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Towards Classifying Cognitive Performance by Sensing Electrodermal Activity in Children With Specific Learning Disorders

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ABSTRACT When children suffer from cognitive disorders, school performance and social environment are affected. Measuring changes in cognitive progress is essential for assessing the clinical follow-up of the patient's cognitive abilities. This process is considered as a challenge in ambulatory settings, where follow-ups should be non-invasive and continuous. Psychophysiological measures are an objective and unobtrusive evaluation alternative for recognizing cognitive changes. This paper aims to validate the relationship between cognition and the changes in physiological signals of children suffering from Specific Learning Disorders (SLD). This validation was carried out in an eHealth rehabilitation context (with the HapHop-Physio game). Electrodermal activity (EDA) signals were collected, processed, and analyzed through a machine learning approach. Obtained results were: a dataset built from wearable physiological data and a supervised classification model. The classification model can identify the children's cognitive performance (class) from the features of the tonic component of the EDA signal (attributes) with an accuracy of 79.95%. The presented results evidence that psychophysiological measures could allow for a highly objective follow-up for patients. They can also lead to creating a basis for further improvement of rehabilitation environments and developing neurofeedback applications.

INDEX TERMS Electrodermal activity, cognitive performance, supervised classification, specific learning disorders.

I. INTRODUCTION

Children suffering from disorders related to learning processes and school performance represent a vulnerable population. Learning disorders affect up to 10% of the world population. Under this condition, academic and cognitive skills are significantly lower than expected according to age [1].

The treatment of these disorders focuses on improving the necessary cognitive skills for learning. Conventionally, the assessment of these disorders and their therapies, use standardized questionnaires and activities. Questionnaires are used for the qualification and evaluation of the condition. Afterward, the questions become the standardized activities for conducting the treatment, whose resources are limited to pencil and paper. This situation is close to what children experience in school, which generates fatigue, lack of motivation, and the desertion of therapies [2].

The HapHop-Physio system is an alternative application that can be used in these therapies. HapHop-Physio is an exer-learning game: children learn and perform physical activity simultaneously while playing [3]. The system supports the rehabilitation therapies of children with learning disorders, focusing on memory and attention functions. Further details of HapHop-Physio are available in [4].

In this work, psychophysiology is used to detect the changes in children's cognitive performance using HapHop-Physio in their therapies without recurring to cognitive test batteries as usual in laboratory environments. Measures from physiological signals and/or psychological events are collected separately, to obtain their counterpart. Physiological signals are readings produced by physiological processes measured from the central or the peripheral nervous system (PNS). Psychological events are the phenomena related to cognition, emotion, experience, and behavior of

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organisms due to stimuli in the physical and social environment. The process of obtaining one from the other is known as psychophysiological inference [5].

Most psychophysiological measures are obtained from brain activity and are assessed using Electroencephalography (EEG). Other tests include functional Magnetic Resonance Imaging (fMRI) in the laboratory or clinical settings [6], [7]. Despite being directly related to cognitive processes [8], these measures tend to be uncomfortable since users cannot move freely, preventing them from experiencing a natural interaction. Thus, measuring electrophysiology through wearables is a good approach for psychophysiological assessments in ambulatory settings [9], [10].

With wearable technology, the invasiveness of the sensors has been substantially reduced [11]. Wearables frequently measure signals derived from the PNS, such as electrocardiogram (ECG), heart rate variability (HRV), electrodermal activity (EDA), electromyogram (EMG), and respiratory measures [12].

Detection of cognitive processes (e.g., memory, attention) from peripheral physiological signals measured with wearable technology has not been addressed in cognitive support technologies. Therefore, this work presents the evaluation of memory and attention activities' performance from measuring EDA and HRV signals with a wearable device (E4 wristband). Assessment is carried out during the interaction of children suffering from Specific Learning Disorders (SLD) with the HapHop-Physio system. Both physiological signals are good indicators of cognitive changes [13]–[15]. The final aim of this paper is going towards the validation of the relationship between cognition (as the class) and changes in these signals (as attributes), demonstrating the feasibility of a machine learning classification approach in a three-class classification task (low, medium, and high performance).

