilities (memory, attention, and perception) through the use techniques and artificial intelligence; contrasted with brain mapping. This tool will support specialists: psychologists, neurologists, among others; in the interpretation of brain neuroplasticity. The results were contrasted with different ANN's, obtaining better performance from the Dendral Processing Network. The tests show that memory, attention, and perception skills in children increased. When the children use Neurostimulator reinforce their ability. Finally, the qEEG shows the region with more brain activity during cognitive processing tasks.

1 INTRODUCTION

Education at its different educational levels was affected by the arrival of the COVID-19 pandemic, the world had to evolve and face new challenges, drastically changing the way of educating. The OECD Program for International Student Assessment (PISA) assesses knowledge and skills for full participation in the knowledge society. Unfortunately, some countries are far below the average in all three subject areas: science, mathematics, and reading (Programme for International Student Assessment, 2021).

This is how the need arises a guide for pedagogical practice that is a reference on educational training. Since 2016 begins an evaluation and update of the National Educational Model in Mexico and receives the name of "New Mexican Family" (SEP, 2016). Instances such as Accreditation Council for Engineering Education, A.C. (CACEI) and, Council for Accreditation of Higher Education A.C. (COPAES), encourage innovative teaching-learning practices in higher education and consider it relevant to improve the curricular plan by competencies to strengthen and promote the use of technological advances, improve teaching, teaching practice and to improve the overall educational quality (COPAES, 2021) (UNESCO, 2013).

On the other hand, researchers address problems with cognitive deficiencies in adults (Boyd , Synnott, Nugent, Elliott , & Kelly , 2017), (Shi, 2020), cognitive abilities in the early development of the infant, and others the emerging role for the adequate training of the educational neuroscientist. Unfortunately, these are worked in isolation, on the one hand, through basic level apps, based on cognitive theory to help students to learn (Yi, Ruan, Gao, & Zhang, 2020) (Aboalela, 2016) and reinforce their cognitive skills (Shi, 2020). Also, using techniques of Artificial Intelligence (AI) (Pritchard & al, 2021) and independently using neurofeedback

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techniques to predict cognitive decline (Giridhar, Long, & and Mircea, 2020) (Cerda, Pérez, Romera, Ortega-Ruiz, & Casas, 2017).

This paper establishes a collaborative work by venturing into AI with Artificial Neural Networks (ANN), mobile technology, educational cognitive neuroscience (neurofeedback) and the national basic-level curriculum proposed by the current Pedagogical Guide of the SEP. The aim is to present a general architecture to build or use a stimulating tool that allows the student to interact and perform brain mapping or quantitative electroencephalogram (qEEG) of the cortical modules and identify the region with the greatest brain activity. Furthermore, a repository trained with RNA's will be generated, which allows measuring the level of mathematical knowledge based on the cognitive abilities (attention, perception, and memory) of infants.

2 PROPOSED SOLUTION ARCHITECTURE

To achieve the aim, the Figure 1 shows the solution where it integrates the strategic techniques of cognitivism in the curriculum mapping, relying on mobile technology, to reinforce the Teaching-Learning Process (TLP) of the basic level exact sciences. The results of the qEEG Cartography are contrasted with AI techniques through ANN.

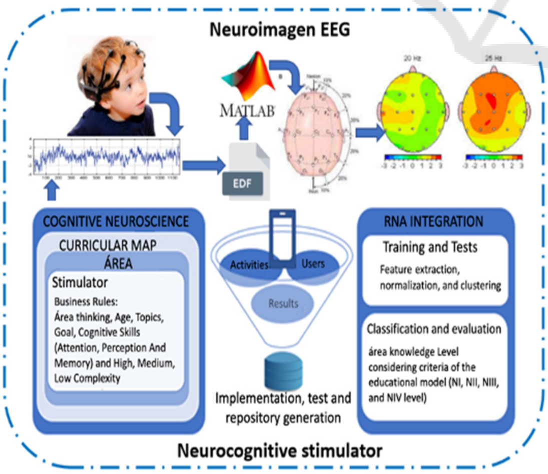

Figure 1: Solution architecture general

Now, Figure 2 shows the standardized protocol for any subject applicable to students who need to measure the teaching-learning process at any educational level, theme, curricular map, including any cognitive ability.

