AN IMPROVED APPROACH FOR REAL-TIME DETECTION OF SLEEP APNEA

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Abstract: The traditional diagnosis of sleep apnea and hypopnea syndrome (SAHS) requires an expensive and complex overnight procedure called polysomnography (PSG). Recently, finding valid alternatives for SAHS diagnosis has attracted much research attention. This paper focuses on the real-time monitoring and detection of SAHS based on the arterial oxygen saturation signal measured by pulse oximetry (SpO_2). We develop a more comprehensive feature set and a more appropriate annotation criterion, if compared to the existing approaches in the literature. To enjoy competitiveness in computational complexity, we also propose a reduced feature set which provides a higher sensitivity and better adaptivity to distinct databases. The performances of 15 commonly used classifiers with different cost matrixes are assessed on different databases, offering detailed insights on the diagnostic abilities of these methods.

1 INTRODUCTION

Sleep apnea and hypopnea syndrome (SAHS) is a common sleep disorder which is estimated to affect 2% of middle-aged women and 4% of middle-aged men (Young et al., 1993). The impacts of SAHS include daytime sleepiness, fatigue, traffic accidents and depression. It is also blamed for linkage to ischemic heart disease, cardiovascular disfunction and stroke. The clinical definition of apnea involves a cessation of airflow for at least 10 seconds while hypopnea is defined as a minimum 10-second airflow reduction with either a blood oxygen desaturation of 4% or a neurological arousal (Magalang et al., 2003). Currently, polysomnography (PSG) is regarded as the golden standard for SAHS diagnosis. However, PSG requires patients to sleep overnight in a sleep laboratory with attended technicians. A variety of recorded signals are then analyzed by sleep specialists for final diagnosis. The time- and cost-consuming natures of PSG limit the its prevalence among public, which makes a readily available, relatively inexpensive and reliable diagnosis alternative much desirable. Existing SAHS detection techniques have been developed based on questionnaires (Netzer et al., 1999), ECG (McNames and Fraser, 2000, Shinar et al., 2000, Heneghan et al., 2008), snoring (Ng et al., 2006) and pulse oximetry (Magalang et al., 2003, Lévy et al., 1996, Olson et al., 1999, Zamarrón et al., 2003, Alvarez et al., 2006, Oliver and Flores-Mangas, 2006, Heneghan et al., 2008, Burgos et al., 2009), either alone or in combination. Due to the strong reflection of arterial oxygen saturation on the airflow fluctuation and the convenience and availability of pulse oximetries, we focus on SpO_2 signal in this paper for SAHS detection strategy.

Previous studies have proposed many quantitative indexes derived from SpO_2 signal for SAHS detection. Among the commonly used time-domain indexes are the accumulative time spent below an a certain saturation level (Magalang et al., 2003, Olson et al., 1999), the oxygen desaturation index (ODI, the number of oxyhemoglobin desaturation below a certain threshold) (Magalang et al., 2003), and the saturation variability index (Delta index) (Magalang et al., 2003, Lévy et al., 1996, Olson et al., 1999). Besides, Zamarrn et al. (2003) exploited the periodogram of SpO_2 signal and discovered that the period 30s to 70s is the interval of interest (P_{30-70}). The four indexes are related to the periodogram as the total area under periodogram, the area enclosed in the periodogram within P_{30-70}, the area ratio of that within P_{30-70} with respect to the total periodogram area, and the peak amplitude of the periodogram in P_{30-70}, respectively. Later on, several non-linear parameters such as approximate entropy (ApEn), central tendency measure (CTM) and Lempel-Ziv complexity (LZC) are also derived from the SpO_2 signal as the indexes for SAHS detection (Alvarez et al., 2006).

However, all the methods mentioned above perform in the context of the overnight SpO_2 records, rendering a delayed off-line analysis and diagnosis. Recently, the idea of real-time SAHS monitoring and diagnosis is proposed as a promising alternative of PSG. The work in (Oliver and Flores-Mangas, 2006) introduces the real-time implementation of SAHS detection but lacks of a performance comparison with the standard PSG detection. Heneghan et al. (2008) adopt the ECG and SpO_2 signals jointly to estimate the apnea plus hypopnea index (AHI) on an epoch basis. Most recently, Burgos et al. (2009) implement a systematic real-time SAHS detection based on the *Apnea-ECG database* (Apn, ny) available online from PysioNet (Goldberger et al., 2000), attaining a classification accuracy of 93.03%, sensitivity of 92.35% and specificity of 93.52%, upon specified training and testing sets. Unfortunately, this database contains only 8 recordings with SpO_2 signal. The limited sample number casts doubts on the adaptivity and robustness of the approach proposed in (Burgos et al., 2009).

