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Indicators of ADHD symptoms in virtual learning context using machine learning technics

Indicadores de síntomas ADHD en el contexto de aprendizaje virtual, utilizando técnicas de aprendizaje automático

Indicateurs de symptômes de Troubles et Déficits d'Attention causés par l'Hyperactivité (TDAH) en contexte d'apprentissage virtuel à l'aide de techniques d'apprentissage automatique

Indicadores dos sintomas TDAH na aprendizagem virtual Contexto usando técnicas de Aprendizagem automática

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RESUMEN

Este artículo presenta un proceso de modelado de usuario, específicamente un modelado de estudiante, en un ambiente virtual de aprendizaje, que permite inferir la presencia o no de síntomas del Déficit de Atención e Hiperactividad (TDAH). El modelo de usuario es construido teniendo en cuenta tres características del estudiante: Conducta de comportamiento (BC), Rendimiento de funciones ejecutivas (EFP), y estado emocional (ES). Para inferir si un estudiante puede tener un perfil asintomático de TDAH, se usa un grupo de reglas de clasificación que usan los resultados obtenidos en cada característica como datos de entrada para su funcionamiento. Basados en las pruebas del modelo propuesto, se obtiene un grupo de entrenamiento que es usado para preparar un algoritmo de aprendizaje automático, el cual podrá realizar y mejorar la tarea de crear el perfil para cada estudiante de acuerdo a si presenta o no síntomas del TDAH o problemas de atención. Esto, puede ser el primer paso para ofrecer recursos de aprendizajes adaptados a las necesidades educativas de estudiantes que presenten este trastorno.

ABSTRACT

This paper presents a user model for students performing virtual learning processes. This model is used to infer the presence of Attention Deficit Hyperactivity Disorder (ADHD) indicators in a student. The user model is built considering three user characteristics, which can be also used as variables in different contexts. These variables are: behavioral conduct (BC), executive functions performance (EFP), and emotional state (ES). For inferring the ADHD symptomatic profile of a student and his/her emotional alterations, these features are used as input in a set of classification rules. Based on the testing of the proposed model, training examples are obtained. These examples are used to prepare a classification machine learning algorithm for performing, and improving, the task of profiling a student. The proposed user model can provide the first step to adapt learning resources in e-learning platforms to people with attention problems, specifically, young-adult students with ADHD.

RESUMÉÉ

Cet article présente un modèle d'utilisateur type chez les étudiants inscrits en mode d'apprentissage virtuels. Ce modèle est utilisé pour prévenir chez les élèves la présence de Troubles et Déficits d'Attention causés par l'Hyperactivité (TDAH). Le modèle est construit pour prendre en compte trois caractéristiques de l'utilisateur qui peuvent aussi être utilisées comme variables dans différents contextes. Ces variables sont : la conduite et comportement (CC), la performance (P) et l'état émotionnel (EE). Pour déduire le profil symptomatique de TDAH d'un étudiant et de ses altérations émotionnelles, ces fonctionnalités sont utilisées comme données dans un ensemble de règles de classification. Ces exemples sont utilisés pour préparer un algorithme d'apprentissage automatique de classification et permettent d'améliorer l'analyse du profil d'un élève. Le modèle d'utilisateur type peut offrir la première étape pour l'adaptation des ressources d'apprentissage aux plates-formes d'enseignement à distance pour des personnes atteintes de troubles de l'attention, en particulier chez les jeunes étudiants atteints de TDAH.

RESUMO

Este artigo apresenta um modelo de usuário para o desempenho dos estudantes nos processos de aprendizagem virtual. Este modelo é usado para inferir a presença de indicadores de Déficit de Atenção com Hiperatividade (TDAH) em um estudante. O modelo de usuários é construído considerando três características dos usuários, as quais podem também ser usadas como variáveis em diferentes contextos. Essas variáveis são: conduta de comportamento, desempenho de funções executivas e estado emocional. Para inferir o perfil sintomático do TDAH de um estudante e seus/suas alterações emocionais, estas características são usadas como entrada em um modelo de regras de classificação. Baseado no teste do modelo proposto, exemplos de treinamento são obtidos. Esses exemplos são usados para preparar um algoritmo de desempenho da preparação da classificação, e melhorar, a habilidade de perfilar um estudante. O modelo do usuário proposto pode prover o primeiro passo para adaptar os recursos de aprendizagem nas plataformas de aprendizagem virtual para pessoas com problemas de atenção, especificamente, estudantes que são adultos-jovens com TDAH.
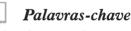
Palabras clave

Déficit de atención e hiperactividad, sistemas hipermedia adaptativos, plataformas virtuales de aprendizaje, modelo de usuario, reglas de clasificación, aprendizaje automático.