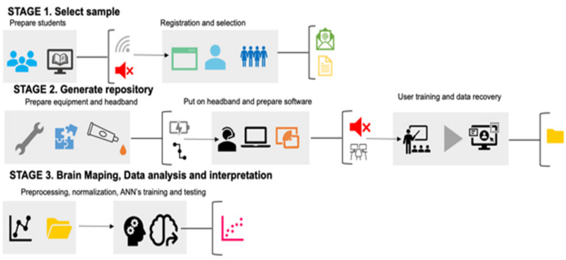

Figure 2: Protocol for obtaining and processing qEEG signals

2.1 Development of the Neurocognitive Stimulator General

The implementation of the architecture (**Figure 1**) and using the protocol of **Figure 2**, a stimulator can be developed where neurocognitive strategies: Perception (Per), Attention (Aten), Memory (Mem) related to the functioning of the human brain and its biological mechanisms of different areas or themes: Mathematical (M), Reading (R), Writing (W), and Object-Oriented Programming (OOP) of any educational level are implemented, considering criteria of the **Table 1**.

Table 1: Thematical to proof architecture general

Thematical	M	R	W	OOP
Sample	290	267	204	285
Grade	Basic level			Superior level
Modality	Presential			Presential Virtual
Axis	Sense, Form space and measure, Logical, Problems resolution			
Tools	Application web, Mobil, Batteries, evaluation test, graphics, images, audios, videos, etc.			
Cognitive abilities	Attention, Perception, Memory			

The neuro stimulator can be from a web application, mobile, presentations to a series of batteries where playful activities oriented to cognitive neuroscience and the curricular map of the selected topic are implemented. These will be used to train, motivate and over time the user manages to think critically and reflectively autonomously, reaching brain neuroplasticity (retaining as much information as possible).

2.2 Repository Construction

Once the theme, educational level, and cognitive skills to be analyzed have been selected, see *Table 1*; The process of selecting users and noise-free workspace with Internet begins. In addition, it will be necessary to collect the personal data of the students to label records. For the collection of brain wave readings, it is necessary: Prepare the Emotiv headband with sufficient charge, moisturize sensors.

- Prepare the Emotiv headband with sufficient charge, moisturize sensors.
- Place students in the classroom or workspace free of noise.
- Put on headband Emotiv Insight, configure, and connect via Bluetooth or USB.
- Identify channel position according to system 10-20 and brain region (Figure 3), these are selected according to cognitive ability, see Table 1.
- Start training of selected topic (Object-Oriented Programming).
- At the same time, starting bandpowerlogger.exe software to collect data, this API **(EMOTIV, 202O)** and Documentation **(Emotiv, 2020)** is available on the Emotiv developer's page.

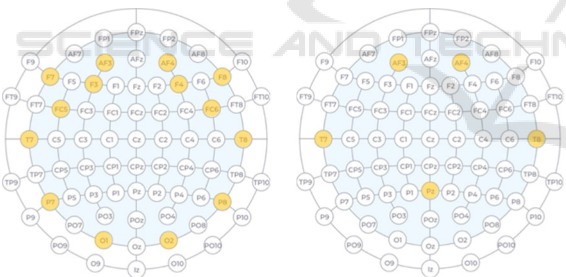

Figure 3: System 10-20, the highlighted sensors are from the Emotiv headband a) Epoc X-14 channels, and b) Insight-5 channels (Emotiv, 2020).

La *Table 2* muestra los datos obtenidos con Emotiv Insight. La primera columna representa la hora en formato Marca de tiempo, las siguientes columnas representan los canales AF3, AF4, T7, T8, Pz, (Figura 3a) con diferentes ondas cerebrales Theta, Alfa, Beta Baja, Beta Alta y Gamma.

El total es de 26 columnas, datos representados en microvoltios. Los datos obtenidos de la Table 2 hacen referencia a un de 10 estudiantes de nivel superior que fueron instruidos para reforzar la temática 4 en dos modalidades, ver Table 1. Capacitación realizada en dos tiempos diferentes (presencial y virtual). El repositorio que puede obtener en https://drive.google.com/drive/folders/1JepmwMsvEuGM7Oknwm3sxzRbyReF07Zd?usp=sharing.