In this paper, we first implemented the method in (Burgos et al., 2009) (labeled as *RT* for short) on another database *St. Vincent's University Hospital / University College Dublin Sleep Apnea Database* (*UCD Database*) (UCD, ny) which can also be found on *PysioNet*. Though *RT* method gets a specificity of 96.04% and accuracy of 89.86%, the sensitivity drops dramatically to 33.82%, which is far from satisfactory. For the purpose of SAHS detection, we would rather misclassify one healthy person as SAHS positive, than let one SAHS patient go unidentified. High sensitivity is preferable over high specificity in this case. With this recognition, our paper offers contributions in the following aspects: (1) Conversion of most of the existing indexes into epoch-based (1-minute based) features. (2) Forming a more comprehensive feature set of SpO_2 signal with higher sensitivity. (3) Proposal of a more appropriate criterion of segment annotations. (4) Proposal of a reduced feature set with better diagnostic ability and computational efficiency. (5) Validation of the performance of the proposed approach on two distinct databases. (6) The performance assessment of 15 classifiers with different cost-sensitivities upon two databases.

The rest of the paper is organized as follows: In Section 2, we introduce the two databases used and explain the new approach in feature extraction. Section 3 describes the experiments and discusses the results. Finally, Section 4 concludes this paper.

2 NEW INVESTIGATIONS

2.1 Database Description

PysioNet provides a variety of physiological signals for biomedical research. Both databases we used are available from the web site, which offer easy validation and assessment of our approach.

- *Apnea-ECG database:* This database contains 8 recordings with SpO_2 signals. Associated with each signal is a reference annotation file created by a sleep expert based on simultaneously recorded respiration and oxygen saturation signals. The annotation is given on a 1-minute basis. Each minute is labeled as '*A*' when apnea was in progress at the beginning of the associated minute, otherwise this minute is label as '*N*'. We name this annotation definition as *AN* for short. To make use of this kind of annotation, the real-time monitoring system is designed to give the detection result minute by minute.
- *UCD database:* This database comprises of 25 full overnight PSG recordings, and each contains an SpO_2 signal in addition to other signals. The annotations are prepared by sleep technologists who detailed the onset time and duration of every apnea and hypopnea event. In order to define the reference annotation on a 1-minute basis, two labeling criteria are used. One is applying the same technique in *Apnea-ECG database*. Considering that the apnea and hypopnea associate with a minimum of 10 second airflow change, in case the events straddle two adjacent segments, the other one marks a single minute as '*Apnea*' if it contains at least 5 consecutive apnea and hypopnea events, otherwise this minute is labeled as '*No apnea*'. This criterion is termed as *AHI5C* in the following.

2.2 Signal Processing

The SpO_2 signals from both databases are downsampled at 1 Hz and the outliers lay in [0, 50%] are removed to avoid outfitting. In the interest of inheriting the merits of existing indexes of the SpO_2, we device to modify the indexes and incorporate them in the real-time detection method. To begin with, the SpO_2 signals are segmented into 1-minute epochs. Then, processings to get the values of the existing indexes are applied to the data within each epoch. For example, the ODI indexes, apart from the ones in (Burgos et al., 2009), set the baseline as the mean of the top 20% of the SpO_2 data within one minute, then sum up the number of samples which fall below it. As a result, the features ODI2, ODI3, ODI4, and ODI5 represent the ODI indexes corresponding to 2%, 3%, 4%, and 5% below of the baseline, respectively. Delta index is viewed as a valid parameter for overnight SAHS detection. To transplant it in our real-time processing, the minimal SpO_2 value in every 12-second interval is picked and the Delta index is derived as the sum of the absolute differences between two successive dips, dividing by the number of intervals, i.e. 5, in one minute. The nonlinear methods such as ApEn, CTM, and LZC can also be easily applied segmentally. In particular, radii of 0.25, 0.5, 0.75 and 1 are selected corresponds the CTM25, CTM50, CTM75, CTM100 features, respectively.

Since the apnea/hypopnea event can last as long as 120 seconds (Oliver and Flores-Mangas, 2006), which exceeds the epoch length, we rule out the frequency-domain indexes in our real-time processing and focus on the ones derived directly from the time-domain recordings.