Key words

Attention deficit hyperactivity disorder, adaptive hypermedia system, virtual learning platform, user modeling, machine learning technics, classification rules.

Mots clefs

Troubles et Déficits d'Attention causés par l'Hyperactivité, Système Hypermédias Adaptatifs, Plate-forme Virtuelle d'Apprentissage, Modélisation de l'Utilisateur, Règles de Classification

Palavras-chave

Desordem de Déficit de Atenção com Hiperatividade, Sistema de Hipermídia Adaptativa, Plataforma de Aprendizagem virtual, Modelagem do Usuário, Aprendizado de Técnicas de Máquina, Regras de Classificação.

1. INTRODUCTION

In the context of e-Learning, many efforts have been conducted to address the individual user's needs to provide adaptive learning processes. To accomplish this purpose, the integration of Adaptive Hypermedia Systems (AHSs) with Virtual Learning (VL), also known as Adaptive Virtual Learning Environment was proposed (Tiarnaigh, 2005; Colan et al, 2002). AHSs are systems with the ability to adapt themselves accordingly for each individual user, providing a more personalized and customizable course to every user. The distinctive elements of an AHS are: a) a user model, which represents information about a particular user, essential for adaptive systems in order to provide adaptation effects; and b) an adaptation process, which is the mechanism that decides how the system should be adapted, according to the features represented in the user model (Brusilvsky & Millan, 2007). This paper is focused on the user model.

On the other hand, Virtual Learning Platforms (VLPs) are applications that use Internet as a way to publish and provide tools for the management of courses, contents and services. These applications offer a good alternative to the classroom-based environment since they could be customized by an administrator in order to suit the needs of specific groups or class of learners (Colan et al, 2002). However, in many VLPs, the content that might be customized is non-adaptive (i.e., the content is the same for all the students).

The benefit of integrating VLPs and AHSs lies in combining the strengths of both systems; VLPs provide administration and support facilities, while AHSs provide a personalization of the learning process according to users' features. A variety of studies have been developed due to this merger (Baldiris, Santos, Barrera et al, 2008; Baldiris, Santos, Huerva et al, 2008; Jurado et al, 2008). This integration, which aims to provide personalized learning and management processes, is a comprehensive field of research. This is because within this field, there is a diversity of users' characteristics and needs, and a diversity of technologies that VLPs support. Within the large variety of users that utilize VLPs, people with disabilities, disorders or illnesses are included. Technology might help these people to achieve quality learning.

This work is centered on young-adults with Attention Deficit Hyperactivity Disorder (ADHD), especially in a university context, who are included in a long life learning process. The reasons for focusing on this group of people are: a) during the last few years, the number of people diagnosed with ADHD has been growing (Kessler et al, 2006), b) the research conducted on ADHD is mostly focused on children and adolescents, forgetting adult population (Peninington & Ozonoff, 1996; Kroes et al, 2001), c) several studies have demonstrated that individuals with this disorder might have difficulties and letdowns, such as school and job failures (Faraone et al, 2000), and d) several studies have reported that most students with deficits such as those that compose the ADHD, who take online courses, drop them in few days because they find the courses hard to follow (Grabinger, 2010).

Based on the above mentioned, our work is focused on providing adult people with ADHD an alternative to perform their education with quality learning processes. In this paper, we present a user modeling approach to infer if a specific student may be suffering from ADHD symptoms. A user model is then created

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considering three features: behavioral conduct, cognitive performance and emotional state. The proposed user model can provide the first step to adapt learning resources in LMSs to people with attention problems, specifically, student-young-adults with ADHD.

This paper is structured as follows: section 2 explains some of the impairments related to the ADHD that we considered in this work. Section 3 provides some outlines of our proposal and describes the user model. Section 4 describes the machine learning process to support future classification of people with ADHD. Finally, section 5 presents some concluding remarks and future work.

