Combining Self-Organizing Maps and Decision Tree to Explain Diagnostic Decision Making in Attention-Deficit/Hyperactivity Disorder

Anderson Martins Silva
Graduate Program
in Electrical and Computer Engineering
Mackenzie Presbyterian University
São Paulo, Brazil
e-mail: 71953371@mackenzista.com.br

Luiz Renato Rodrigues Carreiro
Graduate Program
in Developmental Disorders
Mackenzie Presbyterian University
São Paulo, Brazil
e-mail: luizrenato.carreiro@mackenzie.br

Mayara Miyahara Moraes Silva
Graduate Program
in Developmental Disorders
Mackenzie Presbyterian University
São Paulo, Brazil
e-mail: 72054298@mackenzista.com.br

Maria Cristina Triguero Veloz Teixeira
Graduate Program
in Developmental Disorders
Mackenzie Presbyterian University
São Paulo, Brazil
e-mail: mcris@mackenzie.br

Leandro Augusto da Silva
Graduate Program
in Electrical and Computer Engineering
Mackenzie Presbyterian University
São Paulo, Brazil
e-mail: leandroaugusto.silva@mackenzie.br

***Abstract*—Attention-Deficit/Hyperactivity Disorder (ADHD) presents in children and adolescents as a persistent pattern of inattention, hyperactivity, and impulsivity that interferes with their development. Computational studies on ADHD focus on measures of brain activity of the participants and a few use standardized cognitive tests or behavioral inventories to assess objective indicators for diagnosis. The paper presents a computational proposal in which the combination of two artificial intelligence methods is used to aid the identification of diagnostic indicators for ADHD. The proposal is to combine a neural network of self-organizing maps to group factors from standardized tests and inventories, and a decision tree to classify the most relevant factors. The study included 127 children and adolescents from 6 to 16 years old, 48 with ADHD diagnosis and 79 without ADHD (control group). The most relevant result of the study was the strong contribution of the scores of the Inventory of Behaviors for Children and Adolescents in the diagnosis of the disorder.**

Keywords—Self-Organizing Maps (SOM); Decision Tree; Attention Deficit/Hyperactivity Disorder (ADHD).

I. Introduction

According to the Diagnostic and Statistical Manual of Mental Disorders, 5th edition - DSM-5 [1] Attention-Deficit/Hyperactivity Disorder (ADHD) is a persistent pattern of inattention and/or hyperactivity-impulsivity that interferes with functioning or development. The disorder is characterized by inattention involving, for example, difficulty sustaining attention in tasks or play activities, a state in which the mind seems elsewhere, even in the absence of any obvious distraction, difficulty to follow through with instructions and failing to finish schoolwork, often forgetful in daily activities, chores, or duties in the workplace, losing things, expressing excessive activity or restlessness, and inability to wait one's turn, always in ways that are excessive for one's age or developmental level. ADHD has its initial expressions in childhood and usually persists into adulthood, resulting in impairments in social, academic, and occupational functioning.

The diagnosis of ADHD is clinical, based on the individual's history and expression of symptoms. Because this diagnosis is often based on reports of symptom severity and because these symptoms are also part of other clinical conditions, the diagnostic difficulty is present in the daily lives of the interdisciplinary teams responsible for the evaluation process [2] [3]. Because of the complexity of the diagnostic evaluation, the American Association of Pediatrics recommends the use of an algorithm, both for evaluation and treatment of children and adolescents with ADHD [4]. To support clinical decision making, neuropsychological, behavioral, and adaptive functioning assessment procedures have often been used in conjunction with neurological assessments [5]. Considering the social importance involved in properly issuing a correct diagnosis of ADHD in both children and adolescents, studies must be proposed that discuss which are the best indicators of clinical-neurological, neuropsychological, and behavioral-adaptive diagnostic evaluation when children and adolescents present with complaints of inattention and hyperactivity. Furthermore, for appropriate assessments and interventions to be implemented, differential criteria are needed to correctly characterize and identify attention-deficit/hyperactivity among children and adolescents. Comprehensive assessments in this regard allow a better understanding of the complexity of each case for appropriate guidance, design of the therapeutic intervention, and evaluation of the need for educational and emotional support for patients and families [5].