Combined with the 9 features used in (Burgos et al., 2009), a more comprehensive feature set (labeled as *ALL*) is formed containing 20 features in all. Classification experiments and further feature selection are carried out based on this feature set in the following section.

3 Experiment and Result Discussion

We use weka (Hall et al., 2009), an open source machine learning software as the major tool to assess the performances of 15 classic classification algorithms with their default parameter setting. Besides the Bagging with ADTree suggested in (Burgos et al., 2009), Bagging with REPTree, Support Vector Machine (SVM), Naive Bayes, Multilayer Perceptron (MLP), Radial Basis Function Network (RBFNetwork), Decision Stump, J48 (C4.5) tree and so on are all tested to find out the most appropriate candidates for real-time SAHS detection. All the classification performances, namely, the sensitivity, specificity and accuracy are based on 10-fold cross validations for a more accurate evaluation.

3.1 Comparison between Two Databases

To begin with, we take a look at the performance comparison between the two feature sets, *RT* and *ALL*, using the Bagging with ADTree algorithm recommended by Burgos et al. (2009). The annotation criterion of *Apnea-ECG database*, i.e. *AN*, is applied to *UCD Database* as well. Table 1 lists the results indicating that the *ALL* set achieves a slightly better performance than the *RT* set in *Apnea-ECG database*. On the other hand, for the *UCD Database*, the sensitivity of the *ALL* set increases about 10% over that of the *RT* set, but a sensitivity of 43.07% is still not acceptable for our detection purpose.

3.2 Comparison between Two Annotation Criteria

The second experiment is conducted using the two annotation criteria: *AN* and *AHI5C* on *UCD Database*. The classification results of 15 classifiers are recorded in Table 2 and 3, respectively. Comparing the two tables, it is clear that the *AHI5C* improves the sensitivity to a large extent when compared to the *AN* annotation scheme for both feature sets among all classifiers. Within each table, generally, the *ALL* set obtains a further sensitivity increase over that of the *RT* set.

To enhance the detection sensitivity even more, cost matrixes can be used to suppress the false negative errors. Two cost matrixes, which penalize the weight of the false negatives twice (*Cost Sensitive (2)*) and five times (*Cost Sensitive (5)*) as the one of the false positives, are adopted in cost-sensitive classification experiments. Comparing Table 3 and the gray area and white area of Table 4, which correspond to an even cost, Cost Sensitive (2) and Cost Sensitive (5) experiments, it is verified that sensitivity increases as the weights of the false negatives are added. However, the specificity is compromised as sensitivity goes higher. A trade-off exists between them. The overall accuracy also depends on the proportion of the Apnea/hypopnea minutes in one recording. Say, if a severe SAHS patient with a great proportion of Apnea/hypopnea event undergoes in the test, the high sensitivity schemes lead to a high accuracy, and vice versa. Using the *ALL* feature set, among the 15 classifiers, the Decision Stump and the RBFNetwork seem to be the best candidates which have balanced sensitivity and accuracy around 80% under *Cost Sensitive (2)*. In the case of *Cost Sensitive (5)*, except the Naive Bayes, the Random Tree, the Random Forest and the Decorate tree with J48, other classifiers all obtain sensitivities and accuracies higher than 78%.

3.3 Feature Selection

Previous experiments demonstrate the advantages of the *ALL* set over the *RT* set in sensitivity; nevertheless, the *ALL* set incorporates the features in the *RT* set, potentiating a more complicated and time-consuming classification process, which may undermine the superiority of real-time monitoring. To improve the efficiency, we perform feature selection using the Wrapper Subset Evaluation. A 3-feature set (*S3*) consisting of Delta index, ODI3, and CTM50 is selected due to its strongest diagnostic ability.

3.4 Comparison between the Reduced Feature Set *S3* and *RT*

To offer a more well-rounded assessment of the two feature sets as well as different algorithms, the CPU time (in minutes) spent for training and testing during the 10-fold cross validations are also included. Note that even with a smaller feature number, 3, the *S3* set obtains a higher sensitivity and a comparable or better overall accuracy than the *RT* set of 8 features, as can be seen in Table 5. In terms of computational complexity, for most of the classifiers, using the *S3* feature set reduces the CPU time sometimes more than one half of that using the *RT* set. However, the SVM classifier appears to be an exception. The reason of this exception can be explained as below. The computational complexity of SVM depends on the number of the support vectors (N_{sv}). For some specific algorithm, such as Bunch-Kaufman training algorithm , the complexity ranges from $O(N_{sv}^3 + LN_{sv}^2 + dLN_{sv})$ to $O(dL^2)$ (Burges, 1998), where d is the number of dimensions, L is number of training sequences. In this case, the *S3* feature set may generate more support vectors than the *RT* set does, resulting in the increase of the complexity, but also provides a higher sensitivity.