2. ATTENTION DEFICIT HYPERACTIVITY DISORDER (ADHD)

ADHD is a neurobiologically and neuropsychologically heterogeneous disorder characterized by inattention, hyperactivity and impulsivity (NIMH, 2012). In neuropsychological studies performed on people with ADHD, impairments in some of their cognitive functions, specifically, failures in executive functions (EF) were found (Toplak, Jain, & Tannock, 2005; Mulas et al, 2006; Etchepareborda, Paiva-Barón, & Abad, 2009; Barkley, 1997; Brown, 2002). 'Executive function' has been conceptualized as a term that comprises interrelated higher-order cognitive processes responsible for goal-directed and contextually appropriate behavior (Alvarez & Emory, 2006).

On the other hand, research on ADHD has mainly focused on cognitive aspects, leaving in the background the study of the affective deficiencies of the disorder. In this context, a variety of studies have stated that these affective deficiencies are also important for the adequate diagnosis and treatment of the ADHD (Barkley, 1997; Nicolau, 2002; Reimherr et al, 2005; Sonuga-Barke, 2003). Specifically, these studies indicate that children, young people and adults

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with ADHD show a primary dysfunction in the recognition of emotional stimuli. Furthermore, these people present an important disability to control their emotions, specifically the negative ones such as aggressiveness, depression, sadness, anger and frustration.

Considering both cognitive and emotional deficiencies, a recent model, known as the Dual Pathway Model, states that in ADHD, there are separate pathways for cognitive deficits and motivational deficits. An individual with ADHD presents impairments in either one of these pathways, or both (Sonuga-Barke, 2003).

However, cognitive and/or motivational deficits are not exclusive of ADHD and, at the present time, to evaluate the ADHD in adults is a complex process. In general, to diagnose a person with ADHD requires performing an interview based on diagnostic criteria proposed by international experts grouped in the Diagnostic and Statistical Manual of Mental Disorders -DSM-IV (APA, 2000) or the International Statistical Classification of Diseases and Related Health Problems (ICD-10) of the World Health Organization (WHO) [22], executing retrospective diagnosis of childhood symptoms, discarding

other illnesses or disorders, performing cognitive tests, interviewing the evaluated person and its family, analyzing patient's behavior, and including, if necessary, more complex studies such as Magneto-encephalography and Functional Magnetic Resonance.

In this work, the following processes are considered to infer if a user may have ADHD symptoms: (a) a self-assessment rating scale to characterize and to quantify relevant ADHD behavior symptoms, (b) a key question that aims to discard other disorders, (c) a multimedia version of cognitive tests to obtain deficits in cognitive areas related to executive functions, and (d) emotion recognition techniques to recognize users' emotions in real-time. The user modeling process will support a future solution for improving the quality of learning of people with ADHD. In this work, we are not intending to present a method for detecting ADHD in a medical context.

3. USER MODEL FOR QUALITY LEARNING PROCESSES OF STUDENTS WITH ADHD

The characteristics that are considered in order to infer if a specific student could suffer from ADHD symptoms are obtained by an evaluation of users' behavioral conduct, executive functions performance and emotional state.

The general process to obtain information from the students in each of these characteristics can be described as follows: the students are asked to perform a computer question-based test and some computer cognitive tasks. The tests are used to characterize and to quantify relevant ADHD behaviors in a student. The computer cognitive tasks are used to evaluate the students' executive functions performance. While the user interacts with the system, a mechanism of facial expression recognition is executed to extract information about the emotions expressed by the user (Figure 1).
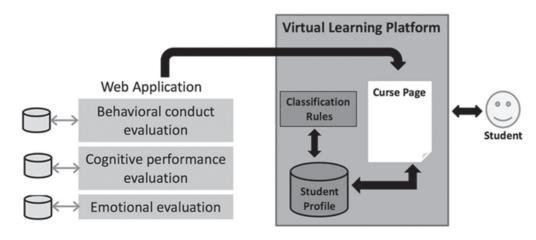
Figure 1. General process of our proposal.

Source. By the authors.

As it is shown, we have considered the implementation of a set of external web applications to evaluate each characteristic considered in the students' profile. In this manner, these tools can be connected with a variety of VLPs. The way we used to embed the set of web applications with the ATutor e-learning platform was the inline frame. Besides, we used the php5-uuid and php5-curl functions to generate a standard identifier also known as universally unique identifier (UUID) to enable Web applications and ATutor to uniquely identify information without significant central coordination; however, some elements in the VLPs need to be adjusted, or incorporated, to complete the user modeling process, these are (a) the creation of a data structure, where the information related to the profile is stored, and (b) the definition of classification rules, from which the user' profile is built.

