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TÍTULO: Aplicación del algoritmo del árbol de decisión en los datos gamificados de la prueba de rendimiento continuo para la detección del trastorno por déficit de atención / hiperactividad.

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RESUMEN: Los tres objetivos principales de este estudio son la evaluación del algoritmo del Árbol de decisión para detectar el trastorno de TDAH, la reducción del número de características requeridas y la predicción aceptable a pesar de la falta de varias características. Los sujetos en este estudio fueron 100 personas entre las edades de 8 y 64 años, 69 de los cuales tenían menos de 18 años y 31 tenían más de 18. De estos, 43 tienen TDAH, 35 son saludables y 22 son sospechosos. Los datos fueron recogidos por la Clínica del Cerebro y Cognición en Teherán usando el juego AIV-2. Los resultados indican que la aplicación de métodos de aprendizaje automático siguen siendo efectivos incluso con la participación de la menor cantidad de características en el proceso de implementación de algoritmos.

PALABRAS CLAVES: aprendizaje automático, árbol de decisión, gamificación, prueba de rendimiento continuo.

TITLE: Applying Decision Tree Algorithm on Gamified Data of Continuous Performance Test for Detection of Hyperactivity / Attention Deficit Disorder.

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ABSTRACT: The three main goals of this study are the evaluation of Decision Tree algorithm for detecting ADHD disorder, reduction of the number of required features, and providing acceptable prediction despite the lack of several features. The subjects in this study were 100 people between the ages of 8 and 64 years, 69 of whom were under 18 and 31 were over 18. Of these, 43 have ADHD, 35 are healthy and 22 are suspected. The data was collected by the Brain and Cognition Clinic in Tehran using the AIV-2 game. The results indicate that applying machine learning methods are still effective even with involvement of the least number of features in algorithm implementation process.

KEY WORDS: machine learning, decision tree, gamification, continuous performance test.

INTRODUCTION.

In healthcare, methods such as usage of questionnaires, cognitive tests, medical examinations to check the physical and neurological status are sometimes frustrating, difficult and costly, and in some cases, test-takers does not provide a positive feedback from participating in these types of processes [1].

In traditional cognitive evaluation methods, the Hawthorne effect is probable when the subject changes behavior on purpose providing invalid test results [2]; thus, the evaluation tests can be used as a gamified applications one of which is the IVA-2 that gamifies the CPT test and is designed based on the DSM's ADHD metrics as listed below:

1. Error types
2. Categorizing the difference between the criteria as visual and auditory
3. Sensory modalities
4. Full Scale Attention
5. Full Scale response control
6. Combined sustained attention
7. Symptomatic scales
8. Sensory modalities

The age range of IVA-2game is between 6 and 96 years. The test takes about 20 minutes to complete in this game, which is about two minutes for the test phase, two minutes for the training phase, and about 15 minutes for the main test phase. Generally, this game evaluates 50 visual and auditory features [3]. In contrast to the goal of this study, the IVA-2 game needs all features to be measured and statistically analyzed to predict ADHD.

Attention deficit / hyperactivity disorder.

Attention deficit / hyperactivity disorder is one of the most common neurodevelopmental disorders and is one of the most advanced early onset neurological disorders [5] that millions of people around the world are affected. Its prevalence among children and adolescents is 5% [6] and 8 to 12% of children worldwide have the disorder [7]. People with this disorder suffer from inactivity, inattention and low tolerance, and inability to maintain focus and concentration [8].

Machine Learning.

Machine learning has influenced statistics because it has more systematically dealt with inherent variables in a dataset. Machine learning algorithms offer various benefits for evaluating cognitive disorders, such as better standardization, increased accuracy, providing timing and response time, simple management and data collection, the ability to record and monitor dynamic indicators (for example, cognitive markers such as reaction time or other cognitive markers such as walking patterns); and providing random stimuli in a better way through repeated interventions. These advantages have led to increased use of machine learning techniques in various domains, including mental health, and have been useful in the diagnosis of cognitive disorders.

DEVELOPMENT.

In this section, we will review some of the studies that have used some kind of machine learning method on the ADHD data.