Additionally, the performances of the *RT* and *S3* feature set based on the *Apnea-ECG database* are also investigated. As shown in Table 6, the *S3* set outperforms the *RT* set as well, even if the *AN* annotation is used in this database. This result lends evidence to the adaptivity and high diagnostic ability of the *S3* feature set.

Since we are more interested in the sensitivity and the overall accuracy, and usually the training time plays a major role in determining the overall classification process, we omit the specificity and CPU time for testing in the following tables of the cost-sensitive results to save space. It is observed that applying the cost matrix improves the sensitivity without too much changes in computational complexity.

Table 1: Performance of RT and ALL feature sets using Bagging with ADTree with AN annotation.

	Apnea-ECG Database		UCD Database	
	RT(%)	All(%)	RT(%)	All(%)
Sensitivity	93.66	94.03	33.82	43.07
Specificity	95.97	95.81	96.04	94.39
Accuracy	94.91	94.99	89.96	89.30

Table 2: Performance of RT and ALL feature sets using different classifiers with AN annotation for UCD Database.

	Sensitivity		Specificity		Accuracy	
Classifier	RT	ALL	RT	ALL	RT	ALL
SVM	0.00	0.16	1.00	0.98	0.90	0.90
RandomTree	0.24	0.31	0.96	0.92	0.89	0.86
J48 trees	0.11	0.23	0.98	0.97	0.90	0.90
NaiveBayes	0.34	0.61	0.94	0.88	0.88	0.85
Bagging.REPTree	0.18	0.22	0.98	0.98	0.90	0.90
Bagging.ADTree	0.18	0.06	0.98	0.99	0.90	0.90
MLP	0.17	0.27	0.98	0.97	0.90	0.90
FT trees	0.16	0.22	0.98	0.97	0.90	0.90
RandomForest	0.19	0.17	0.97	0.98	0.89	0.90
RBFNetwork	0.09	0.00	0.99	1.00	0.90	0.90
Decorate trees.J48	0.17	0.21	0.98	0.98	0.90	0.90
ADTree	0.25	0.10	0.97	0.99	0.90	0.90
REPTree	0.15	0.18	0.98	0.98	0.90	0.90
DecisionStump	0.00	0.00	1.00	1.00	0.90	0.90
SimpleCart	0.20	0.28	0.97	0.96	0.89	0.89

Evaluating the sensitivity, the overall accuracy and the complexity all together, within the scope of *UCD Database*, under the *Cost Sensitive (2)*, the Decision Stump and the RBFNetwork with the *S3* set are good options for apnea detection, as can be seen in Table 7. In the *Cost Sensitive (5)* case, the Decision Stump, RERTree, ADTree, RBFNetwork, J48 are all good choices if the *S3* set is adopted. According to Table 8, for *Apnea-ECG database*, maybe due to the size of the records and statistical properties of the data, all classifiers work generally well in terms of accuracy and sensitivity. We can then choose the classifier based on the UserCPU time accordingly.

4 CONCLUSIONS

This paper provides improvements to the existing methods of real-time SpO_2 signal monitoring and SAHS detection in terms of a more comprehensive feature set and a more appropriate segment annotation criterion with a higher classification sensitivity. Furthermore, a feature selection technique is employed to find out a reduced feature set which only comprise of 3 indexes, namely, the Delta index, ODI3 and the CTM50. The reduced feature set not only lowers the computational complexity, but also enjoys a

Table 4: Performance of RT and ALL feature sets using cost sensitive different classifiers with AHI5C annotation for UCD Database, gray area corresponds to Cost Sensitive (2), and white area corresponds to Cost Sensitive (5).