An explanation of each of the characteristics considered for the user profile and their usage to infer if a student may be suffering from ADHD symptoms is presented below.

3.1 Behavioral Conduct

In order to characterize and to quantify user behaviors that may be relevant to ADHD symptoms, the short version of the Adult ADHD Self-Report Scale – v1.1 (ASRS v1.1) is used (Daigre et al, 2009). This scale is proposed by the WHO and validated for Spanish speakers. The scale is consistent with the evaluation criteria of DSM-IV (APA, 2000). The test consists of six items and takes less than five minutes to be completed. The evaluation scale for each item has five possible answers: never, rarely, sometimes, often and very often. In the first three items, the options from sometimes to very often are considered as negative, and in the last three items, the options from often to very often are recognized as the positive ones. Four o more

positive answers are estimated to suggest the presence of symptoms consistent with ADHD in adults. To mitigate false-positive results, a key question that aims to discard disorders different than ADHD has been included. The result of the evaluation for the behavior conduct is either positive or negative.

3.2 Executive Functions Performance

To extract information about the executive function performance of a user, computer-based neuropsychological tests/tasks are frequently used. The tests used in this research allow to evaluate the following areas of the EF: (a) Sustained Attention (SA), which refers to the ability to maintain a stable performance level over a period of time, (b) Mental Flexibility (MF), which is the capacity of shifting the focus of attention and moving between tasks having different cognitive requirements, (c) Working Memory (WM), which is the capacity to store, monitor and manage information, and (d) Verbal Learning (VL), which refers to the capacity to obtain, hold and remember words. We evaluate these areas, which are deficient in people with ADHD (Marchetta, 2007). In this work, we apply the Sustained Attention Task (SAT) (Wilkins, Shallice, & McCarthy, 1987), to evaluate the sustained attention area; the Concept Shifting Test (CST) (Van der Elst et al, 2006), to check mental flexibility; and the Rey Auditory Verbal Learning Test (RAVLT) (Rey, 1958) to evaluate the last two areas, working memory and verbal learning. Even though there are a number of implementations of these cognitive tests for computer, we implemented our own tools. This is because most of these implementations are given as licensed software.

Generally in these kinds of test, statistics are used to define the performance of a patient. We compare the patients' results with

the normalized data, according to age and education level of people without cognitive problems on each of the three tests (Rey, 1958; Rey, Feldman, Rivas et al, 1999). Considering that we have different evaluation scales for the tests, we compare the patients' results on each test to the mean (μ) of its normalized data in terms of its standard deviation (σ). Based on the guidance of Ferran Viñas Poch, PhD, and Beatriz Caparrós Caparrós, Psychologists with experience on ADHD and associate professors from the Girona University, we classify the students' results using the parameters defined immediately (Table 1).

Table 1. Patient results per each test.

Statistic	Student Result	Assigned Value
Below μ-2 σ	Very Low	1
Between μ - 2 σ and μ- σ	Low	2
Between μ - σ and μ + σ	Medium	3
Between μ + σ and μ + 2σ	High	4
Above μ + 2σ	Very High	5

Source. By the authors.

For the final executive functions perfor-mance result, a number from 1 to 5 is assigned for the possible results on each of the three tests. The final result is obtained by adding the values acquired in these tests. The scale for the final executive functions performance classification is shown below (Table 2).

Table 2. Range for final executive functions performance classification.

Ranges	Classification
{3, 4}	
Very Low	
{5, 6, 7}	Low
{8, 9, 10}	Medium
{11, 12, 13}	High
{14, 15}	Very High

Source. By the authors.

As it is shown, the possible results of the executive functions performance are: very high, high, medium, low, and very low. The ranges for the final classification are obtained considering the limits of the possible results (e.g. two very low results [2x1] and one low [2] should produce a final very low [4], but two low results [2x2] and one very low [1] should produce a final low result [5]. The rest of the ranges are constructed in the same manner).

3.3 Emotions shown by the user

The emotions shown by a particular user allow supporting the detection of ADHD symptoms. The set of emotions that we are interested in capturing are: sadness, anger, disgust, fear, happiness and a neutral state. These emotions will be obtained from the users' facial expressions through a real-time emotion recognition system. The expressions are captured using images taken with a webcam while the user is working on the LMS.