The papers' remaining is organized as follows: in section II, the papers related to every step in identifying cognition through physiological signals are detailed. Part III identifies the experimental pipeline followed to obtain data and analyze it. Section IV details the obtained results from the implementation of machine learning algorithms. In section V, the data analysis is presented in terms of the significance of results and comparisons to other works. Finally, section VI summaries the findings and provide insights regarding future work.

II. RELATED WORKS

The classification of cognition through physiological signals in eHealth contexts has not been thoroughly addressed compared to emotion recognition [16]. Three aspects are essential in the identification of cognition through physiological signals:

- The sensing and analysis techniques.
- The definition of the ground-truth on the cognitive state and its elicitation process.
- The procedure to obtain the cognition (psychophysiological inference).

Through a systematic mapping process addressing these three aspects, the construction of state of art was carried out with 27 papers.

In the literature, there are a variety of commercial devices used to measure physiological signals. Examples of these devices are the Biopac GSR100C [17], the NeXus 4 [18], the NeXus 10 [14], [19], the Affective Q sensor [20], and the PowerLab 16SP System [21]. However, only 18.2% of the papers use wearable technologies in their experiments. Wearable technology allows moving results from the laboratory to a free-living environment [22]. None of the related works carried out experiments outside laboratory settings [23]–[26] due to unsuitable sensors for daily activities, like Brain-Computer Interfaces.

Statistical analysis [14], [17]–[19], [27] and machine learning [8], [13], [18], [21], [28]–[31] were found as the most-used analysis techniques for the processed signals (to infer the psychological event from the physiological signal). Authors established relationships between EDA/HRV changes and cognitive states such as cognitive load [13], [14], [21], [23], [24], [32], [33], attention [8], [28], memory [19], autistic aspects [17], engagement [20], anxiety states and stress [27], and different cognitive tasks [30] under impairment conditions [31]. There are works recognizing cognition from EEG signals. Analysis techniques require deep learning capabilities in this type of works since this signal's resolution is higher [34]–[37]. However, these works do not include EDA/HRV signals in the analyzed data.

The analysis also depends on the number of signals: 37.5% of the works only used EDA as a data source; 42.9% used two physiological signals (complementing EDA with measures such as HRV), and 14.2% used three or four input signals. From the papers that only used the EDA signal, 42.9% performed the analysis with the signal's SCR component, 28.6% with the SCL component, and 28.6% of the works did not discriminate between them. Reasons for using one or the other component are varied and depend primarily on each study's conditions and objectives. However, the SCL component can provide more information to classify different cognitive abilities [30].

The most common way to identify cognitive states is to measure performance indices from tasks [19], [21], [27], [38], standardized tests [8], [14], [17], [30], [31], self-reports [13], [28], and expert observations [18]. However, these identification strategies are considered subjective and cannot be measured continuously [39]. Measuring these indices is known as establishing the ground-truth. Only one paper carried out a more objective process for defining the ground-truth for the cognitive state: analyzing the signal's variation according to standardized indices of cognitive activity [20].

The time and frequency domains help in extracting the features of the physiological signals. The psychophysiological inference needs the labeling of signal data according to the cognitive states. This process was performed through binary classes, three, four, and five classes in related works.

The accuracy of the classification does not exceed 88% in the binary classification [8].

Healthy adults are the most common population (71.4%) for the recognition of cognitive states. Experiments with children deal with one-year-old children to seek changes in the attentional processes [40] and treat children with Autism Spectrum Disorder (ASD) in two different game-play settings [41], [42]. Technology evaluated in the papers varies between games for entertainment [33], [43], and technology aids for diagnosis [44].