ADHD Datasets and Machine Learning.

In 2016, Chang Chu et al., collected data from 217 children divided into three groups: 1. Having ADHD disorder; 2. Sleep breathing interruption and 3. ADHD in combination of sleep breathing interruption. They applied three different models of machine learning to this dataset. Data from this study were collected from 2011 to 2015 on children aged 6 to 12 years [9].

In another research, Bledsoe et al. used datasets collected from information of attention / focus tests on a number of children and questionnaires completed by their parents to determine whether a child has ADHD using machine learning techniques [10]. Riyadh colleagues in 2016, worked on data collection ADHD-200. They developed a framework that initially finds high-frequency subdivided brain networks directly across the entire brain network of ADHD and normal individuals [11].

Winter Scoggel et al. in a 2013 study on the data of 85 people, including 37 women and 48 men with ADHD, Applied random forest machine learning methods and variance analysis. The data they used were obtained from common shoulders, tests of executive functions of neuropsychology, and executive skills in everyday situations [12]. Chang et al. (2012) used the ADHD 200 dataset collected through FMRI or functional magnetic resonance imaging [13]. In 2011, Anvarada et al. [14] used the decision tree algorithm to predict ADHD in children. In their study, machine learning method was applied to questionnaire data that had been collected during 6 months.

Machine Learning and Gamified Data in mental health

In this section, we present research backgrounds on the use of machine learning techniques in health applications and in particular cognitive disorders such as amnesia, schizophrenia, autism, attention deficit / hyperactivity disorder and depression.

Rodriguez et al. in 2018 designed a serious game called Panoramix that aimed to evaluate key cognitive areas, especially cognitive impairment indices - episodic memory, attention, semantic memory, working memory, procedural memory, and gnosis. Their method was to redesign classical tests using Gamification and digitally simulate them. Their rationale was that these games, which were adapted from the tests mentioned above, would evaluate the parts that these tests targeted [15]. They applied decision tree learning algorithms, back-vector machine learning, and logistic regression to the data collected. The results of the decision tree algorithm applied to the aggregated data are shown in Table 1.

Table 1: The result of implementing the decision tree algorithm by Rodriguez et al.

Game	**Decision Tree Precision**
Semantix	75%
Procedurix	95%
Episodix	50%

Lopez and Tucker in 2018 [16] applied a machine learning approach to information derived from a gamified work and visual facial information to estimate one's performance. Training data of this method was such that when new data were available, the individual's dataset was updated and used in the training phase. This model was able to predict the performance of individuals before completing a task with an accuracy of 0.768. In this method, Bayesian regression algorithms, support vector machine and neural network were used. In 2016, Brata et al. [17] collected data sets through a gamified educational game. In this study, they divided a number of students into four groups based on the data and applied their machine learning methods to a new student's data before the game was completed to guess in which category does this student fall? The accuracy of this method was 79% and the Bayesian and nearest neighbor methods were used. The data set used in this study belonged to 76 students.

Unlike most of the reviewed studies in the literature that use ADHD data through traditional or magnetic tests, in this paper we use machine learning methods on gamified data. To the best of our knowledge, there is no other study that uses machine learning on gamified data sets. This paper would be the first study that tries to predict ADHD deficit with the minimum number of features, the dataset was obtained via the CPT test.

Data and Methodology.

Data collection.

The population used in this study was 100 people (67 men and 33 women). They range in age from 8 to 64 years, 69 of them were under 18 and 31 were over 18 years old. The clients selected for this test were randomized and their condition was assessed at the Tehran Brain and Cognition Clinic. 43 clients had ADHD, 35 of them were healthy and 22 were suspicious. Figure 1 shows the distribution of data records by target property. Each of them went to the Tehran Brain and Cognition Clinic at different times and performed IVA-2.

The game routine is that two options 1 and 2 are shown in the image, 1 as the target and 2 as the noise. The tester must click on the target option according to the audiovisual requests and a feedback is recorded for each of these stimuli that is displayed.