The standard process to build a real-time emotion recognition system consists of four steps: (1) image acquisition, which is the process of capturing the users' image; (2) face detection, in which using the captured image, the face is detected; (3) feature extraction, which is the process of extracting information associated with the activation of different muscles of the face; and (4) emotion classification, which uses the information acquired in the previous step to decide the most probable emotion of the user in a specific moment.

For the first step, a web application that captures a video from the webcam of the student and splits the video into frames is utilized. The Adobe Flash Builder is used for this implementation. Machine learning methods will be used for steps 2, 3 and 4, considering that good results have been obtained applying these

techniques for classifying expressions of basic emotions (Littlewort, Bartlett, Fasel et al, 2004; Michel & El Kaliouby, 2003).

In the second and third steps, the Machine Perception Toolbox (MPT), which contains open source libraries for real-time perception primitives, will be used. Using the MPT, face detection, eye detection, blink detection and color tracking can be performed (Littlewort, Bartlett, Chenu et al, 2004). This toolbox is based on a system developed by Viola and Jones (2001), consisting on a cascade of classifiers trained by boosting techniques. The MPT includes enhancements to the process proposed by the Viola and Jones face detector (e.g., employing the Gentleboost algorithm instead of the Adaboost, and enabling smart feature search and a novel cascade training procedure, as in Viola & Jones, 2001).

For the fourth step, a K-nearest neighbor rule will be used in order to check how our system works. The Support Vector Machines method is planned to be used in future implementations. This is because some studies have demonstrated the effectiveness of this algorithm in the emotion classification task (Michel & El Kaliouby, 2003).

The emotion recognition system begins when the user authorizes the capture of the images from his/her webcam. The complete process to obtain the emotional state will be repeated constantly. Then, an analysis of the different emotions shown by the student is performed. This analysis consists in determining the predominant emotion from the captured group, i.e. the emotion that repeats the most in the group. Since the system works in real-time, this predominant emotion can change in time.
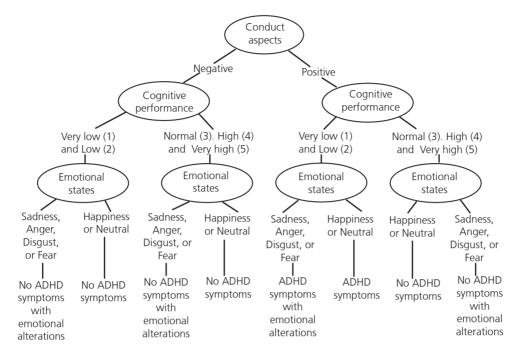
3.4 Classification rules

The abovementioned characteristics can be used in contexts different than ADHD. A set of classification rules must be defined then, to use the results of the evaluation of these characteristics for determining if a user presents ADHD symptoms and/or emotional alterations.

In order to define the classification rules, the psychologists in this work suggested that (a) behavioral conduct should present higher significance than executive functions performance; (b) the emotional state should be only used to define if the student presents emotional alterations. Using these rules, the student might be classified into one of the following four classes: (1) ADHD symptomatic-free, (2) ADHD symptomatic without emotional alterations, (3) ADHD symptomatic with emotional alterations, and (4) ADHD symptomatic-free with possible emotional alterations.

When the classes corresponding to No ADHD symptoms (with or without emotional alterations) occur from a positive in the behavioral conduct and a normal, high or very high executive functions performance, the student may present another disorder different than ADHD or could be a false negative. In the same manner, these situations may happen when those classes of No ADHD symptoms occur from a negative in the behavioral conduct and a very low or low executive functions performance.

The tree (Figure 2), shows the rules that have been defined for the student classification.

Figure 2. Classification tree.

Source. By the authors.

4. SUPPORTING USER MODELING PROCESS THROUGH MACHINE LEARNING TECHNIQUE

Since our overall proposal is to offer adaptive learning resources to students with ADHD, the user modeling process is an important issue. This is because the user model provides the approach to identify if a specific student presents ADHD symptoms.

However, the presence of ADHD symptoms might be a reason why students do not finish the tasks used for the classification. A machine learning classification task has been proposed then, to infer if a student who did not finish these tasks might have ADHD symptoms. The automatic classification process has been divided into three steps: information acquisition, classification algorithm selection, and classification process validation.