Given the previous state-of-the-art summary and to the best of our knowledge, few works (e.g., [8], [42]) have objectively identified changes in the cognition of children suffering from a cognitive disorder by using physiological signals. In [8], anxiety-related arousal was differentiated from arousal related to attention processes (binary subject dependent classification) with an accuracy of 84% based on heart rate indices on children with ASD. In [42], authors designed playful experiences for children with ASD assessing physiology-based data such as EDA and HRV; they identified the arousal activity (a two-class subject dependent classification task) with an accuracy of 77%. However, these works do not target a cognitive aspect, such as performance. Wearable technologies were not used to collect data in therapeutic rehabilitation with a technology suited for it. The analysis was approached as a binary classification, and accuracy was not as high as expected.

III. MATERIALS AND METHODS

In this section, the experiment to collect the EDA signal is described. First, a brief description of the devices and tools that were used. Then, the design of the experiment and a data analysis pipeline is detailed.

A. DEVICES AND TOOLS

The HapHop-Physio game focuses on the rehabilitation of memory and attention functions. Specifically, it trains the auditory and visual components for learning abilities and the training of reading and writing processes. It has an electronic mat as an input device that induces physical activity when the child interacts with it [4]. In this experiment, HapHop-Physio was used to train and evaluate the children's learning abilities.

The E4 wristband (Empatica, Milano, Italy) was used to collect the EDA and HRV physiological signals during the interaction with HapHop-Physio. The device is as easy to use as wearing a watch. It is a portable wireless device designed for comfortable, continuous, and real-time data acquisition, making it the ideal device (wearable) according to the study's requirements. The unobtrusive monitoring and easy access to raw data are some advantages of this wearable [45].

The EDA measures the changes in conductivity produced in the skin due to increases in sweat glands' activity. The signal has two components: the phasic component (Skin Conductance Response - SCR) and the tonic component (Skin Conductance Level - SCL). This separation helps in the analysis at a macro level (larger pieces with SCL) or a micro-level (related to events or SCR) [46]. The HRV is the fluctuation in the time intervals between adjacent heartbeats. It is generated by heart-brain interactions and dynamic, non-linear autonomic nervous system processes [47].

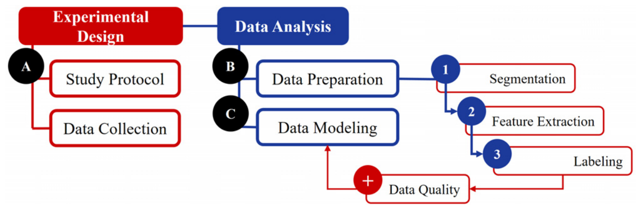

FIGURE 1. Experimental design and data analysis pipeline.

In the experiment, EDA and HRV signals from 14 children diagnosed with SLD were collected through the E4 wearable device. In the E4 wearable, the sensors used to obtain both signals are different. For HRV, an optical sensor is implemented, while two dry electrodes are used to measure the EDA. The HRV is computed from the reflected amount of light with a proprietary algorithm. This algorithm ruled out various signals as they featured many motion artifacts.

On the other hand, EDA signals were complete since the data's robustness is determined by the wristband's automatic noise artifact detection algorithm. Therefore, since the wearable optical sensors were susceptible to motion artifacts [48], the device discarded many HRV signals. For this reason, this signal was removed from the analysis, and the focus was on EDA.

Matlab was the tool used to perform the decomposition process of the EDA signal. Similarly, in this environment, the filtering and the feature extraction of the signal was performed.

The open-source software application Weka[1] was used to generate the classification models of the dataset and to test the accuracy of the models. To evaluate the performance of the model, the 10-fold Cross-Validation (CV) technique was used. This technique allows estimating how well the results of a model will generalize to an out-of-sample dataset [49].

B. METHODS

Data preparation for further analysis and the dataset construction is reported in the order described in Fig. 1.

