Pairwise Classifier Approach to Automated Diagnosis of Disorder Degree of Obstructive Sleep Apnea Syndrome: Combining of AIRS and One versus One (OVO-AIRS)

K. Polat, S. Güneş, and Ş. Yosunkaya

Abstract— Artificial Immune Recognition System (AIRS) is an immune inspired supervised classification algorithm and also works in classifying of multi class datasets. But the performance of AIRS classifier in classifying multi class datasets is generally lower than its performance in case of classifying two class datasets. In order to overcome this problem, we have combined the one-versus-one (OVO) and AIRS in the diagnosis of disorder degree of obstructive sleep apnea syndrome (OSAS) that affects both the right and the left cardiac ventricle. The OSAS dataset consists of four classes including of normal (25 subjects), mild OSAS (AHI (Apnea Apnea and Hypoapnea Index)=5-15 and 14 subjects), moderate OSAS (AHI<15-30 and 18 subjects), and serious OSAS (AHI>30 and 26 subjects). In the extracting of features that is characterized the OSAS disease, the clinical features obtained from Polysomnography used diagnostic tool for obstructive sleep apnea in patients clinically suspected of suffering from this disease have been used. The used clinical features are Arousals Index (ARI), Apnea and Hypoapnea Index (AHI), SaO2 minimum value in stage of REM, and Percent Sleep Time (PST) in stage of SaO2 intervals bigger than 89%. We have used two fold cross validation to split OSAS dataset and also used the classification accuracy, sensitivity- specificity analysis, and confusion matrix to evaluate the performance of proposed method. While AIRS algorithm obtained 90.24% classification accuracy, the proposed method based on AIRS algorithm and OVO achieved 98.24% classification accuracy. These results show that the proposed method can confidently be used in the determining of disorder degree of OSAS.

***Index Terms*— Artificial Immune Recognition System, One versus One, Obstructive sleep apnea syndrome (OSAS), Polysomnography.**

I. Introduction

In this study, we have performed the real world application of AIRS with one-versus-one (OVO-AIRS) and in this way categorized the disorder degree of obstructive sleep apnea syndrome. The aim of this study is both to diagnose the OSAS and to improve the performance of AIRS classifier using OVO approach.

AIRS is a resource limited supervised learning algorithm inspired from immune concepts. In this algorithm, the used immune mechanisms are resource competition, clonal selection, affinity maturation and memory cell formation [1]. There are some works regarding AIRS classifier in literature. Among these, artificial immune recognition system (AIRS), an immune-inspired algorithm for supervised classification task is applied to the Duke Energy outage data for outage cause identification using three major causes (tree,
animal, and lightning) as prototypes by Xu et al [2]. Hamaker et al. explored the effects of adding non-Euclidcan distance measures to the basic AIRS algorithm using four well known publicly available classification problems having various proportions of real, discrete, and nominal features [3]. Watkins et al. revisited the Artificial Immune Recognition System (AIRS) that has been developed as an immune-inspired supervised learning algorithm and discussed certain unnecessary complications of the original algorithm [4].

Sleep Apnea Syndrome is a very common sleep disorder among public. Obstructive Sleep Apnea is a syndrome characterized by reduced oxygen saturation and repeated upper respiratory tract obstruction episodes during full night sleep.

SAS is considered as clinically relevant when the breath stops during more than 10 seconds and take places more than five times per sleep hour. These non breathing episodes can sometimes recur more than 300 times a night. Health studies confirm that more than 30 of these non breathing episodes per night should be taken into account as abnormal. There exist two types of apneic events that may cause insufficient pulmonary ventilation during sleep, Apnea and Hypopnea. Apnea is defined as the total absence of airflow, followed by the reduction of oxygen levels in arterial blood. The term hypopnea is used when the breath doesn't stop but decrease over 50% of its normal value, followed by the reduction of oxygen levels in arterial blood [5-7].

There are some works related to diagnosis and

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screening of OSAS in literature. Among these, ALL-ANI et al. used artificial neural network and signals of respiratory and cardiac activities (Nasal Airway Flow (NAF) and Pulse Transit Time (PTT)) issued by the technique of PolySomnoGraphy (PSG) to diagnose OSAS [7]. The combination of Sample Entropy Approach and Heart Rate Variability were used to detect the OSAS by Al-Angari et al. and obtained 72.9% classification accuracy [8]. Campo et al. assessed the validity of approximate entropy (ApEn) analysis of arterial oxygen saturation (SaO2) data obtained from pulse oximetric recordings as a diagnostic test for obstructive sleep apnea (OSA) in patients clinically suspected of suffering this disease [9]. Kwiatkowska et al. assessed the obstructive sleep apnea syndrome using Pulse Oximetry and Clinical Prediction Rules with a fuzzy logic approach [10].