Table 2: Lectura de la diadema EMOTIV INSIGHT

Time	AF3/θ	AF3/$\propto$	T7/β	Pz/γ	T8/θ	T8/$\propto$
1633403866	9.895	3.427	4.579	6.576	0.653	0.43
1633403867	14.071	2.845	6.196	6	0.336	0.247
1633403868	10.04	2.875	4.529	7.216	0.308	0.195
1633403869	6.68	3.958	2.572	6.511	0.659	0.334
1633403870	5.597	4.125	2.512	6.572	0.63	0.307
1633403871	108.232	10.331	2.827	8.585	0.581	1.229
1633403872	56.869	9.811	3.408	12.347	0.513	1
1633403873	7.865	5.807	5.371	6.942	0.471	0.633
1633403874	12.491	8.026	7.07	6.851	0.466	0.58
1633403875	128.967	24.681	6.767	10.361	2.117	3.302
1633403876	249.941	32.937	7.259	10.627	2.418	3.917
1633403877	8.081	6.379	6.286	12.085	0.427	0.418

2.3 Generate Brain Mapping or qEEG

This stage performs a treatment of the data in Table 2 to normalize them, standardize the length, the type of data required and select the most representative characteristic fields or attributes. To select these last features, the functions of the channels with respect to the headband used (Figure 4) and brain waves were considered, see Table 3.

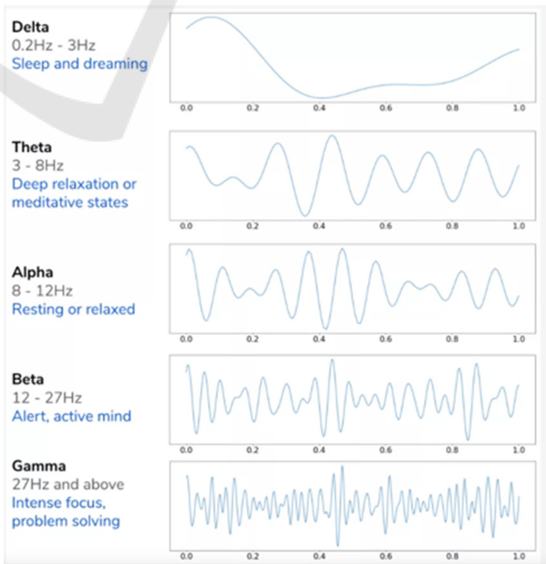

Figure 4: Brain waves in typical EEG (Emotiv, 2020).

With the data from Table 3 matrix was generated with the readings of the sensors (AF3, AF4, T7, T8, Pz, and each with the Beta High and Gamma wave). The Beta wave is engaged in a task and the Gamma wave is related to several tasks of high cognitive processing: the way of learning, the ability to learn new information and the process of simultaneous information (Donoghue, Schaworonkow, & Voytek, 2021).

The same process, we used the EMOTIV EPOC+ headset with 14 sensors. For brain mapping (qEEG), see Figure 7 y Figure the International System 10-20 and sensor configuration were used (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4).

Table 3: Electrodes EEG, Regions of the cortex cerebral associated with brain functions (Bitbrain Technologies, 2018)

Channel	Cerebral Cortex	Brain Functions related with brain lobes
AF3, AF4, F7, F3, F4, F8, FC5, FC6	Previous Frontal Central	Reasoning, speech and movement control, emotions and problem solving. Sensorimotor
T7, T8	Temporal	Memory, meaning and interpretation, and processing of auditory stimuli
Pz, P7, P8	Parental	Attention, perception, and processing of stimuli related to the senses (temperature, touch, pressure, pain)
O1, O2	Occipital	Vision

The qEEG is a useful tool to evaluate the neurophysiological characteristics of individuals with various disorders and consists of graphically digitizing the reading of brain waves through colours: red, green, blue, black, and white. The headband is connected and configured via Bluetooth to a PC and through the EMOTIVPRO license, the qEEG data is obtained in .edf format; This file and through the execution of EEGLAB functions in MATLAB, allows neuroimaging.

2.4 Data Analysis and Interpretation

The Criteria for Selecting ANN for Classification by Level of Knowledge are: The ANN has the 10 characteristic attributes (AF3, AF4, T7, T8, Pz, and each with the Beta High and Gamma wave), see Table 2, and one represents the class that determines the level of knowledge (5-10). Official Gazette of the Federation, 2018 establishes 4 classifications that indicates expected learnings, see **Table 4**.