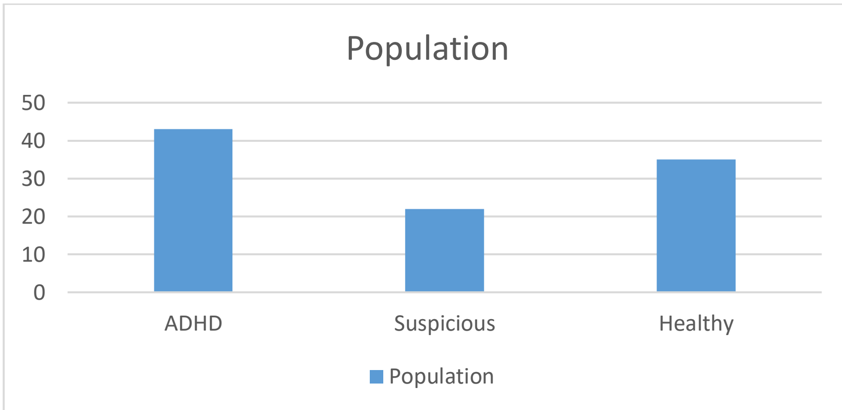

Figure 1. Distribution of sample datasets used in this paper commensurate with target specificity (hyperactivity defective).

After each person completes the game, a number of files are formed inside the game server, including 15 PDF files. Each file is a special report of information. In these files there is a score of features in the form of Auditory, Visual or Combined. An example of such file is presented in Attachment A. In this study, these files are used to form the dataset. Information is entered into the dataset for each of the categories shown in Table (2), to apply the decision tree algorithm to each of them individually or in combination.

Table 2: The features of the dataset and the number of subcategories associated with each one.

#	Feature	Number of Subcategories
1	Full Scale Attention	9
2	Full Scale response control	5
3	Combined sustained attention	6
4	Symptomatic scales	5
5	Sensory modalities	23

In this study, we have used the Jupiter Framework and Scikit-learn Machine Learning Library which is an open source python library for machine learning built based on SciPy, NumPy, and Matplotlib.

The overall process

The overall process of training the model and evaluation of the result is as follows:

1- Loading the batch data for the selected feature to test, as explained in section 3.3.

2- Loading the Algorithm Package.

3- Creating an instance of the algorithm.

4- Separation of the dataset into two train and test subsets.

5- Training the decision tree algorithm using the train dataset.

6- Predicting the test dataset and evaluation of the results using accuracy score function.

Feature Selection for Train and Test steps.

This section explains the feature selection process. To do this, we have selected several modes as to which part of the data enters the model learning and testing phase that include:

1. All symptoms are selected advised by the experts
2. Only the features related to one symptom is selected
3. A combination of the features from two or more symptoms are selected

Testing the Sensory modalities

This category includes several subcategories such as Combined sustained attention, full scale attention, and full-scale response control in addition to the features related to self-control including self-control, presence, resilience, agility, accuracy, and competence.

Testing the full-scale attention

The full-scale attention is a criterion for measuring one's overall ability to respond quickly and accurately along with maintaining focus. This general index first measures performance under low demand conditions. This includes features such as Vigilance, Acuity, Elasticity, Focus, Dependability, Stability, Speed, Quickness, and Swiftness [18].

Testing Full scale response control.

The full-scale response control is one of the global criteria for measuring an individual's overall ability to adjust and provide appropriate responses. Factors used in this index include the ability to avoid responding to third parties, the timing of diagnostic reactions, and the individual's ability to maintain their mental processing speed during the IV-2 test. This feature includes subcategories of Prudence, Reliability, Consistency, Stamina, and Fine Motor Hyperactivity [18].

Testing Symptom scales.

Subcategories of this feature are Comprehension, Steadiness, Persistence and Sensory/Motor.

Testing Combined sustained attention.

Combined sustained attention is a general criterion for assessing one's ability to respond quickly and accurately to stimuli under low-demand conditions. The Combined sustained attention includes subcategories of the characteristics of the full-scale attention, the full-scale response control, and the symptom scales. These features are sleekness, reliability, intelligence, flexibility, reliability and consistency [18].

-- Test on the characteristics of the full-scale attention and symptom scales.