In this study, we have determined both the degree of OSA disease including mild OSA, middle OSA, and heavy OSA that determined according to specialist's aspects and important symptoms about OSA disease via Polysomnography device. These important symptoms are Arousals Index (ARI), AHI (Apnea and Hypoapnea Index), SaO2 minimum value in stage of REM, and Percent Sleep Time (PST) in stage of SaO2 intervals bigger than 89%. The OSA disease was diagnosed using pairwise AIRS based on AIRS classifier and OVO. While AIRS algorithm obtained 90.24% classification accuracy, the proposed method based on AIRS algorithm and OVO achieved 98.24% classification accuracy using two fold cross validation. Motivated by the above idea, in the present study, AIRS with one versus one can be used as a possible diagnostic tool for OSA syndrome.

II. MATERIAL

A. Subjects and Polysomnography Device

We have studied on the 83 subjects (59 men and 24 women) who were referred as clinical suspicion of OSAS. The patients were sequentially recruited from the outpatient clinic. Subjects varied in age from 17 to 83 years, with an average age of 49 years. The mean body mass index (BMI) was 36.83 kg/m2. The patients are normal subjects (25 persons), mild OSAS (14 persons), moderate OSAS (18 persons), and serious OSAS (26 persons). The Review Board on Human Studies at our institution approved the protocol, and each patient gave his or her informed consent to participate in the study. Table 1 presents the statistical measures of used clinical features and characteristics. In this table, the mean values, standard deviation, variance, and p value of used clinical characteristics and clinical features obtained from Polysomnography device have been given to explain the importance of used features.

Polysomnography device is a diagnostic tool during which a number of physiologic variables are measured and recorded during sleep [11]. However, Polysomnography is an invasive method. All sleep studies were performed in our Sleep Unit, regularly from midnight to 8 a.m. Patients were evaluated after a single-night pulse oximetry recording obtained from nocturnal pulse oximetry connected to a simultaneous polysomnographic study. This technique included continuous monitoring using a polygraph and included electroencephalogram (EEG), electrooculogram (EOG), chin electromyogram (EMG), air flow, electrocardiogram (ECG) and measurement of chest wall movement [11].

The polysomnographic reports were examined in periods of each 30 s of night sleep and during stages 1-3 and REM agreement with the Rechtschaffen and Kales method [12]. Apnea was explained as the absence of airflow for more than 10 s [13], and hypopnea as the reduction of respiratory flow ≥50% attached by a 3% or more decrease in the saturation of hemoglobin [14]. The average of apnea-hypopnea index (AHI) was computed in hourly samples of sleep [9, 15, 17].

III. THE PROPOSED METHOD

In this work, in order to improve the classification performance of AIRS classifier, we have combined the AIRS classifier with one versus one approach and applied to diagnosis of disorder degree of OSAS which is a real-world application and is also important disease among public. In this way, pairwise AIRS structure is proposed and shown its superiority. Figure 1 shows the block diagram of this combination method. We have used majority voting scheme to combine the results obtained from pairwise AIRS models.