1) STUDY PROTOCOL

A quasi-experimental pilot study was conducted to determine the changes in the cognitive domains of memory (visual/auditory-verbal) and attention (visual/auditory) after receiving treatment with the HapHop-Physio application for eight weeks. However, only the memory domain was evaluated for this paper since the attention module was still under development.

Considering the rehabilitation goal of HapHop-Physio, this study attempted to classify cognition using the EDA signal of children with SLD based on non-invasive measurement procedures.

The autonomy and integrity of patients who voluntarily participated were respected. An informed consent signed by

[1] https://www.cs.waikato.ac.nz/ml/weka/

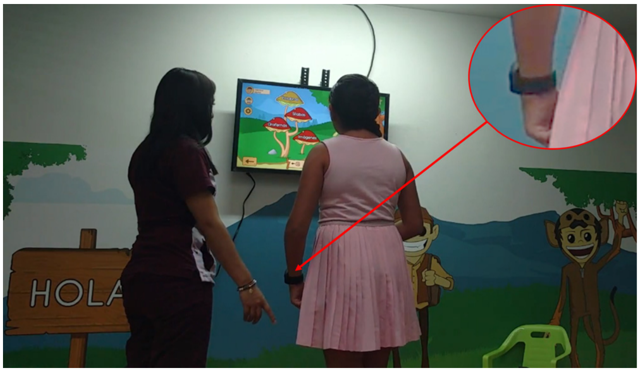

FIGURE 2. Child playing with HapHop-Physio while wearing the E4.

the children's parents and approved by the Ethics committee from *Universidad del Cauca*, in session 6-1.38/6 from 04.29.2015, guaranteed the confidentiality and privacy of the information collected the study.

Three phases comprised this study. The first phase was applying the ENI (*Evaluación Neuropsicológica Infantil*) [50], a test battery developed in Spanish for Latin American children with similar language backgrounds. The ENI determines the presence of cognitive and behavioral changes in children who were under suspicion of some type of cognitive alteration. In the second phase, the population presenting low average, limit, or very low percentile scores in one or more of the cognitive skills evaluated were selected to follow a rehabilitation process with the HapHop-Physio therapeutic program. An evaluation of the children's cognitive profile was the third phase of the study to check the progress or degradation of the first assessment's cognitive difficulties.

a: DATA COLLECTION

In every therapy session, the E4 wristband was placed on the child's non-dominant side and turned on. Children wore the wristband when carrying out the therapies under a neuro-psycho-pedagogy specialist (Fig. 2).

While the recording time began, the game was set up. Next, the specialist selected the first game in the first therapy session according to the ENI battery results. In the following sessions, game selection depended on the progress of the child. A therapy session was conducted for as long as the specialist thought it was appropriate, according to her professional judgment and the child (between 20 and 30 minutes). Finally, the recording time is ended as soon as the specialist indicated the end of the session.

Signals were collected from 14 children, during a total of 130 recording sessions. Each game session lasted approximately 25 minutes, generating an approximate of 54 hours of EDA signal recordings, with a sampling frequency of 4 Hz and a measurement range from 0.01 to 100 μSiemens.

2) DATA PREPARATION

It was essential to identify the stimuli that caused changes in the child's physical response (Fig. 3) during the rehabilitation treatment. Thus, the non-stationary signals' preparation had three major tasks: the signal segmentation, the data (features) extraction from the segments, and the data labeling.

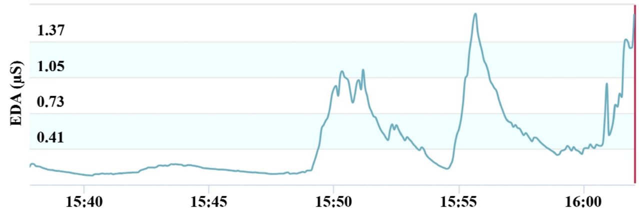

FIGURE 3. Example of an EDA signal obtained from the E4 device.