Table 4: Class for training and test

Class	Learning description	Value or range
NI	Insufficient	Menor o igual a 5
NII	Basic	Mayor que 5 y menor o igual que 7
NIII	Satisfactory	Mayor que 7 y menor o igual que 9
NIV	outstanding	Mayor que 9

With the previous data, the repository was normalized, to train and test its operation using different classifier methods like: Multilayer Perceptron (MLP), Nearest Neighbor (LinearNNSearch), Radial Base Functions (RBF), Support Vector Machines (SMO) and Neural Network with Processing Dendritic (DMNN), each with criteria different, see Table 5. Likewise, identify the ANN with the best performance.

Table 5: The criteria used for each classifier method

Classifier Methods	Learning algorithm	**Learning rate by Thematical**			
		M	R	W	OOP
DMNN	Hyper boxes	57	59	55	60
MLP	Backpropagation (Hidden layers)	9	8	10	9
SVM	Hyperplane (Polynomial nucleus)	1	1	1	1
KNN	Euclidean distance (K)	1	1	1	1
RBF	Hybrid learning (Cluster groups)	**2**	**2**	**2**	**2**

2.5 Results and Discussions

The tests performed in the First and second phase we used 1046 instances in four thematical to basic and superior level in times different. **Table 6** shows, the results obtained of the two stages in the 3 cognitive skills implementing the different themes of **Table 1**, performing 2 tests a) manual or face-to-face, b) Application or virtual session.

For mathematical thinking was the first test that we report in (Cortes, Gutierrez, Avila, & Flores, 2020). Now, we try with other thematical like Reading, Writing, and Object-Oriented Programming and we had good results.

Table 6: Average assessment in the two stages

Thematical	Instances	First phase			Second phase		
		Manual or presential			Application or virtual session		
		Mem	Aten	Per	Mem	Aten	Per
M	290	6.6	8	7.4	7.5	8.3	8.1
R	267	7	8.2	7.9	8.1	8.4	8.9
W	204	6.9	7.8	8	7.1	8.5	8
OOP	285	7.2	8	7.5	8	8	7.9
Average evaluation		**6.9**	**8**	**7.7**	**7.6**	**8.3**	**8.2**

The average evaluation of the first stage when using any of the tools of **Table 1** and carried out manually or face-to-face, reaches a 7.5 with respect to the three cognitive skills.

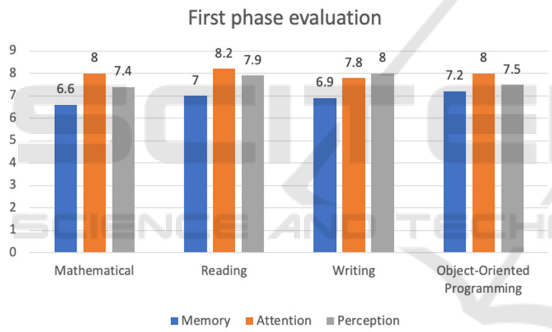

Figure 5: Average rating of first phase by theme

For a second stage, training was carried out with the application or through virtual sessions for two or three weeks and despite the short training or reinforcement time 8.0 is reached, see Figure 6.

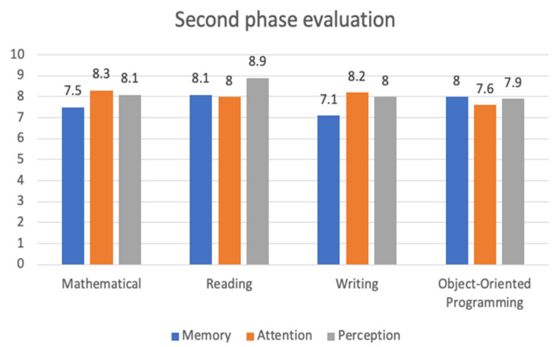

Figure 6: Average rating of second phase by theme

Obtaining the arithmetic mean for the three cognitive skills. Figure 7 shows, that there is a relevant improvement in memory and perception.