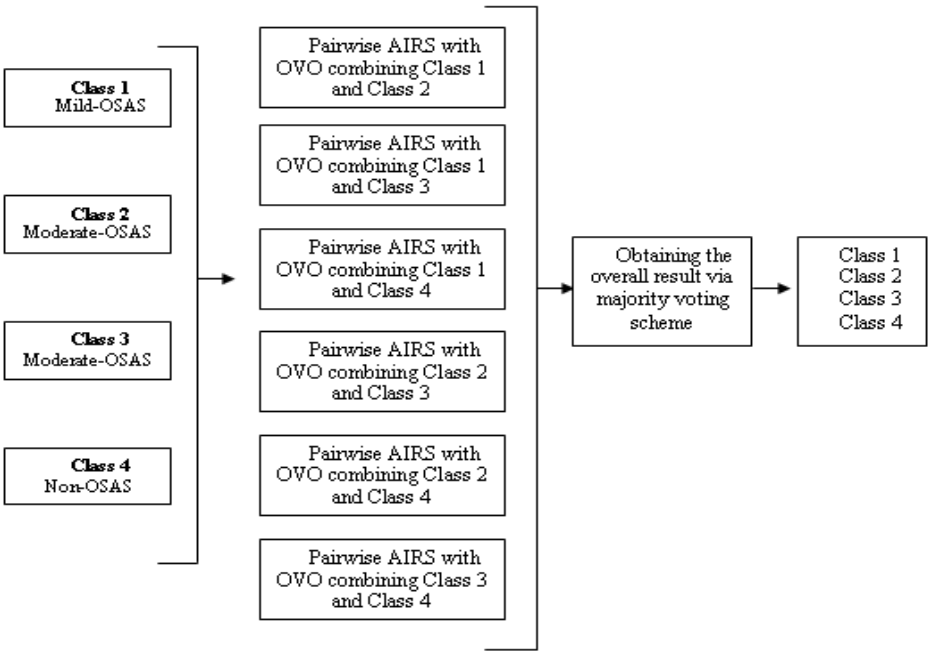

Fig.1. The block diagram of proposed method

Table 1. The statistical measures and values of used clinical features and characteristics

The used features		**Non-OSAS**	**Mild OSAS**	**Moderate OSAS**	**Serious OSAS**
Clinical characteristics	Age (years)	From 17 to 70 Mean: 49 Variance: 152.86 Std. Dev.: 12.36 p value: >0.05	From 31 to 63 Mean: 47 Variance: 79.05 Std. Dev.: 8.89 p value: >0.05	From 36 to 67 Mean: 50 Variance: 73.19 Std. Dev.:8.55 p value: >0.05	From 17 to 83 Mean: 51 Variance: 142.03 Std. Dev.:11. 917 p value: >0.05
	BMI (kg/m^2)	Mean: 30.85 Variance: 33.31 Std. Dvt.: 5.77 p value: >0.05	Mean: 33.49 Variance: 135.75 Std. Dvt.: 11.65 p value: >0.05	Mean: 48.58 Variance: 50.31 Std. Dvt.: 7.09 p value: >0.05	Mean: 32.4 Variance: 39.315 Std. Dvt.: 6.27 p value: >0.05
Clinical features obtained from Polysomnography device	Arousals Index (ARI)	Mean: 24.666 Variance: 296.26 Std. Dvt.: 17.21 p value: >0.05	Mean: 54.929 Variance: 466.69 Std. Dvt.: 21.60 p value: <0.05	Mean: 126.4 Variance: 3236.4 Std. Dvt.: 56.88 p value: <0.05	Mean: 270 Variance: 18412 Std. Dvt.: 134.69 p value: <0.05
	AHI (Apnea and Hypoapnea Index)	Mean: 4.05 Variance: 5.01 Std. Dvt.: 2.23 p value: >0.05	Mean: 12 Variance: 9.32 Std. Dvt.: 3.05 p value: >0.05	Mean: 26.67 Variance: 100.69 Std. Dvt.: 10.03 p value: <0.05	Mean: 61.869 Variance: 367 Std. Dvt.: 19.15 p value: <0.05
	SaO_2 minimum value in stage of REM	Mean: 87.24 Variance: 46.20 Std. Dvt.: 6.79 p value: >0.05	Mean: 87.214 Variance: 17.10 Std. Dvt.: 4.13 p value: <0.05	Mean: 79.33 Variance: 206.67 Std. Dvt.: 14.37 p value: <0.05	Mean: 71.52 Variance: 238.09 Std. Dvt.: 15.45 p value: <0.05
	Percent Sleep Time (PST) in stage of SaO_2 intervals bigger than 89%	Mean: 94.81 Variance: 112.67 Std. Dvt.: 10.61 p value: >0.05	Mean: 82.84 Variance: 528.71 Std. Dvt.: 22.99 p value: <0.05	Mean: 77.62 Variance: 572.73 Std. Dvt.: 23.93 p value: >0.05	Mean: 28.312 Variance: 232.24 Std. Dvt.: 15.23 p value>0.05

*Note: Std. Dev. means standard deviation,

A. AIRS Classification Algorithm: Classification stage

AIRS is a supervised classification algorithm and uses the resource competition, clonal selection, affinity maturation and memory cell formation. The feature vectors presented for training and testing process are called as Antigens while the system units are called as B cells. Similar B cells are represented by Artificial Recognition Balls (ARBs) and these ARBs compete with each other for a fixed resource number. The memory cells formed after the whole training Antigens were presented are used to classify test Antigens. The AIRS algorithm consisted of four stages, which are initialization, memory cell identification and ARB generation, competition for resources and development of a candidate memory cell, and memory cell introduction [1]. Figure 2 shows the training and testing phases of AIRS classification algorithm. For more detailed information about AIRS, the reader is referred to [1], [16].