First, segmentation was performed by the duration of each mini-game in HapHop-Physio. Since the time taken to clear each mini-game and the number of levels solved by each child was different, the segmentation was not uniform. The segments' cleaning process was based on three rules to guarantee the quality of the EDA segment [51]:

1. EDA not higher than 0.05 μS
2. EDA changes faster than ± 10 μS/s
3. EDA data surrounding ± 5 s of invalid portions

Second, features from each signal segment were extracted for building the dataset, following the regular procedure found in the literature [52]: (a) filtering the segment to detect motion artifacts or weak sensor readings, and (b) extracting features to represent the segments.

Before filtering the EDA segments, they were decomposed, and the tonic component of EDA was obtained by using a convolution process with a Sinc function in the time domain [53], [54]. This component was selected for analysis since it represents time changes due to variations generated by the phasic component. The SCL slowly varies over time in an individual depending upon his/her psychological state, and it is associated with both cognitive and emotional arousal [55].

It is impossible to label each of the SCRs produced by the child's interaction with HapHop-Physio because many SCRs might be found for each mini-game. For this study, the SCL component (attributes) were assigned to the results (class) achieved by the child during a mini-game. This means the class of one instance from the dataset results from one session's mini-game from one child. Once the decomposition process was performed, the SCL segments of EDA were filtered using a low pass filter specially adapted for their number of samples.

To extract the features, multiresolution analysis techniques were found to represent the information contained in non-stationary signals. The Wavelet Transform (WT) is a widely used technique for multiresolution analysis of EDA data [56]–[59]. The study of the SCL segments was performed to obtain the features in the Wavelet domain. The Daubechies wavelet of order 10 (db10) was used as the mother Wavelet [60] along with the Mallat algorithm [61]. Ten decomposition levels (detail coefficients) of each segment were obtained in the Wavelet domain.

The following features were selected: total amplitude, normalized amplitude, and absolute amplitude from each detail coefficient (i.e., each representation of the segment in the Wavelet domain) and the first and second derivative of the detail coefficient. Four statistical variables were

TABLE 1. Features extracted in the Wavelet domain.

Type	Name
Amplitude variations	Total amplitude (r) Normalized amplitude (n) Absolute amplitude (a)
Mathematical rates of change	Base signal (d1 to d10) First derivate (+d1) Second derivate (+d2)
Statistical variables	Mean (m) Variance (v) Kurtosis (k) Standard deviation (std)

also selected: the mean, the variance, the kurtosis, and the standard deviation. Table 1 summarizes the features.

Third, after segmentation and feature extraction, each segment was labeled according to changes in cognitive activity. For the labeling, five variables related to cognition were outlined. The information about these variables was available in the HapHop-Physio database, according to the scoring system of the game. Data from each segment was labeled according to the information of these variables:

- Session: a game session is equivalent to the therapy session. Each session has a variable number of mini-games. The stimulated cognitive domains in the child's profile should increase as the game's therapy sessions continue. Therefore, the game session is considered an indicator of cognitive development.
- Level: HapHop-Physio has five levels of difficulty. In the therapy session, the game level is considered an indicator of cognitive workload [33].
- Score: the score of the mini-games depends on the game level. Each level is consistent with the average percentile of cognitive ability. Thus, the game score is equivalent to the child's memory span [62].
- Performance: this variable was established in terms of the game score in HapHop-Physio. The game's reward is in stars: players collect one, two, or three stars for each completed mini-game. This represents a low (less than 25% of the mini-game was completed), medium (at least 25% of the mini-game was achieved), and high performance (at least 75% of the mini-game was performed). Game performance is considered a measurement of **cognitive performance**.
- Time: it is the variable that measures the duration of each mini-game. Game time gives information about the length of the cognitive load and the organization's speed and planning of the child's executive functions [63]. The variable is a proximate measurement of cognitive processing length/speed.

The **cognitive performance** variable was the selected class to carry out the classification, based on:

- The small range of values avoiding an undersampling of the dataset instances. This is a three-class dataset: low performance, medium performance, and high performance.
- It is a representative variable of the set of cognitive variables.