Computational studies can help professionals in diagnostic assessments, especially using machine learning algorithms. Kam et al. [7] used an artificial intelligence algorithm called

 ISBN: 978-1-61208-885-3

decision tree for screening ADHD by monitoring the school activities of 153 children using 3-axial actigraph and obtained results consistent with previous studies. In turn, Lee et al. [8] analyzed the classification of ADHD in children through brain activity measurements. In their work, they used a neural network algorithm called self-organizing maps allowing categorizing characteristics of children with and without clinical indicators of ADHD.

Unlike previous proposals presented in the literature, this work aims to combine two artificial intelligence techniques. In the first step, standardized test results are grouped by means of Self-Organizing Maps (SOM) and, in a second step, the groups with a high level of overlap are analyzed using a decision tree algorithm, which helps discover which attribute is discriminative in the diagnosis of children and adolescents with suspected ADHD.

Besides Section I, that aims to contextualize the work and present the objective, the work is organized into six parts. Section II presents the theoretical framework and justification of the study. Section III presents the proposed use of two artificial intelligence algorithms to aid in the diagnosis. In Section IV, the procedures for developing the study are described, including the computational development with the application of two artificial intelligence techniques. In Section V, the contribution of standardized cognitive tests or behavioral inventories is described, as well as the proposal to solve the diagnostic doubt within the self-organizing maps and then the classification by the decision tree for understanding the characteristics of the diagnosis of the disorder. Finally, in Section VI, we present the conclusion and recommendations for further studies.

II. Related Work

A. Elements of Attention Deficit/Hyperactivity Disorder (ADHD)

ADHD is part of the group of neurodevelopmental disorders beginning in childhood, but a substantial proportion of children with ADHD remain relatively impaired into adulthood [9]. From a cognitive-behavioral point of view, it is characterized by deficits in several cognitive functions, such as attention, especially selective, sustained, alternating, and divided attention, deficits in inhibitory control, processing speed, organization, ability to inhibit distracting information, deficits in cognitive flexibility, hyperactivity behaviors, restlessness, and impulsivity. ADHD affects 5.29% of the world's child population. Of this population, 30% up to 70% maintain symptoms into adulthood [11] [12]. According to DSM-5 [1], ADHD can be classified according to the predominance of symptomatic axes as predominantly inattentive presentation, predominantly hyperactive-impulsive presentation, or combined presentation. Behavioral patterns are important in the diagnosis of ADHD. Here are some descriptions from parents regarding the children: difficulty listening, obeying, following routine rules, often postponing and forgetting daily activities, difficulty following direct instructions, difficulty regulating feelings of frustration, exacerbation of motor activity, maybe impulsive in changing activities before they are completed, having difficulty waiting their turn, may have impairments in social relationships. These behaviors may contribute to high-stress [13] family or school environments. Given the importance of collecting various pieces of information in cognitive neuropsychology and behavior analysis, the treatment and multivariate analysis of the data can help us obtain relevant information in understanding ADHD complaints, and the artificial intelligence techniques used become key elements in diagnostic discrimination.

B. Self-Organizing Maps (SOM)

According to Merényi et al. [14], a SOM network provides clustering and visual representation of data in low dimension. This technique preserves the topological structure of the data in a lattice of neurons. The grid can be defined as a rectangular or hexagonal grid, as in Figure 1, usually two-dimensional, in an ordered manner such that the most similar neurons are grouped with neurons that are close in the grid, and the opposite is true for less similar neurons that are far apart in the grid, providing a topological view of the data. All neurons in the grid must undergo exposure to different realizations of the input dataset to ensure that the self-organization process matures. The algorithm then proceeds to initially randomly choose synaptic weights with small values. Once the grid has been initialized, we have the presence of three essential processes used to construct the self-organizing map. They were summarized by Kohonen [15] and Kubat [16] as follows:

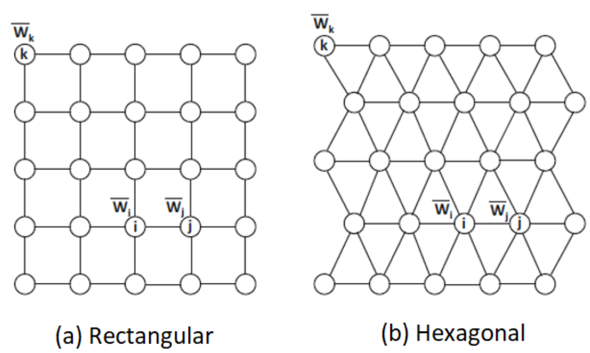

Figure 1. Topological Map - Rectangular and Hexagonal Grid ([17, p.451])

1) Competition: The synaptic weight vector is calculated for each *j* neuron of the grid with the same dimension as the input dataset through the inner product between the synaptic weight vector and the input data vector, this function being the basis for choosing the winning neuron. The maximization of this function has mathematical equivalence with the minimization of the Euclidean distance between the synaptic weight and input data vectors.

$$X = [x_1, x_2, ..., x_m]^T \quad (1)$$

X is the input vector of the space *m* transposed.

$$W_j = [w_{j1}, w_{j2}, ..., w_{jm}]^T, \ j = 1, 2, ..., l \quad (2)$$

W_j is the synaptic weight vector of each neuron in the grid.

$$i(X) = \arg \min_j \left\| X - W_j \right\|, \ j = 1, 2, ..., l \quad (3)$$

i(X) is the index that summarizes the competitive process between neurons.

2) Cooperation: The basis for cooperation between neighboring neurons is provided by the winner neuron that shows the spatial location of the topological neighborhood of neurons neighboring the winner $h_{j,i(X)}$;

$$h_{j,i(X)} = \exp\left(-\frac{d^2{}_{j,i}}{2\sigma^2}\right) \quad (4)$$

where $d_{j,i}$ is side distance and σ is the effective width of the topological neighborhood.

3) Adaptation: Neighboring neurons to the winner increase their discriminant function values based on the input dataset and as appropriate adjustments applied to their synaptic weights improve a subsequent input dataset.

$$W_j(n+1) = W_j(n) + \eta(n) h_{j,i(X)}(n)(X - W_j(n)) \quad (5)$$

where *n* equals epoch, $\eta(n)$ is the learning rate, and $h_{i,j(x)}(n)$ is the neighborhood function.

C. Decision Tree

A decision Trees is an Artificial Intelligence algorithm capable of organizing attributes from a dataset in priority, so that it can generate a path that leads to a decision for a classificatory attribute [18] [19].

The entropy (Shannon's) [20] measures the impurity of the dataset, being a measure of the heterogeneity of the input dataset (S) relative to its classification (c). The *Gain(S,A)* is given by the equation 6 and the entropy of *S* is given by the equation 7. Thus, the key factor is the use of a gain function that allows the attributes (A) to be compared to select the most relevant one. The attribute chosen is the one that maximizes the information gain which is calculated as being [20]:

$$Gain(S, A) = Entropy(S) + \Theta \quad (6)$$

S is the input dataset, *A* are the attributes Θ represents the probability of *A* multiplied by its entropy.

$$Entropy(S) = \sum_{k=1}^{c} -p_i log_2 p_i \quad (7)$$

$$\Theta = -\sum_{v \in Values(A)} p(A_v) Entropy(A_v) \quad (8)$$

The information gain is given by the equation 6 and represents the expected reduction in entropy when the value of the attribute *A* is known, since the process calculates the gain for each attribute, choosing the attribute with the highest gain to be tested in the set *S*. This process creates the division of objects to form the decision tree, giving rise to the node, labeling the attribute, and creating branches for each attribute value.