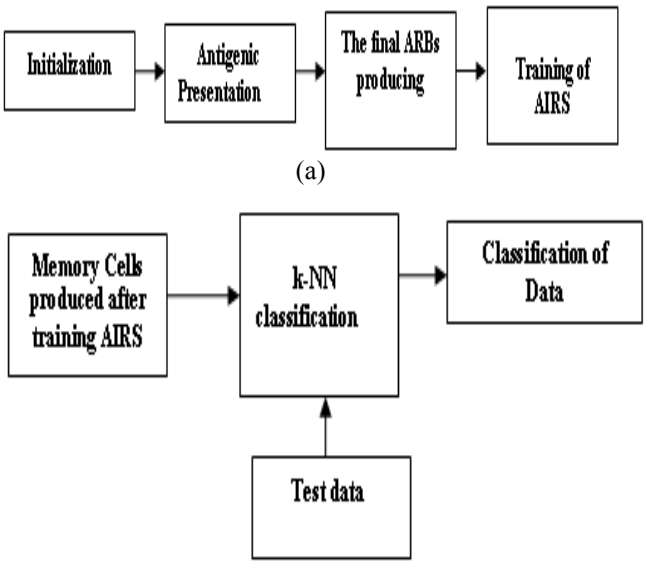

Fig.2. The training (a) and testing (b) phases of AIRS classification algorithm

IV. The Empirical Results and Discussion

In this study, we have used two fold cross validation to split OSAS dataset and also used the classification accuracy, sensitivity-specifity analysis, and confusion matrix to evaluate the performance of proposed method.

The obstructive sleep apnea syndrome was diagnosed using AIRS with one versus one method. In the diagnosing of OSAS, we have used the clinical features including Arousals Index (ARI), AHI (Apnea and Hypoapnea Index), SaO2 minimum value in stage of REM, and Percent Sleep Time (PST) in stage of SaO2 intervals bigger than 89% obtained from Polysomnography device records. These clinical features were selected using the correlation among all the clinical features obtained from Polysomnography Reports. Pairwise AIRS with one versus one method have been used to diagnose the normal (healthy) subjects without OSA and patients suffering from OSA (patients have degrees including mild OSA, middle OSA, and heavy OSA). There are four classes consisting of normal (25 subjects), mild OSAS (AHI=5-15 and 14 subjects), middle OSAS (AHI=15-30 and 18 subjects), and heavy OSAS (AHI>30 and 26 subjects).

While AIRS classifier alone obtained 90.24% classifier accuracy in the diagnosis of OSAS, pirwise AIRS with OVO achieved success rate with 98.24%. These obtained results are obtained using two fold cross validation. The obtained results are shown in Table 2.

Table 2. The obtained classification accuracies and sensitivity and specificity values from the proposed method and AIRS classifier on the diagnosis of obstructive sleep apnea syndrome using two fold cross validation

Method	Class 1 Mild-OSAS	Class 2 Moderate-OSAS	Class 3 Serious-OSAS	Class 4 Non-OSAS
AIRS	Accuracy (%): 95.12 Sensitivity (%): 94.11 Specificity (%): 100	Accuracy (%): 100 Sensitivity (%):100 Specificity (%): 100	Accuracy (%): 100 Sensitivity (%):100 Specifity (%): 100	Accuracy (%): 95.12 Sensitivity (%): 93.54 Specificity (%):100
	Overall Classification Accuracy (%)	%90.24		
Pairwise AIRS with OVO	Accuracy (%): 96.36 Sensitivity (%): 94.45 Specificity (%):100	Accuracy (%): 100 Sensitivity (%):100 Specificity (%): 100	Accuracy (%): 100 Sensitivity (%):100 Specificity (%): 100	Accuracy (%): 100 Sensitivity (%):100 Specificity (%): 100
	Overall Classification Accuracy (%)	%98.24		

These results have shown that the combination of AIRS and one versus one has produced very promising results on the determining of disorder degree of obstructive sleep apnea syndrome including mild-OSAS, moderate-OSAS, serious-OSAS, and non-OSAS. In this study, we have also shown the superiority of the proposed method comparing the AIRS classifier in the case of both multi class dataset and real-world application dataset.

V. Conclusions and Future Work

In this paper, a novel pairwise classifier based on AIRS classifier and one versus one model is proposed to determine the disorder degree of OSAS which is important disease among public and has four classes including as normal subjects, mild OSAS, moderate OSAS, and serious OSAS. The proposed method has obtained better results than AIRS classifier on the diagnosis of OSAS. The obtained results have implied that the proposed method could also be used in classification of multi class datasets. In future, instead of one versus one approach, the one against all and half against half approaches could be used in the constructing of pairwise classifier. This method can help to clinicians in the stage of medical decision making on the diagnosis of OSAS.

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