A labeled dataset was generated per child, and the general dataset was built by concatenating the individual datasets. This public dataset can be found in Kaggle: https://www.kaggle.com/carolinarico/cognition-in-children-through-eda.

Finally, a framework for data quality was used to guarantee the dataset [64]. The generated dataset had the following problems: (i) imbalanced classes, (ii) high dimensionality, and (iii) low amount of data. These problems were identified in the individual datasets, and solutions were also applied to the general dataset.

3) DATA MODELING

With the dataset built, machine learning classification algorithms were used to model the labeled data [65]. This classification is the psychophysiological inference of the children's cognitive state. Data modeling is the final stage of the methods that will help fulfill this work's objective: find and validate a relationship between cognition and physiological signals changes.

The classification algorithms were selected due to their extensive use in the literature. The classification was performed with nine different algorithms:

- Ensemble meta-algorithms: Boosting, Bagging, Random Forest.
- Support Vector Machines algorithms: SMO and LibSVM
- Neural Networks algorithms: Multilayer Perceptron (MLP)
- Decision Trees algorithms: J48
- Probabilistic algorithms: Naïve Bayes
- Non-parametric algorithms: KNN

Personal models from individual datasets were generated to compare them with the general model. The subject-dependent classification was performed to obtain the accuracies of the classification models. For the evaluation and selection of the algorithm, 10-fold cross-validation was used. The average of instances correctly classified in each fold's test set was obtained, and the standard deviation. From these parameters, the best algorithm was selected.

IV. RESULTS

A total of 360 features were extracted from representing the SCL segments in the Wavelet domain: 36 features for each of the 10 levels. With the features' extraction, a general dataset with 945 samples (instances), 360 features (attributes), and different output classes according to the defined cognition labels was generated.

The quality problems found in the dataset were solved. Regarding the first problem, the classes were balanced by generating synthetic instances through oversampling. By employing a Wrapping approach, the classifier's relevant attributes were selected [64], solving the second problem. Due to the scope of the experiment, the third problem could not be addressed.

TABLE 2. Personal classification results with performance class.

Dataset		Best algorithm	Accuracy
ID	Instances		
Set_A	71	RandomForest	88.41%
Set_B	61	iBk	80.00%
Set_C	89	iBk	83.53%
Set_D	80	RandomForest	85.31%
Set_E	86	RandomForest	75.50%
Set_F*	49	RandomForest	96.47%
Set_G*	47	RandomForest	97.87%
Set_H	55	iBk	84,25%
Set_I	75	RandomForest	94.14%
Set_J	57	iBk	92.52%
Set_K	82	RandomForest	85.71%
Set_L	47	SMO	82.35%
Set_M	72	RandomForest	82.99%
Set_N	74	RandomForest	90.20%

TABLE 3. General classification results with performance class.

Algorithm	Correctly classified instances	Accuracy
AdaBoostM1(J48)	137	71.81% ± 2.07%
Bagging (J48)	132	69.05.% ± 1.83%
RandomForest	153	79.95% ± 2.25%
SMO	81	42.27% ± 3.09%
LibSVM	109	57.10% ± 3.48%
MulitlayerPerceptron	125	65.61%± 10.83%
J48	116	60.86% ± 4.66%
NaiveBayes	81	42.33% ± 3.90%
iBk	135	70.56% ± 2.05%

A. PERSONAL RESULTS

The classification algorithms were applied to each individual dataset. Datasets for the F and G patients could not be balanced because of its classes' final distribution. A possible explanation is that both children exhibited an excellent and consistent performance throughout the study. In these cases, imputation methods do not work. Since the class is unbalanced, the classification is biased. Table 2 contains information on the best classification algorithm and the accuracy percentage for each personal model. The percentages vary from 75.50% to 97.87%, with a mean of 87.09%. A cross-validation of the machine learning models was performed.