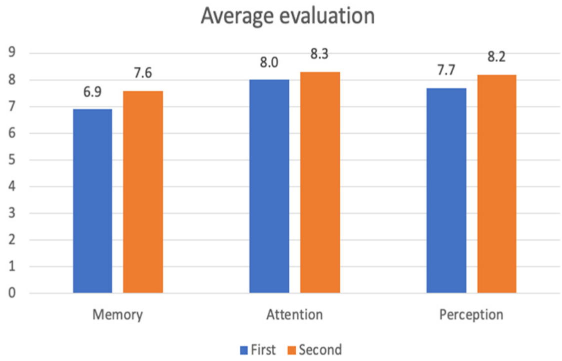

Figure 7: Average results of the three cognitive skills in the First and Second stages

The cartography obtained will serve to contrast the results obtained in the evaluation stages when using a neurocognitive stimulator (Junk Kyung, Hye Youn, & al, 2021). Figure 7 shows the behavior of each user. In addition, we can see graphically, dynamic changes in a region of the brain during cognitive processing tasks. Colors represent brain activity, blue indicates a deficiency connection, and red an excessive connection.

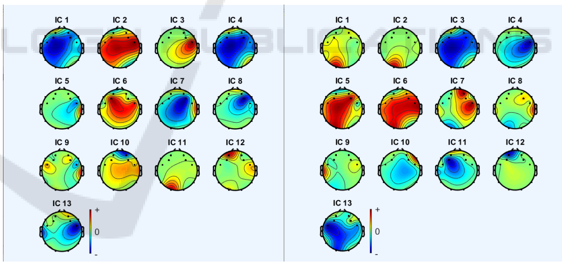

Figure 8: qEEG while the users used mathematical Neurostimulator before stimulation.

For a second phase, parents were asked for their support so that students could download the app and use it for two weeks, and a second evaluation was applied, the results are shown in Figure 6; in which it is observed that the 1st, 2nd grade students improved their memory capacity than the 3rd grade students. 3rd grade improved their ability to perceive. In figure 4a it is observed the students of all grades.

Finally, to measure the cognitive learning process of the different topics during the training and testing process, configuring the criteria selected from Table 5, a standarized repository was achieved, implementing the different AI techniques.

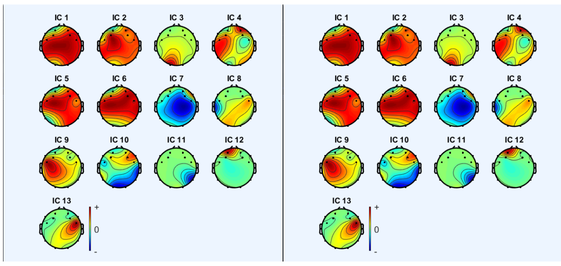

Figure 9: qEEG while the users used mathematical Neurostimulator after stimulation.

The data of Table 7 were obtained using 100%, 80%, 70%, 50% of the samples for training and the remaining percentage for testing, from the results obtained the arithmetic mean was obtained reaching a classification percentage of 99% (Table 4) when working with DMNN proposed by (Humberto & Elizabeth, 2014).

Table 7: Behaviour of classifiers methods

Thematical	**Classifiers Methods**				
	DMNN	**MLP**	**SVM**	**KNN**	**RBF**
Mathematical	99.757	99.25	96.25	96.75	99.50
Reading	99	100	99	98	97
Writing	98	97	96	95	96
OOP	99.2	99	96.5	95.7	97.7
Overall average	**99**	**98.8**	**96.9**	**96.3**	**97.5**

3 CONCLUSIONS AND FUTURE PERSPECTIVES

In the current context of education according to PISA, this article allows to attend to the education and integral training of students, achieving the interaction of Neuroscience, education, current technology and AI in favor of mathematical cognitive development, reading, writing, OOP in its 3 skills (attention, perception and memory) of students from basic to higher level, impacting the growth of our country and society, facing the effects on education in Mexico due to the lags caused by the COVID-19 pandemic.

The architecture, protocol and tools proposed in this paper ensure that students of any subject reinforce their cognitive skills and participate actively and autonomously in their cognition, motivated under the key competence of "learning to learn", ensuring that the student reinforces what has been learned, retaining it in the long term.

In addition, the proposal allowed to measure the level of mastery of various topics, through the DMNN due to its great performance. Finally, the data obtained through a neurostimulator (manual, web, mobile or virtual) allowed to obtain the brain mapping or qEEG that could be a support tool and interpreted by psychologists, neurologists, among others; to achieve brain neuroplasticity in students of different educational levels.

For future research, the proposal will be used as a brain-computer interface using neurofeedback techniques to stimulate the brain. In addition, we will obtain your qEEG and automatically perform the interpretation through the DMNN, without the need to consult a specialist.

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