Machine Learning Approach for Distinction of ADHD and OSA

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ABSTRACT: *The purpose of this study is to find an efficient way to discriminate between Attention-deficit/ hyperactivity disorder (ADHD) and Obstructive sleep apnea (OSA). The study collected 120 children (aged 6-12 years) data between 2011 and 2015, who were divided into three groups, ADHD, OSA and a combination of ADHD and OSA. Each group based on the doctor's determination, using the DSM-IV diagnostic standards. The data included four questionnaires as follow: CBCL, DBRS, OSA-18 and CSHQ. Therefore, in order to speed up the whole process of clinical diagnosis classification, we train and test three machine learning models to find the best way to help clinical doctor to diagnosis. The study results indicate that in all of subscale items, there were 21 item show significantly difference among three subgroups, especially in the DBRS. Our results also show that Neural Network model has better computational efficiency than CHART and CHAID for subgroups classification.*

Keywords: Attention-deficit/hyperactivity disorder, Obstructive sleep apnea, Machining learning.

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1. Introduction

Attention-deficit/ hyperactivity disorder (ADHD) is one of the most commonly neurodevelopmental disorder in children, and is characterized by inattention, hyperactivity and impulsivity [1 , 2]. The prevalence of ADHD is estimated to affect about 5-7% of school-aged children worldwide [3 , 4], and 6-12% in Taiwan [5 , 6]. Some long-term follow-up studies indicate that approximately 60-80% of school-age children with ADHD whose symptoms persist until adolescence, and 40-60% of them continue into adulthood [7-9].

Recently several studies note the relationship between ADHD and sleep disorder[10 , 11]. About 25-55% of children and adolescents with ADHD experience problems with sleep [12]. Studies indicate that children with ADHD have some sleep disorder problems, such as having trouble falling asleep, snoring, daytime sleepiness, and unwillingness to go bed. Because ADHD and Obstructive sleep apnea (OSA) have similar symptoms, the asscociation of sleep with ADHD is multificated and complex. Therefore, doctors need to consider more factors, and ofthen need match a variety of clinical tools, such as Wechsler Intelligence Scale for Children (WISC-III), Disruptive Behavior Disorders Rating Scale (DBRS), Child Behavior Checklist (CBCL) and Continuous Performance Task (CPT). In order to further identify or rule out the possible impact of comorbidity of ADHD-related factors. We also need to consider the OSA effects on children with ADHD, so to be screening through sleep questionnaire, such as The OSA-18 quality of life questionnaire (OSA-18) and the children's sleep habits questionnaire (CSHQ).

However, due to the accessibility of information generated by a lot of tests and time-consuming, So many scholars consider to this point, Thus began using Machining learning Concepts to aid diagnosis of ADHD [13 , 14]. Through past experience or information, the computer automatically analyzes for law,building models, and continuously corrected. Gradually adjust the model and method, it allows us to predict the unknown data and analysis. Find the difference between ADHD and key indicators of general subjects were, such as the use of Support Vector Machine, SVM. In the clinical scales, looking for highly effective assessment indicators of ADHD, and through this a way to scale the content for review [15]. On the domestic health insurance database to analyze related comorbid ADHD through association rule mining [13], but rarely have the literature study conducted for ADHD and OSA.

Therefore, this study hope to design a fast screening model. In odrer to reduce patient waiting time and the province to accelerate the process of diagnosis, samples were collected by parents and teachers questionnaires. Using maching learning models as follow: CART, CHAID and Neural network model to look the best way to discriminate among ADHD, OSA, and both of them.

2. Method

2.1 Research Design

A total of 120 subjects aged 6-12 years old were made up of referrals from the Children's Psychology Department at the medical center. This study picked up the first-time questionnaires data from the database between 2011-2015.