B. GENERAL RESULTS

By balancing the general dataset, the number of instances increased to 1,916. By selecting the relevant features, the number of attributes decreased to 31. It is important to mention that the input dataset for the MLP neural network had the 360 first attributes obtained in the feature extraction process. The data was normalized since this algorithm is sensitive to feature scaling. The final results of the classification models with ten-fold cross-validation of the models are shown in Table 3. The best algorithm for this dataset was Random Forest, with an accuracy of 79.95%.

The Kappa statistic was calculated to evaluate and guarantee the quality of the accuracy of the classification algorithm. It compares the observed accuracy of a random classifier with the expected accuracy. This technique measures how closely the classified instances matched the data labeled as ground-truth [66]. The Kappa statistic for the Random Forest classifier in the general model is 0.698 (probed by the confusion matrix – Fig. 4).

a	b	c	<-- classified as
594	13	20	a = low
45	467	112	b = medium
51	144	470	c = high

FIGURE 4. Confusion matrix from the Random Forest classification model with the Performance label.

Other metrics indicating quality in the classification accuracy are the recall and the area under the curve (AUC). For the general classification model, each of these measures' weighted average is 0.799 and 0.861, respectively. The recall metric indicates the ability of the classification model to identify all relevant instances. The AUC metric calculates the overall performance of the classification model [67].

V. DISCUSSION

This study classifies the cognitive performance in children with SLD from features of EDA signals, aimed to validate its relationship. The accuracy in the classification model (79.95%) is a useful marker of the robustness in the psychophysiological inference. Results from evaluation metrics indicate a substantial agreement in the classification accuracy and the generation of an excellent general classification model. These results justify HapHop-Physio as a cognitive support technology.

This work presented considerable differences regarding similar papers in the literature. First, sensing the physiological signals through wearable devices allows for less invasive monitoring in ambulatory environments. Second, as the game scoring system is based on the ENI battery's cognitive indices, this cognitive activity was acquired objectively and unobtrusively. Selecting cognitive performance as an indicator of the child's cognitive state during the interaction with the game has not been addressed before. Moreover, data analysis with machine learning addresses the psychophysiological inference giving confidence in the achieved results. This is due to: (i) comprising four essential steps in processing and characterizing the physiological signals, and (ii) finding non-linear patterns between the signal and the cognitive state.

A. SIGNIFICANCE OF THE RESULTS

Two main results were presented: a dataset built from wearable physiological data collected in a real clinical environment. A classification model was generated to recognize cognitive states from physiological data in the rehabilitation eHealth context.

- Since changes in the children's cognitive domains are progressive, its relationship with the physiological responses should have the same nature. The EDA's SCL component to building the dataset provided a better insight into the signal's behavior while children interacted with HapHop-Physio.
- When employing machine learning algorithms to make the psychophysiological inference, encouraging results

can classify different cognitive indicators, according to the rehabilitation aim.

- Deep learning algorithms' performance highly relies on the amount of data and its complexity [68]. Neural networks were implemented, yet the configuration that provided the best results in accuracy had only one hidden layer in the MLP algorithm. Several configurations in the MLP algorithm were tested (up to four hidden layers). However, these results did not exceed the accuracy of the Random Forest algorithm.
- General classification accuracy presents a lower value than personal classification accuracies. As demonstrated in other domains [69], better performance in classification is expected in small to medium-sized datasets when algorithms are trained with a single individual (subject-independent). However, the subject-dependent classification models were more accurate in this particular problem.
- Based on the achieved results, this work's aim was completed. It can also be confirmed that HapHop-Physio is a cognitive support technology; i.e., it does impact the cognitive progress of the children. Besides, the evaluation of this progress has a highly objective component. Thanks to this, health professionals can make better decisions regarding the course of cognitive rehabilitation.