-- Test on the characteristics of Full-Scale response control and symptom

--Test on features of Full-Scale response control, symptom scales, and full scale attention index

--Test on the characteristics of full-scale response control, symptom scales, sensory modalities, and full-scale attention index

These categories have been compiled in various ways to predict the target attribute appropriately, based on our hypothesis, using part of the attributes, without all the attributes being used. Table (3) is an example of the attributes of the sensory nature in which the mean, minimum and maximum values for the attributes of this category are shown. A similar table for the other categories is given in Appendix (B).

Feature	Minimum	Maximum	Average
Self-control (Combined)	4	129	87.54
Self-control (Auditory)	18	125	90.87
Self-control (Visual)	0	130	88.23
Execution (combined)	0	112	74.27
Execution (Auditory)	0	112	71.47
Execution (Visual)	0	117	82.38
Resilience (combined)	30	137	85.20
Resilience (Auditory)	24	125	82.83
Resilience (Visual)	8	145	88.65
Agility (combined)	11	133	92.50
Agility (Auditory)	15	141	92.35
Agility (Visual)	47	125	95.20
Precision (combined)	0	120	79.35
Precision (Auditory)	0	119	79.38
Precision (Visual)	0	119	83.41

Table 3. features of the sensory nature.

Model Selection.

Based on our study of background research, we chose the decision tree algorithm. Decision tree is one of the supervised machine learning algorithms that can be used for pre-labeled data. The decision tree has a tree structure similar to that used for decision making and data definitions. The tree is composed of a number of nodes and branches such that the leaves represent classes or categories and the middle nodes are attributes, which help to make the decision. In the decision tree for each node, the direction of movement is determined by the value of that node in the sample. Each internal node corresponds to a variable and each edge represents a probable value for that variable. Each leaf node indicates the amount of classification. Finally, we move to the leaves by moving from root to node, which identifies the data cluster [19].

Train and Test steps.

The dataset used in this study consists of 100 samples. 80 samples of this dataset which their labels are specified are used for machine learning model training. The remaining 20 samples are used to evaluate the algorithm.

Evaluation process of the created model.

We use the accuracy index to evaluate the model. The accuracy index is obtained using the equation (1).

$$\text{accuracy} = \frac{\text{true negative+true positive}}{\text{dataset size}} = \frac{\text{true pridictions}}{\text{dataset size}} \quad (1)$$

Results.

By applying the features with different combinations in the model training phase, in the evaluation step, different results are obtained. The result of applying the decision tree algorithm are shown in table 4.

Table 4. The results of the algorithm on different combinations of dataset features.

Selected category	accuracy	Number of categories / symptoms used
Full scale response control, Symptom scale, Sensory modalities and full-scale attention	90	4 out of 7
Sensory modalities	85	1 out of 7
Full scale attention	70	1 out of 7
Full scale response control	86	1 out of 7
Symptom scales	70	1 out of 7
Combined sustained attention	55	1 out of 7
Full scale attention and symptom scales	60	2 out of 7
Full scale response control and symptom scales	80	2 out of 7
Full scale response control, symptom scale and full-scale attention	60	3 out of 7

As shown in table 4, the decision tree algorithm had accuracy of between 55 and 90 percent. It is evident that the results of this algorithm change with the change of the feature set. It can be concluded that with fewer features one can come close to the diagnosis of ADHD. Among these categories the Full-scale response control has an acceptable accuracy of 86 percent which is an acceptable result. This algorithm has 90 percent accuracy when using four feature sets. Combined sustained attention were also less accurate than other groups but overall it can be said that even with one category you can have a good relationship. Finally, it can be seen that the accuracy of the decision tree algorithm is close to the accuracy of the statistical method applied to the whole clusters.

CONCLUSIONS.

The goal of this study was to predict ADHD disorder using the gamified continuous performance test (CPT) dataset applying the decision tree algorithm. The algorithm had an accuracy of 55 to 90 percent based on the used dataset. It can be concluded from table 4 that the accuracy of the algorithm in the optimum case is 90 percent when using four categories and it has an accuracy of 86 percent on the

Full-scale response control. The results of this study approves that the use of machine learning methods with analysis of minimum number of features can provide acceptable predictions.

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