The data were selected, and divided into 70% of the training group and 30% of the test group for machine learning. And selection CART, CHAID , and neural network model building, Finally, compare the effectiveness of these three models. (Fig.1)

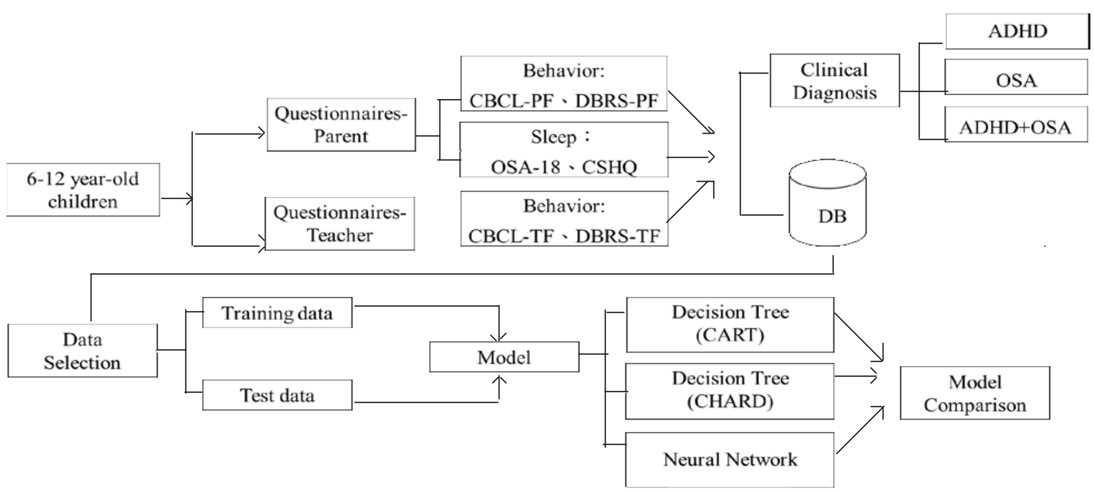

Figure 1. Research Design

2.2 Subject

The effective sample size for this study was 120 subjects, who are school-age children of 6-12 years old from 2011 to 2015 year. All of the subjects were made up of referrals from the Children's Psychology Department at the medical center, and in conjunction with the doctor's clinical assignment, divided into the ADHD group, OSA group and a combination of ADHD and OSA (ADHD+OSA). Each group has forty children. The exclusion criteria were mental retardation (FIQ <70), mental retardation, or drug abuse. (IRB number: 100-0777A3)

2.3 Measures

The study collected for the first time to see the doctor's scale data, including: CBCL, DBRS, OSA-18 and CSHQ, filling in questionnaires by parents and teachers. There were forty subscale items. (Table 1)

• Child behavior checklist (CBCL)

The Children behavior checklist is a parent and/or teacher rated measure of symptoms of ADHD in children aged 4-16 years. The measure includes 137 questions, reporting on child behaviors in the past six months, and each item is scored on a three-point Likert scale. In the study, we pick up nine scales from the parent form consistent with internalizing behavior, externalizing behavior, depression/anxiety, thought obsessive, somatic complaint, social withdraw, hyperactive, aggressive behavior and delinquent; eight scales from the teacher form consistent with internalizing behavior, externalizing behavior, anxiety, social withdraw, unwelcome 'self-destruction' inattention and aggressive behavior.

• Disruptive Behavior Rating Scale Form (DBRS)

The Disruptive Behavior Rating Scale Form is completed by parents and teachers, which is a 49- question screening measure. The scale consists of five subscalesy : inattention, hyperactivity/impulsivity, ADHD, opposite defiant behavior (ODD) and conduct disorder (CD) on a four-point Likert scale.

• The OSA-18 quality of life questionnaire (OSA-18)

The OSA-18 quality of life questionnaire includes eighteen items subdivide in five subscales, and total score. The subscales consist of sleep disturbance, physical symptoms, emotional distress, daytime function, and caregiver concerns. Each item is scored on a seven-point Likert scale.

• The children's sleep habits questionnaire (CSHQ)

The children's sleep habits questionnaire is designed to measure the statements of children's sleep habit and possible difficulties with sleep of children aged 4-12 years. It is a 33-question measure, included eight subscales: bedtime resistance, sleep onset delay, sleep duration, sleep anxiety, night wakings, parasomnias, sleep disordered breathing and daytime sleepiness.

2.4 Data analysis

All analyses were carried out with the SAS software (Enterprise Guide 6.1 and Enterprise Miner 13.1). A value of $p < 0.05$ was considered statistically significant. Using Classification and Regression Trees, Chi-Square Automatic Interaction Detector, and Neural Network to build model.