Classifier	Sensitivity(RT)		Sensitivity(All)		Specificity(RT)		Specificity(All)		Accuracy(RT)		Accuracy(All)	
SVM	0.52	0.66	0.72	0.87	0.90	0.77	0.85	0.72	0.81	0.81	0.81	0.81
RandomTree	0.52	0.67	0.57	0.56	0.88	0.75	0.85	0.86	0.78	0.78	0.78	0.78
J48 trees	0.61	0.83	0.69	0.84	0.87	0.69	0.84	0.71	0.81	0.81	0.81	0.81
NaiveBayes	0.40	0.43	0.63	0.65	0.96	0.95	0.91	0.90	0.81	0.81	0.84	0.84
Bagging.REPTree	0.64	0.81	0.73	0.84	0.86	0.70	0.86	0.76	0.80	0.80	0.82	0.82
Bagging.ADTree	0.60	0.82	0.76	0.88	0.89	0.71	0.84	0.71	0.82	0.82	0.82	0.82
MLP	0.62	0.81	0.73	0.87	0.86	0.68	0.86	0.72	0.80	0.80	0.83	0.83
FT trees	0.64	0.82	0.68	0.79	0.86	0.70	0.84	0.73	0.80	0.80	0.80	0.80
RandomForest	0.58	0.75	0.64	0.73	0.86	0.74	0.89	0.84	0.79	0.79	0.83	0.83
RBFNetwork	0.51	0.66	0.82	0.87	0.90	0.78	0.77	0.72	0.80	0.80	0.78	0.78
Decorate trees.J48	0.61	0.82	0.64	0.70	0.87	0.69	0.85	0.80	0.80	0.80	0.79	0.79
ADTree	0.59	0.82	0.74	0.89	0.90	0.70	0.85	0.70	0.82	0.82	0.82	0.82
REPTree	0.64	0.82	0.73	0.88	0.85	0.69	0.85	0.69	0.80	0.80	0.82	0.82
DecisionStump	0.59	0.59	0.81	0.84	0.87	0.87	0.79	0.75	0.80	0.80	0.80	0.80
SimpleCart	0.63	0.81	0.68	0.79	0.85	0.71	0.83	0.73	0.80	0.80	0.79	0.79

Table 5: Performance of RT and S3 feature sets using different classifiers with AHI5C annotation for UCD Database.

	Sensitivity		Specificity		Accuracy		CPU Time Training		CPU Time Testing	
Classifier	RT	S3	RT	S3	RT	S3	RT	S3	RT	S3
SVM	0.24	0.59	0.99	0.91	0.79	0.83	4.8295	7.2387	0.4396	0.4066
RandomTree	0.41	0.57	0.94	0.86	0.81	0.79	0.0577	0.0750	0.0005	0.0007
J48 trees	0.47	0.60	0.95	0.92	0.83	0.84	0.0918	0.0489	0.0005	0.0008
NaiveBayes	0.38	0.65	0.96	0.90	0.81	0.84	0.0154	0.0077	0.0049	0.0032
Bagging.REPTree	0.49	0.60	0.94	0.91	0.83	0.84	0.4310	0.3103	0.0013	0.0022
Bagging.ADTree	0.53	0.58	0.93	0.93	0.82	0.84	4.4422	1.7258	0.0076	0.0073
MLP	0.48	0.57	0.94	0.93	0.82	0.84	11.9256	4.5718	0.0022	0.0011
FT trees	0.47	0.59	0.94	0.92	0.82	0.84	1.0506	0.8379	0.1581	0.0404
RandomForest	0.45	0.55	0.93	0.89	0.81	0.80	0.5621	0.6591	0.0033	0.0038
RBFNetwork	0.45	0.57	0.93	0.93	0.81	0.84	0.3250	0.2916	0.0056	0.0041
Decorate trees.J48	0.47	0.61	0.94	0.91	0.82	0.84	3.7413	1.9616	0.0019	0.0009
ADTree	0.53	0.58	0.92	0.93	0.82	0.84	0.4673	0.1850	0.0006	0.0011
REPTree	0.48	0.60	0.94	0.92	0.82	0.84	0.0413	0.0299	0.0002	0.0007
DecisionStump	0.59	0.81	0.87	0.79	0.80	0.80	0.0137	0.0068	0.0008	0.0005
SimpleCart	0.48	0.57	0.93	0.90	0.82	0.82	0.7726	0.9300	0.0013	0.0009

Table 6: Performance of RT and S3 feature sets using different classifiers with AN annotation for Apnea-ECG database.