The first step refers to the acquisition of the training and test sets of instances used to prepare the classification algorithm. Data for these sets will be provided for the results of some test scenarios, where users are asking to present the computer test submitted before in order to know the ADHD symptoms. Results from other studies such as the one developed by Marchetta (2007), might be also used for defining the training and test sets even if these results consider areas that are more cognitive than the ones used for this work.

The second step of the process is to define the best algorithms for developing the classification task. In this work, this refers to the best algorithm to classify a user in the adequate ADHD symptomatology. We will test some classification algorithms such as ID3 (Quinlan,

1986), ID4.5 (Quinlan, 1993), and also some mixed algorithms using boosting and bagging processes. The design of the classification task is determined as follows:

- The object task: to classify a particular user according to few input data in a specific ADHD symptomatology characterization.
- The possible values for the class are: (a) ADHD symptomatic-free, (b) ADHD symptomatic without emotional alterations, (c) ADHD symptomatic with emotional alterations, and (d) ADHD symptomatic-free with possible emotional alterations.

- The attributes and their values are: age (a discrete number among 18 to 60), education level (EL) (between 7 and 12 years of studies, 13 or more years of studies), BC (positive or negative), MF-CP (very low, low, medium, high and very high), WM/VL-CP (very low, low, medium, high and very high), SA-CP (very low, low, medium, high and very high) bb and R-TE (happiness, sadness, anger, disgust, fear and neutral). The characteristics in parentheses are the possible values for each of the attributes.

The third step is the validation of the classification process, measuring the precision of the task and other features.

Table 3. Shows some examples of instances that might be used for the training set.

Training examples								
Attribute								Class
I	A	E.L (y)	B.C.	M.F.	WM.V.L	S.A.	E.S.	
2	23	12	+	Low	Low	Low	Sad	ADHD + E.A
3	35	18	-	High	High	High	Happy	No ADHD
4	19	15	+	Low	High	Low	Frustrated	No DHD + E.A
5	30	16	-	Low	Very Low	Medium	Happy	No ADHD
6	27	16	+	Very Low	Low	Very Low	Neutral	ADHD
7	50	18	-	Low	Low	High	Happy	No ADHD

I: Instance, A: Age, E.L.: Education Level, B.C.: Behavioral Conduct, M.F.: Mental Flexibility, W.M.V.L: Working Memory and Verbal Learning, S.A.: Sustained Attention, E.S.: Emotional State, +: Positive B.C., -: Negative B.C., ADHD+: Possible ADHD symptoms, ADHD- : No ADHD symptoms.

Source. By the authors.

Instances 4 and 5 can be possible cases of disorders different than ADHD or false negatives (Table 3).

5. CONCLUSION AND FUTURE WORK

The overall goal behind this work is to provide quality learning processes to people with attention problems, specifically to adults with ADHD. This is because these people may find the classical education hard to follow, and might find in virtual learning an alternative to perform their education. We have built a user model that considers some deficient characteristics in the ADHD, which can be used to infer if a specific student may have ADHD symptoms. The work presented in this paper can be the first step to deliver personalized learning resources to students with the ADHD.

For improving the results, a machine learning classification task is suggested instead of a manual classification task. Two main reasons for using machine learning classification are when the classification task is large for manual performance, and when the value of a characteristic is absent for a student, the machine learning algorithm can still infer the classification for that particular student.

The expected result of applying machine learning techniques is that this automatically performed classification can be compared with those suggested by professionals on the ADHD. This comparison will indicate how good the provided diagnosis is.

We plan to test a variety of classification algorithms in order to choose those that offer better accuracy. Furthermore, we also plan to use another classification algorithm in the context of the automatic emotion recognition to improve this process.

Considering the findings referring to other neurological and psychiatric disorders that may present the same deficiencies as ADHD through this research, we plan to expand the range of users to which this development can be addressed. On one hand, this project can be extended to other disorders by applying specific rating scales for each of them; on the other hand, the project can offer a generalized user model that considers cognitive and emotional dysfunctions.

Although psychologists are supervising the performance on this work in order to build a system as realistic as possible, we are not intending to present a method for detecting ADHD in a medical context. We would recommend a person to look for professional advice in case this person feels this disorder is seriously affecting her/ his life.

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