III. Proposed Method

The work presents a proposal for an unsupervised learning model as a method used in the identification of the neurons of the grid with greater diagnostic doubt of ADHD, that is, the diagnostic doubt in the neuron shows that it is difficult for both a machine learning algorithm and an expert to make a diagnosis. Thus, the paper brings a proposal to apply a decision tree on the neurons that show overlap to suggest which attributes are more discriminative. To understand this overlapping, the entropy (of Shannon) was calculated with the purpose of measuring the impurity of the neuron with its dataset, that is, the closer the entropy is to one, the greater the impurity of the neuron's dataset. Given this fact, a combination of SOM with the decision tree algorithm, which is a supervised model used in data classification to help identify one or more attributes from standardized assessment tools, such as cognitive tests and behavioral assessment inventories were sought. These tools were used to test the learning of ADHD characteristics. The objective of this decision tree algorithm was to verify the accuracy of the model for the confirmation of cases with ADHD diagnosis by identifying which assessment tools best contributed to this ADHD confirmation.

IV. Materials and Methods

The study sample consisted of 127 children and adolescents between 6 and 16 years old, 48 with a clinical diagnosis of ADHD and 79 from the control group, with no diagnosis of ADHD. The attributes that make up the neuropsychological tests and behavioral inventories applied in this study are Attention Cancellation Test (TAC), Trails (TT), Wechsler Intelligence Scale for Children (WISC-III), Wechsler Intelligence Scale for Children (WISC-IV), Wechsler Abbreviated Scale of Intelligence (WASI), Child Behavior Checklist for ages 6-18 (CBCL/6-18) and Teacher's Report Form for ages 6-18 (TRF/6-18). These attributes were normalized by the z-score method [21] to standardize the different scales of the attributes. The normalized data property is used to train the network SOM using the package available in R language [22]. In this library, the functions *somgrid* and *som* are used to parameterize and train the map, respectively. For the size of the map topology, the dimension 4x4 was chosen. With this, the hypothesis of the study was to find neurons with a representative density of objects and with a significant class distribution.

With the trained map, the analyses made were the density of objects in each neuron, the distance between neurons, the quality of adjustment of the neurons, the contribution of the attributes in the formation of neurons, and the distribution of the label of each object in each neuron. In addition to the outputs analyzed, the representativeness of the number of objects contained in each neuron with the label attribute was sought in the table generated by the SOM. In this way, the neurons of greater relevance were identified, that is, with larger numbers of objects generated by the SOM algorithm.

From this point on, the entropy algorithm (Shannon's) was used on each neuron in the network to select the neuron with the highest class overlap along with the representativeness of objects that are difficult cases to diagnose.

By identifying neurons with overlapping classes, their objects are selected from the database generated by the SOM network for training and validation of the decision tree algorithm. The result of the decision tree brought a hierarchy of attributes in order of discrimination for cases of diagnostic doubt, and the validation of the algorithm shows the performance of the classification.

A. *Rating Performance Evaluation*

Table I shows the confusion matrix that was used to analyze the classification performance of the decision tree. The table indicates the prediction of the positive and negative scenarios, as well as current true and false scenarios [23]:

- TN is the correct number of negative predictions;
- FP is the number of false positive predictions;
- FN is the number of false negative predictions;
- TP is the correct number of positive predictions.

Table I. CONFUSION MATRIX

	Predicted Negative	Predicted Positive
Current False	TN	FP
Current True	FN	TP

From the confusion matrix, it is possible to measure the performance of the algorithm by calculating the accuracy, as follows:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (9)$$

$$Error = (FP + FN)/(TP + TN + FP + FN) \quad (10)$$

After this stage, it is possible to better understand the model's contribution to the understanding of Attention Deficit Hyperactivity Disorder, as well as to the diagnostic evaluation of patients. The next section presents the results obtained in this work.

V. RESULTS

The training result of the SOM network can be seen in two different visualizations, depicted in figure 2 and 3. figure 2 presents the attributes, common to the trials, graphically distributed in each neuron. The sizes indicate the contribution that each attribute has to the formation of the neuron. Note that neighboring neurons have similarities among the attributes. In figure 3, the diagnosis, an attribute that is not used in training the SOM, is projected on the map, allowing visualization of which neurons have the overlap of class 1 (group diagnosed with ADHD) and 2 (control group without ADHD). The network could not separate the diagnosed cases in neuron 4.