3. Example of Verification and Results

3.1 Sample description

A total of 120 subjects mean age was 8.26±1.78, and 92(77%) were boys. The characteristics of the three groups were as follows: ADHD group (M: F=31:9); OSA group (M: F=27:13); and a combination of ADHD and OSA (M: F=34:6).

3.2 Behaviour problems among subgroups

There are 26 subscale items from CBCL and DBRS questionnaire. In order to know the relationship between behaviour problems and three subgroups, the study used ANOVA to compare them. Table 2 presents that seventeen items had significant ($p < 0.05$), especially in the DBRS. Externalizing behavior, delinquent, inattention, and aggressive behavior from CBCL; inattention, hyperactive/ impulsivity ADHD, ODD and CD score from DBRS were highly significant ($p < 0.0001$) than others.

3.3 Sleep problems among subgroups

The results of sleep problems show that sleep disturbance, emotion distress and daytime function of the OSA-18, and sleep disordered breathing are significant ($p < 0.05$) (Table 3). Although the subscale items of OSA-18 are not highly significant then sleep disorder breathing from CSHQ, it is still a way that maybe we could use only OSA-18 questionnaire to fast screening test about ADHD with OSA. Because OSA-18 including 18-term, it may spend less time for parents to fill in those questions.

Behavior subscale item			Sleep subscale item	
CBCL-Parent	**CBCL-Teacher**	**DBRS-Parent**	**OSA-18**	**CSHQ**
internalizing behavior	internalizing behavior	Inattention	sleep disturbance	bedtime resistance
externalizing behavior	externalizing behavior	hyperactivity /impulsivity	physical symptoms	sleep onset delay
depression/anxiety	anxiety	ADHD	emotional distress	sleep duration
thought obsessive	social withdraw	ODD	daytime function	sleep anxiety
somatic complaint	unwelcome	CD	caregiver concerns	night wakings
social withdraw	self-destruction	**DBRS-Teacher**	OSA Total	parasomnias
hyperactive	inattention	Inattention		sleep disordered breathing
aggressive behavior	aggressive behavior	hyperactivity /impulsivity		daytime sleepiness
delinquent		ADHD		
		ODD		

Table 1. Subscale items

	ADHD (N=40)		OSA (N=40)		ADHD + OSA (N=40)			
Subscale item	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**F**	**p (ANOVA)**
CBCL-Parent								
internalizing behavior	61.43	11.53	56.33	11.63	61.88	11.17	2.95	0.0561
externalizing behavior *	63.75	11.21	54.58	11.42	65.28	10.59	12.79	< .0001
depression/ anxiety	59.43	11.50	55.10	10.88	56.55	12.54	1.48	0.2324
thought obsessive	61.75	10.74	56.78	9.75	61.23	11.71	2.66	0.0740

somatic complaint	57.50	11.55	54.85	11.19	56.95	12.60	0.58	0.5600
social withdraw	61.18	12.32	56.15	10.92	62.03	13.30	2.73	0.0691
hyperactive *	65.58	12.57	56.48	11.07	66.78	13.58	9.13	0.0002
aggressive behavior *	61.25	11.22	54.33	9.02	64.13	11.61	9.17	0.0002
delinquent *	60.58	11.72	52.65	8.90	63.33	12.30	10.34	< .0001
CBCL-Teacher								
internalizing behavior	57.43	12.31	51.48	11.75	54.85	11.38	2.41	0.0945
externalizing behavior *	62.30	12.13	48.48	11.14	61.88	10.82	23.04	< .0001
anxiety	56.93	10.43	52.00	8.21	53.65	8.96	2.36	0.0988
social withdraw	58.80	9.98	55.50	10.35	58.18	10.37	1.24	0.2937
unwelcome *	61.63	13.51	51.28	8.74	59.73	12.72	7.37	0.0010
self-destruction *	62.68	12.15	52.63	9.33	61.15	11.59	9.01	0.0002
inattention *	62.35	9.65	52.75	8.32	63.00	10.56	18.25	< .0001
aggressive behavior *	63.18	11.89	51.15	7.78	60.83	9.92	13.99	< .0001
DBRS-Parent								
inattention *	15.13	6.88	7.90	6.08	14.45	6.34	17.12	< .0001
hyperactivity/ impulsivity *	12.58	7.29	6.10	5.33	12.43	7.18	12.22	< .0001
ADHD *	27.70	13.28	14.00	10.58	26.88	12.40	16.99	< .0001
ODD	8.43	5.84	6.20	5.45	9.28	6.22	3.06	0.0507
CD *	0.53	0.98	0.05	0.32	0.63	1.19	4.12	0.0187
DBRS-Teacher								
inattention *	12.85	7.27	4.63	4.73	12.88	7.74	23.61	< .0001