B. COMPARISONS WITH OTHER RESEARCH WORKS

- In terms of the classification accuracy value, the presented results are better compared to other works addressing cognition. In [24], the value varied between 50% and 60% in a three-class classification (with leave-one-subject-out validations), and [23] obtained a value of 75% in the classification using only the EDA (leave-one-subject-out cross validation test). In [30], the accuracy did not exceed 66% in a four-class model with two signals (EDA and HRV) as input attributes (leave-one-subject-out cross-validation). However, these independent subject models do not show results regarding test datasets. Also, in [8], [26], the classification values ranged between 88% and 90%. However, the used datasets combined different physiological signals and different cognitive states and subject dependent classifications.
- The use of several signals means a larger number of features, a more extensive processing load, and more time invested in obtaining results. By using just one signal as the EDA, processing was faster, considering the analysis domain (Wavelet domain). The processing time needed to be less to obtain the same results as other research works [23].
- This work allowed the collection of data from children with SLD in a real clinical rehabilitation environment. Other datasets were built-in laboratory environments [25], [26]. The obtained dataset constitutes a good basis for detecting other cognitive states, even co-occurring events such as behavior and emotions.
- None of the related works (including this study), reaches a testing phase of the model, only training and validation. Therefore, it cannot be said that there is an effective prediction of cognitive processes from the EDA signal. In this regard, more research is needed before obtaining a reliable model that can be used in real applications.

C. LIMITATIONS OF THE STUDY

Within this study, it is important to recognize its four main limitations. First, an EDA signal decomposition process using more validated tools in the state of the art can help to improve the classification results obtained by making comparisons with the originally used convolution process.

Second, complementing the tonic component of the signal with the Non-Specific Skin Conductance Responses (NS.SCRs) may improve the features used as inputs to the classification model. Unfortunately, this analysis was not possible in this study because the annotations made for labeling the signals did not take into account the NS.SCRs. Also, some data related to this component was eliminated when performing the EDA signal's cleaning process.

Third, the subject dependence classification performed is also a limitation. Therefore the proposed model must be updated by an independent subject model for future deployment of the model. However, before addressing an independent-subject model, it is necessary to guarantee a homogeneous data collection.

Finally, the quality of the signal obtained by the E4 wristband needs to be improved by addressing motion noise cancellation [70] and the users' wrists' size, critical in this study because of the experiments that were performed with children.

D. FUTURE WORK

The obtained results provide a basis for future research regarding the analysis of the EDA signal, NS.SCRs would be considered to complement the SCL component. Concerning the dataset, its size will be increased in participants and/or by using the remaining signals received from the E4 wristband. Signals include (i) processing the Blood Volume Pulse (BVP) from the pulse plethysmography (PPG) sensor off-line to obtain HRV signal with higher quality, (ii) the motion-based activity from the three-axis accelerometer, and (iii) the peripheral skin temperature. Tests within the Deep Learning field need to be performed to improve the classification models' accuracy by taking advantage of its capabilities in feature extraction and feature selection (e.g., autoencoders). Likewise, the EEG signal measurement will be considered a baseline to identify cognitive processes in the HapHop-Physio context and the data from the attention activities.

Regarding the generalizability of the experiment, it would be a significant contribution to evaluate the EDA classification model for cognitive performance in real activities of children's daily lives. Examples of application scenarios include progress in the school day, checking the rehabilitation activities at home, and verifying their cognitive performance according to their ages.

Finally, these results can be compared to healthy children's performance to analyze and compare data to diagnose SLD.

VI. CONCLUSION

This study classified cognitive performance from the EDA signal during a cognitive rehabilitation therapy performed by children with SLD. An analysis from supervised machine learning algorithms was made to find patterns and validate the relationship between EDA data and cognitive states.

In this paper, five variables of cognition were addressed, being cognitive performance, the best evaluated. It was measured at three levels: low, medium, and high, obtaining a general classification model with 79.90% accuracy. The accuracy of this model is better compared to other works addressing cognition through EDA. Thus, finding the relationship between cognition and the EDA signal verified the purpose fulfillment of HapHop-Physio.

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