Table II presents for each neuron the percentage of objects of each class. Neuron 4 is the one with the highest concentration of objects (40%) and overlapping classes in the whole dataset.

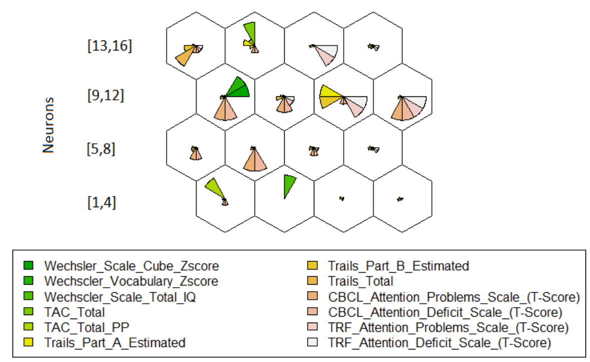

Figure 2. Contribution of the attributes in the formation of the neuron

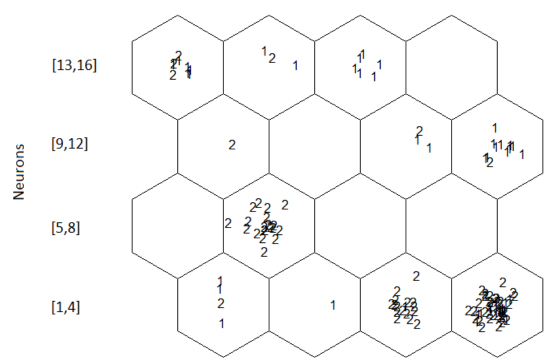

Figure 3. Scattering of objects diagnostic within neurons

The result of the decision tree with the data mapped onto neuron 4 can be seen in Figure 4. The result shows that the Child Behavior Checklist for ages 6-18 attribute, specifically the probability of attention problems scale (T-score) [24] [25] neurons had the highest discrimination.

Table II. COMPARATIVE DIAGNOSIS BY THE NEURON DIMENSION 4X4

	Diagnostic	1	2	Total
neuron	1	3 (6.2%)	1 (1.3%)	4 (3.1%)
	2	1 (2.1%)	0 (0.0%)	1 (0.8%)
	3	1 (2.1%)	16 (20.3%)	17 (13.4%)
	4	16 (33.3%)	35 (44.3%)	51 (40.2%)
	6	0 (0.0%)	20 (25.3%)	20 (15.7%)
	9	0 (0.0%)	1 (1.3%)	1 (0.8%)
	11	2 (4.2%)	1 (1.3%)	3 (2.4%)
	12	11 (22.9%)	1 (1.3%)	12 (9.4%)
	13	6 (12.5%)	3 (3.8%)	9 (7.1%)
	14	2 (4.2%)	1 (1.3%)	3 (2.4%)
	15	6 (12.5%)	0 (0.0%)	6 (4.7%)
Total		48 (100.0%)	79 (100.0%)	127 (100.0%)