hyperactivity/ impulsivity *	10.20	7.33	2.38	3.58	9.83	6.76	18.88	< .0001
ADHD *	23.00	13.78	7.00	7.36	22.70	13.60	24.68	< .0001
ODD *	6.63	5.47	1.75	2.64	5.15	4.78	9.56	0.0001

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Table 2. Behaviour problems among subgroups

	ADHD (N=40)		OSA (N=40)		ADHD + OSA (N=40)			
Subscale item	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**F**	**p (ANOVA)**
OSA-18								
sleep disturbance *	10.88	3.80	14.78	5.52	13.65	5.15	6.77	0.0016
physical symptoms	12.68	4.78	14.03	5.77	14.45	5.72	1.16	0.3173
emotional distress *	12.78	4.32	9.58	3.89	12.35	4.61	6.58	0.0020
daytime function *	12.78	3.35	10.05	3.75	11.50	4.50	4.90	0.0090
caregiver concerns	15.50	5.57	14.80	6.13	15.48	6.47	0.17	0.8428
OSA Total	64.60	15.45	63.23	20.89	67.43	21.85	0.48	0.6216
CSHQ								
bedtime resistance	11.55	1.95	11.38	1.51	11.90	1.95	0.87	0.4221
sleep onset delay	2.23	0.77	2.58	0.59	2.40	0.74	2.46	0.090
sleep duration	6.28	1.01	6.25	1.15	6.35	1.10	0.09	0.9127
sleep anxiety	6.88	2.22	6.93	2.12	7.08	2.23	0.09	0.9138

night wakings	4.05	1.38	4.40	1.32	4.73	1.85	1.94	0.1489
parasomnias	9.48	2.18	9.33	1.97	9.63	2.48	0.18	0.8332
sleep disordered breathing *	3.85	1.25	5.68	2.10	5.45	2.10	11.42	< .0001
daytime sleepiness	14.38	2.85	13.73	2.84	14.43	2.99	0.73	0.4846

Table 3. Sleep problems among subgroups

	Training data					Test data					Misclassification
Model	**FN**	**TN**	**FP**	**TP**	**ROC**	**FN**	**TN**	**FP**	**TP**	**ROC**	**Rate**
Neural Network	12	40	14	16	0.681	4	19	7	8	0.750	0.342105
CART	1	13	41	27	0.603	2	7	19	10	0.551	0.578947
CHAID	3	40	14	25	0.863	7	15	11	5	0.519	0.684211

Table 4. Model comparison

3.4 Machine Learning

To find an efficient way to discriminate among Attention-deficit/ hyperactivity disorder, Obstructive sleep apnea, and ADHD + OSA group, the study used three methods to build the fast screening test model. Divide subject into 70% of the training group and 30% of the test group for machine learning. And selection CART, CHAID , and neural network model building, Finally, compare the effectiveness of these three models (Table 4).

The results show that nerual network algorithms was well-suited to the classification task at hand, because it had less misclassification rate than CRAT andd CHAID model.

4. Conclusion

In the above discussion, we found an important association between ADHD children sleep quality and attention to the impulse patterns. Find hyperactive and impulsive behavior in behavioral measures in the table in this study we have significant correlation DBSR questionnaire can be separated from ADHD, OSA and OSA ADHD + Scale important types of patterns. And the result on the sleep test (Table3), OSA-18 is also capable of displaying ADHD, OSA and ADHD + OSA. Finally benefit in comparison model constructed neural network also saw an excellent performance to distinguish these three subgroup. In the present study we suggest that three ADHD, OSA and ADHD+OSA children if they can distinguish more earlier, it will be able to prescribe the right medicine and treatment with a suitable way.

