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ANALYSIS SLEEP APNEA USING MACHINE LEARNING: ONE POSSIBILITY

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ABSTRACT

Obstructive Sleep Apnea (OSA) is a public health problem, sometimes under-reported due to the difficulty in its diagnosis. Therefore, health professionals seek alternative diagnostic methods based on clinical and epidemiological parameters. Here, was evaluated the predictive capacity of the anthropometric and clinical parameters of the free access database provided by Penzel *et al*7 and Dublin Sleep Apnea Database of the University Hospital / University College of St. Vincent in the diagnosis of OSA. The database is composed of 56 participants of both sexes, aged between 27 and 63 years. The following indicators were evaluated: weight, height, body mass index, sex and age. SPSS® software was used for statistical analysis of the database. Only low cost methods were used, reproducible and innocuous, reaching AUROC of 0.98, 0.96 and 0.94 for BMI, weight and age, respectively, in the prediction of OSA. The evaluated indices presented high power prediction from the OSA and, due to the reproducibility and ease of application, can be used in the construction of a classifier algorithm that will allow the early diagnosis of OSA.

Abbreviation: Obstructive Sleep Apnea (OSA); Areaunderthe ROC curve (AUROC); Body Mass Index (BMI); electrocardiogram (ECG); Standard Deviation (SD); Support Vector Machine (SVM); Apnea Hypopnea Index (AHI).

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INTRODUCTION

The Obstructive Sleep Apnea (OSA) is a disorder characterized by partial (hypopnea) or complete obstruction (apnea) of the upper airways during sleep (Oulhaj *et al.*, 2017). Its diagnosis is made through the detection of the frequency of episodes of apnea and/or hypopnea through nocturnal polysomnography and characterized by the presence of five or more events per hour during sleep(Silva *et al.*, 2014; Oulhaj *et al.*, 2017).

The OSA is one of the most prevalent sleep disorders, affecting approximately 3 to 7% of men and 2 to 5% of women in the general population. Regardless it is a common disease, it is still underdiagnosed, with about 75 to 80% of cases remaining undiagnosed (Aurora *et al.*, 2015). The potentially fatal consequences of this disorder include arterial hypertension, pulmonary hypertension, heart failure, nocturnal cardiac dysrhythmias, myocardial infarction, and ischemic stroke(Roedig *et al.*, 2014). OSA requires a complex diagnostic process because it is not an easily detectable disease, in this way health professionals seek alternative diagnostic methods that have the ability to predict the probability and severity of OSA based on simple information

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such as clinical characteristics and family history (Kim *et al.*, 2017). In this context Moody *et al.*, (2000), offered a challenge to the scientific community: the development of OSA diagnostic methods based on the information obtained through patients electrocardiogram (ECG)(Moody *et al.*, 2000). However, in addition to ECG-related data, clinical variables that were more accessible and easier to apply than the ECG, such as weight, height, age, gender, and other characteristics were provided and were eventually underused. Therefore, knowing the relationship between overweight, advanced age and male gender and the development of OSA, The aim of the present study was to innovate, since the predictive capacity of noninvasive clinical data was analyzed (body mass index, gender and age), provided by Penzel *et al* (2000) and St. Vicent's University Hospital/ University College Dublin Sleep Apnea Database. And later this data will be used in the construction of an OSA classifier based on computational models.

MATERIALS AND METHODS

Data base

The data(Goldberger *et al.*, 2000; Penzel *et al.*, 2000) and St. Vicent's University Hospital/ University College Dublin Sleep Apnea Database used in the present study are freely accessible, and are available in http://www.physionet.org/physiobanWdatabaselapnea-ecg/ and http://physionet.fri.uni-lj.si/ physiobank/database/ucddb/HEADER.shtml. The database (Goldberger *et al.*, 2000; Penzel *et al.*, 2000) consists of 32 participants of both genders, aged between 27 and 63 years. The subjects were randomly selected over a 6-month period (September 02 to February 03) from patients referred to the Sleep Disorders Clinic at St Vincent's University Hospital, Dublin, for possible diagnosis of obstructive sleep apnea, central sleep apnea or primary snoring. Subjects had to be above 18 years of age, with no known cardiac disease, autonomic dysfunction, and not on medication known to interfere with heart rate. Twenty-five subjects (21Man, 4Female) were selected (age: 50 ± 10 years, range 28-68 years; BMI: 31.6 ± 4.0 kg/m², range 25.1-42.5 kg/m²). Noninvasive (body mass index, gender and age) and low-cost data were used for this evaluation; more information is available at Physiobank.

Classification of Sleep Apnea: Based on the recommendation of American Academy of Sleep Medicine (AASM) a AHI > 5 was used to classify patients in risk(Ramos*et al.*, 2016).

Statistical Analysis

The SPSS® version 19.0 (Statistical Package for the Social Sciences, Chicago, IL, USA) was used for database and statistical analysis. The results were expressed as mean, median and standard deviation (mean or median±SD). The Kolmogorov-Smirnov test was used to verify the normality of the variables: age, weight, height and body mass index. Then, the sample was divided into two groups stratified according to ApneaHypopnea Index (AHI) of the participants (denominated: normal AHI group - formed by participants with normal AHI and altered AHI group - formed by altered AHI participants). The groups were compared using the Student's t-test for independent samples if the data distribution was normal, and if they did not present normal distribution the test applied was Mann-Whitney U. The chi-square test to evaluate the prevalence of overweight and gender in the groups with normal AHI and altered AHI. The calculation of the ROC curve refers to the ability of the body mass index, weight and age to discriminate participants with OSA. The altered AHI index was used as standard in the analysis of the ROC curve. The areas under the ROC curve and the confidence intervals were determined, and if these indexes obtain satisfactory values they will be used as input in the classifier development. The results were considered statistically significant if p <0.05.