	Sensitivity		Specificity		Accuracy		CPU Time Training		CPU Time Testing	
Classifier	RT	S3	RT	S3	RT	S3	RT	S3	RT	S3
SVM	0.90	0.94	0.94	0.94	0.92	0.94	0.3670	0.5009	0.0365	0.0345
RandomTree	0.91	0.90	0.94	0.94	0.93	0.92	0.0171	0.0128	0.0002	0.0003
J48 trees	0.93	0.95	0.96	0.94	0.95	0.95	0.0307	0.0111	0.0003	0.0003
NaiveBayes	0.83	0.96	0.96	0.91	0.90	0.94	0.0054	0.0025	0.0015	0.0007
Bagging.REPTree	0.94	0.95	0.95	0.94	0.95	0.94	0.1204	0.0591	0.0002	0.0006
Bagging.ADTree	0.94	0.95	0.96	0.94	0.95	0.94	1.3038	0.5981	0.0035	0.0019
MLP	0.93	0.96	0.96	0.93	0.94	0.94	4.0764	1.5718	0.0005	0.0005
FT trees	0.93	0.94	0.96	0.95	0.94	0.95	0.3584	0.223	0.0346	0.013
RandomForest	0.93	0.92	0.96	0.95	0.94	0.93	0.1486	0.1181	0.0008	0.0008
RBFNetwork	0.88	0.94	0.96	0.93	0.92	0.94	0.1303	0.0981	0.0022	0.0013
Decorate trees.J48	0.92	0.94	0.95	0.94	0.94	0.94	1.2263	0.5012	0.0008	0.0004
ADTree	0.93	0.94	0.96	0.95	0.95	0.94	0.1378	0.0606	0.0002	0.0002
REPTree	0.94	0.95	0.95	0.94	0.95	0.94	0.0126	0.0061	0.0002	0.0003
DecisionStump	0.91	0.94	0.96	0.90	0.94	0.92	0.0055	0.0018	0.0002	0.0003
SimpleCart	0.93	0.94	0.95	0.94	0.94	0.94	0.1989	0.1434	0.0002	0.0002

Table 7: Performance of RT and S3 feature sets using cost sensitive different classifiers with AHI5C annotation for UCD Database, gray area corresponds to Cost Sensitive (2), and white area corresponds to Cost Sensitive (5).

Classifier	Sensitivity(RT)		Sensitivity(S3)		Accuracy(RT)		Accuracy(S3)		CPUT. Training(RT)		CPUT. Training(S3)	
SVM	0.52	0.66	0.75	0.87	0.81	0.74	0.84	0.76	5.7517	7.0192	9.0884	9.5365
RandomTree	0.52	0.67	0.56	0.56	0.78	0.73	0.78	0.77	0.0575	0.0566	0.0755	0.0759
J48 trees	0.61	0.83	0.72	0.87	0.81	0.72	0.82	0.75	0.0917	0.0842	0.0590	0.0589
NaiveBayes	0.40	0.43	0.69	0.73	0.81	0.81	0.84	0.83	0.0159	0.0156	0.0081	0.0088
Bagging.REPTree	0.64	0.81	0.73	0.84	0.80	0.73	0.82	0.77	0.4396	0.4297	0.3321	0.3107
Bagging.ADTree	0.60	0.82	0.73	0.88	0.82	0.73	0.82	0.75	4.5216	4.4795	1.7380	1.7005
MLP	0.62	0.81	0.73	0.88	0.80	0.72	0.82	0.75	11.9846	11.9186	4.5610	4.5643
FT trees	0.64	0.82	0.72	0.88	0.80	0.73	0.83	0.75	1.0545	1.1292	0.9349	0.9794
RandomForest	0.58	0.75	0.63	0.71	0.79	0.74	0.79	0.77	0.5643	0.5560	0.6817	0.6603
RBFNetwork	0.51	0.66	0.81	0.86	0.80	0.75	0.80	0.77	0.3382	0.3401	0.3080	0.2930
Decorate trees.J48	0.61	0.82	0.72	0.84	0.80	0.73	0.82	0.76	4.3842	4.4547	1.9924	3.1778
ADTree	0.59	0.82	0.72	0.88	0.82	0.73	0.82	0.74	0.4611	0.4672	0.1817	0.1832
REPTree	0.64	0.82	0.73	0.87	0.80	0.73	0.82	0.75	0.0378	0.0370	0.0285	0.0288
DecisionStump	0.59	0.59	0.81	0.84	0.80	0.80	0.80	0.77	0.0128	0.0148	0.0065	0.0078
SimpleCart	0.63	0.81	0.68	0.80	0.80	0.73	0.79	0.74	0.7533	0.6710	1.0750	0.9569

Table 8: Performance of RT and S3 feature sets using cost sensitive different classifiers with AN annotation for Apnea-ECG database, gray area corresponds to Cost Sensitive (2), and white area corresponds to Cost Sensitive (5).