In the past, when check ADHD children, hyperactive and impulsive mix who tend to believe that there is no association between sleep and ADHD condition. Now through personnel for sleep quality requirements found in this important experiment. Further experiments but this is the lack of personnel to identify and explore. If this direction in a number of experimental studies have started for OSA detection and treatment of common ADHD can be a two-pronged approach to address important moment both remission and treatment of development and learning in children in. This will not only help children in this important stage of life to be happy to learn, be able to better focus on schoolwork. And an important breakthrough in this field of research and medical information that can help an important breakthrough.

This study was also studying in the normal limit is too small a sample group of children can't be explored in more detail, but the research behind this really is a very important development in the child's normal data collection is essential. But in Taiwan, the legal and personal privacy is very disease oriented. So the collection is very difficult. And generally do not have special needs of children, if not into the hospital for detailed examination, the study team is very sorry also hope that the latter way if additional funding or grants sponsored by the Institute will help the children with ADHD and found sleep test can be obtained more friendly treatment.

References

[1] Polanczyk, G., Rohde, L.A. (2007). *Epidemiology of attention*-deficit/hyperactivity disorder across the lifespan. *Curr Opin Psychiatry,* 20 (4) 386-92.

[2] American Psychiatric, Association. (2013). Diagnostic and statistical manual of mental disorders : DSM-5. Washington, D.C.: American Psychiatric Association.

[3] Willcutt, E.G. (2012).The prevalence of DSM-IV attention-deficit/hyperactivity disorder: a meta-analytic review. *Neurotherapeutics,* 9 (3) 490-9.

[4] Polanczyk, G., et al., (2007). The Worldwide Prevalence of ADHD: A Systematic Review and Metaregression Analysis. *American Journal of Psychiatry*, 164 (6) 942-948.

[5] Huang, H.-L., (2009). The Secondary Exploration on Attention Deficit Hyperactivity Disorder (ADHD) Research. *Research in Applied Psychology*, (41) 20-26.

[6] Tzang, R.-F., Wu, K.-H., Liou, C.-P. (2002) Prevalence of Attention-deficit/Hyperactivity Disorder in a Taiwanese Elementary School., *Taiwanese Journal of Psychiatry*. 202-212.

[7] Faraone, S.V., Biederman, J., Mick, E. (2006).The age-dependent decline of attention deficit hyperactivity disorder: a meta-analysis of follow-up studies. *Psychological Medicine*, 36 (02) 159-165.

[8] Ginsberg, Y., et al., (2014). Underdiagnosis of attention-deficit/hyperactivity disorder in adult patients: a review of the literature. *Prim Care Companion CNS Disord,* 16 (3).

[9] Murphy, K., Barkley, R.A. (1996). Attention deficit hyperactivity disorder adults: comorbidities and adaptive impairments. *Compr Psychiatry,* 37 (6) 393-401.

[10] Kirov, R., et al., (2004). Is there a specific polysomnographic sleep pattern in children with attention deficit/hyperactivity disorder? *Journal of Sleep Research*, 13(1) 87-93.

[11] O'Brien, L. (2003). The effect of stimulants on sleep characteristics in children with attention deficit/hyperactivity disorder. *Sleep Medicine,* 4 (4) 309-316.

[12] Corkum, P., Tannock, R., Moldofsky, H. (1998).Sleep disturbances in children with attention-deficit/hyperactivity disorder. *J Am Acad Child Adolesc Psychiatry,* 37 (6) 637-46.

[13] Tai, Y.M., Chiu, H.W. (2009). Comorbidity study of ADHD: applying association rule mining (ARM) to National Health Insurance Database of Taiwan. *Int J Med Inform,* 78 (12) p. e75-83.

[14] Tenev, A., et al., (2014). Machine learning approach for classification of ADHD adults. *Int J Psychophysiol*, 93 (1) 162-6.

[15] Chung-Yuan, C. (2015). Analysis of ADHD Scale Items for Identifying Determined Features Using Support Vector Machine, in Institute of Biomedical Informatics. National Yang-Mng University: Taipei City. p. 47