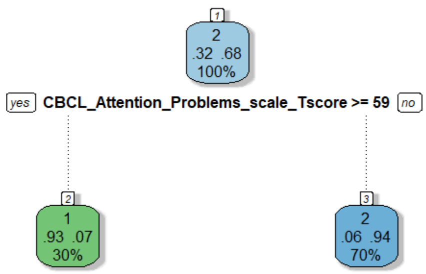

Figure 4. Decision Tree of Neuron 4

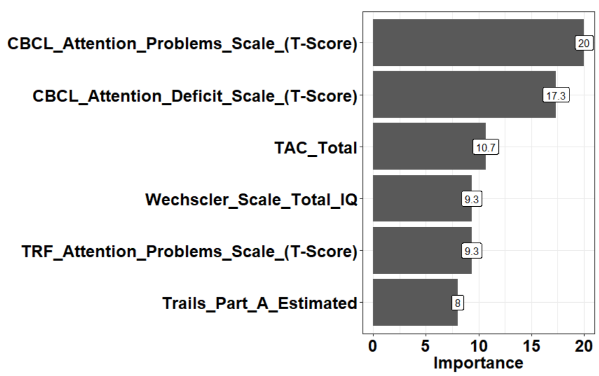

Figure 5. Importance of the attributes in neuron 4 by decision tree

Finally, Figure 5 allows you to visualize all six attributes with greater discrimination for cases with greater complexity relative to the integration of clinical evaluation and evaluation using tests for a confirmation of the diagnosis.

VI. Conclusion and Future work

Data from the behavioral assessment inventory presented in [5] can generally be more susceptible to respondent bias because it is based on the answers of the subject. This bias is less so when using cognitive tests which are assessment measures applied directly to the person. Mathematical understanding and model generation is likely to become more difficult using only behavioral inventories. Since ADHD demands the use of both types of measures, in this study both tools were used to apply the decision tree. In the study, it was possible to group the children with and without ADHD by SOM, which made it possible to understand from the perspective of each grouping what was most important in their formation.

The self-organizing map contributed especially to the formation of groups and the understanding of clusters with class overlapping, which is the proposal of this work. In this case of overlapping to diagnose a disorder, the decision tree was used to classify the attributes that contributed to the formation of the ADHD group. With this, the predominance of characteristics that helped in the understanding of ADHD in children and adolescents in the study was observed.

The application of the decision tree identified six attributes, namely two of cognitive assessment and four of behavioral assessment, that showed relevant discrimination to make the diagnosis. The Child Behavior Checklist for ages 6-18 attribute the one that showed the highest discriminative power. However, the incidence of low T-scores on the attention problems scale and attention deficit scale does not necessarily imply that the child has ADHD. The results presented showed the difficulty and complexity of finding indicators that define ADHD, as already signaled by some authors [5] [6] [8] [26] [27]. Importantly, the diagnosis of ADHD is a clinical diagnosis that considers the measurement of behavioral correlates of attentional deficits and indicators of hyperactivity and impulsivity in more than one environment. With the Child Behavior Checklist for ages 6-18 attribute being a parent-reported measure, the validity of these two scales for identifying ADHD will likely be confirmed. However, when disregarding the scales, one should consider the evaluations made with the cognitive tests that directly make cognitive measurements and are essential to decide the diagnosis of ADHD. In this study, the tests that contributed the most to this decision tree were the Attention Cancellation Test (ACT) and the Trail Test (TT).

The study presented as a relevant factor the case of overlapping diagnoses of neurons when using the SOM and, in conjunction with the decision tree, was able to separate 88% of the cases. This way, future works can collaborate with the technique addressed in the study through supervised data procedures. These tools can help in making comparisons between results of standardized tests aiming to reduce possible biases of behavioral evaluations based on informants' reports. Future studies can test the same decision tree on larger samples to see if the attributes that showed higher accuracy are maintained. By doing so, the best indices of cognitive and behavioral assessment instruments that contribute to the increased accuracy of ADHD diagnosis may be identified. Since this study controlled for no comorbidities in the ADHD group, it is recommended for future studies to use sample groups with and without ADHD comorbidities from other psychiatric and neurodevelopmental conditions. This type of sample may allow the testing of new and more complex models due to the natural overlap of signs and symptoms between ADHD and some of these comorbidities.

 ISBN: 978-1-61208-885-3

Acknowledgment

We thank the Academic Excellence Program of the Coordination for the Improvement of Higher Education Personnel (CAPES-PROEX), Process number 1133/2019, (CAPES-PROSUC) in mode II, the National Council for Scientific and Technological Development (CNPq, Cases 307730/2017-4 and 307443/2019-1), the Mackenzie Research Fund (MACK-PESQUISA) of Mackenzie Presbyterian University, and the Foundation for Research Support of the State of São Paulo (FAPESP, Cases 2018/01063-0 and 2019/20757-1) for financial support.

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