Classifier	Sensitivity(RT)		Sensitivity(S3)		Accuracy(RT)		Accuracy(S3)		CPUT. Training(RT)		CPUT. Training(S3)	
SVM	0.93	0.94	0.95	0.96	0.92	0.92	0.94	0.92	0.3719	0.3266	0.5186	0.4751
RandomTree	0.91	0.91	0.92	0.91	0.92	0.92	0.92	0.92	0.0158	0.0161	0.0128	0.0128
J48 trees	0.95	0.96	0.97	0.98	0.94	0.93	0.94	0.92	0.0273	0.0267	0.0111	0.0118
NaiveBayes	0.84	0.85	0.96	0.97	0.90	0.91	0.93	0.93	0.0057	0.0057	0.0025	0.0026
Bagging.REPTree	0.95	0.96	0.97	0.98	0.95	0.94	0.94	0.93	0.1154	0.1023	0.0591	0.0533
Bagging.ADTree	0.94	0.97	0.97	0.98	0.95	0.92	0.94	0.93	1.3119	1.2822	0.5981	0.6020
MLP	0.94	0.96	0.97	0.98	0.94	0.91	0.94	0.93	4.1073	4.0772	1.5718	1.5707
FT trees	0.94	0.96	0.97	0.98	0.94	0.93	0.94	0.93	0.3500	0.3267	0.2230	0.2086
RandomForest	0.94	0.95	0.95	0.97	0.94	0.93	0.93	0.93	0.1428	0.1257	0.1159	0.1068
RBFNetwork	0.90	0.93	0.96	0.98	0.93	0.93	0.93	0.91	0.1358	0.1394	0.0994	0.1010
Decorate trees.J48	0.93	0.95	0.96	0.97	0.94	0.93	0.93	0.92	1.2735	1.3409	0.5895	0.7642
ADTree	0.94	0.97	0.96	0.98	0.94	0.92	0.94	0.92	0.1378	0.1373	0.0598	0.0603
REPTree	0.95	0.96	0.97	0.98	0.94	0.93	0.94	0.93	0.0121	0.0118	0.0058	0.0059
DecisionStump	0.91	0.91	0.96	0.96	0.94	0.94	0.92	0.91	0.0047	0.0043	0.0018	0.0019
SimpleCart	0.94	0.96	0.97	0.98	0.94	0.93	0.94	0.93	0.1955	0.1723	0.1462	0.1364

Table 3: Performance of RT and ALL feature sets using different classifiers with AHI5C annotation for UCD Database.

	Sensitivity		Specificity		Accuracy	
Classifier	RT	ALL	RT	ALL	RT	ALL
SVM	0.24	0.57	0.99	0.93	0.79	0.84
RandomTree	0.41	0.58	0.94	0.85	0.81	0.78
J48 trees	0.47	0.57	0.95	0.92	0.83	0.83
NaiveBayes	0.38	0.62	0.96	0.91	0.81	0.84
Bagging.REPTree	0.49	0.62	0.94	0.92	0.83	0.84
Bagging.ADTree	0.53	0.56	0.93	0.90	0.82	0.82
MLP	0.48	0.59	0.94	0.93	0.82	0.84
FT trees	0.47	0.61	0.94	0.92	0.82	0.84
RandomForest	0.45	0.55	0.93	0.93	0.81	0.83
RBFNetwork	0.45	0.51	0.93	0.94	0.81	0.83
Decorate trees.J48	0.47	0.57	0.94	0.89	0.82	0.81
ADTree	0.53	0.57	0.92	0.93	0.82	0.84
REPTree	0.48	0.60	0.94	0.91	0.82	0.83
DecisionStump	0.59	0.81	0.87	0.79	0.80	0.80
SimpleCart	0.48	0.58	0.93	0.89	0.82	0.81

better diagnostic ability than the existing feature sets. Moreover, cost sensitive classifications are carried out among 15 popular classifiers based on two distinct databases, which substantiate the effectiveness and robustness of the proposed reduced feature set and provide guidelines of classifier selections with the associated real-time detection strategies.

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