RESULTS AND DISCUSSION

The sample consisted of 51,8% (n= 29) of males and 48,2% (n = 27) of females. Mean, medians values ± standard deviation of the age, anthropometric variables and prevalence of gender and status nutritional of the studied sample are described in Table 1. All analysed indicators, except gender, were able to predict the AOS in the sample (Table 2), however, the BMI presented the largest area under the ROC Curve (AUROC); (0.98; p<0.001). Several studies(Penzel *et al.*, 2002; De Chazal, Penzel and Heneghan, 2004; Mendez *et al.*, 2010) were performed using the database provided by Penzel *et al* (Penzel *et al.*, 2000), and University College Dublin Sleep Apnea Database, however, these studies are focused on the classification of OSA using electrocardiogram (ECG), whose equipment has a high cost when compared to non-invasive methods such as anthropometric evaluation.

Table 1. Samplecharacteristics

Variables	AHI standart (n=13)	AHI non-standart (n=43)	p-value
Age (years) $^{\dagger b}$	31±6,13	52±8,3	<0.001
Height (m) $^{\dagger b}$	1,71±0,08	1,76±0,07	0.831
Weight (kg)^{*a}	66,15 ± 8,54	97,5 ± 16,80	0.022
BMI (kg/m^2)^{*a}	21,69±2,19	32,18±5,09	0.006
BMI$^{\#}$			
Eutrophic	92.30% (n=12)	58.13% (n=25)	<0.001
Overweight	7.70% (n=1)	41.87% (n=18)	
GENDER$^{\#}$			
Women	53.84% (n=7)	46.1% (n=20)	0.643
Men	46,.6% (n=6)	53.49% (n=23)	

Abbreviations: BMI – body mass index; *: Student's t-test for independent samples; † Mann –Whitney test; ^{a}Values are given as mean ± SD (standard deviation); ^{b}Values are given as median ± SD (standard deviation); $^{\#}$ Chi-square.

Table 2. Area under the ROC curve

Variables	AreaROC curve	Std. Error	p-valor	Asymptotic 95% ConfidenceInterval	
				LowerBound	*UpperBound*
Age	0.94*	0.03	<0.001	0.88	0.99
Gender	0.54	0.09	0.691	0.36	0.71
Weight	0.96*	0.02	<0.001	0.92	1.00
BMI	0.98*	0.01	<0.001	0.96	1.00

Abbreviations: BMI – body mass index. *: Area under the ROC curve demonstrating discriminatory power for Obstructive sleep apnea (lower limit of CI 95% >0.50).

The diagnostic methods develop based on the ECG signals made available by Moody *et al*(Moody *et al.*, 2000) have an accuracy of approximately 83-93%. However, using only low-cost non-invasive innocuous methods, the present study achieved an AUROC of 0.98, 0.96 and 0.94 for BMI, Weight and age, respectively, in the prediction of OSA. The OAS is a serious public health problem and the complications caused by it, such as hypertension, diabetes mellitus and cardiovascular diseases, generate high costs to public health. Moreover, risk factors such as male gender, advanced age, diabetes mellitus and heredity have been associated with an increased prevalence of obstructive sleep apnea in the general population(Schwartz *et al.*, 2008; Kim *et al.*, 2017). The method considered gold standard for the diagnosis of OAS is the polysomnography, which has the disadvantage of generating stress for the patient, in addition to being expensive(Ramos *et al.,*2016). The use of the variables age, gender and BMI will allow the development of an inexpensive, accessible and high accuracy tool which will be developed using data classification methods. The Machine Learning methods are being increasingly used to improvise the precision of health diagnosis such as the Support Vector Machine (SVM) (Jeon *et al.*, 2018).

The theoretical foundations on the support vector machine were introduced by Vapnick and consist of a classification method for two classes. The basic idea of this method is to construct a hyperplane with a decision surface in which the margin of separation between the two classes is maximized(Ribeiro *et al.*, 2015). This method has been successfully implemented by Ribeiro *et al* (2015), which, when using only non-invasive indicators, obtained an accuracy of 98.28% in the classification of diabetic patients. Thus, it is important to emphasize that the early diagnosis of OSA will facilitate its treatment and reduce the occurrence of complications, favoring the patient's quality of life (Neto *et al.*, 2015). The use of ECG is partially advantageous. However, it is worth mentioning that its use as an apnea detection parameter presents limitations, since the presence of pathologies such as diabetes, myocardial infarction and chronic heart failure, are of tenrelated to OSA and can generate false results(Shokoueinejad *et al.*, 2017). In addition, ECG requires a skilled professional for its execution, which adds to the fact that the electrocardiogram equipment will not always be available in remote locations. Therefore, clinical indicators, such as BMI, Weight and age, present a high precision in the prediction of OSA, showcasing themselves as an alternative to the development of tools for the diagnosis/screening, based in Machine Learning methods, of OSA patients.

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