Clinical Practice for Diagnostic Causes for Obstructive Sleep Apnea Using Artificial Intelligent Neural Networks

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Abstract. Sleep apnea is a serious sleep disorder phenomena which happens when a person's breathing is paused during sleep. The most common diagnostic technique that is used to deal with sleep apnea is Polysomnography (PSG) which is done at special sleeping labs. This technique is expensive and uncomfortable. New automated methods have been developed for sleep apnea detection using artificial intelligence algorithms, which are more convenient and comfortable for patients. This paper proposes a novel scheme based on deep learning for sleep apnea detection and quantification using statistical features of ECG signals. The proposed approach is experimented with three phases: (1) minute-based apnea classification, (2) class identification and minute-by-minute detection for each ECG recording unlike state-of-the-art methods which either identify apnea class or detect its presence at each minute and (3) comparison of the proposed scheme with the well-known methods that have been proposed in the literature, which may have not used the same features and/or the same dataset. The obtained results demonstrate that the proposed approach provides significant performance improvements when compared to state-of-the-art methods. The outcome of this study can be used as an assistant tool by cardiologists to help them make more consistent diagnosis of sleep apnea disorder.

Keywords: Obstructive sleep apnea · Deep learning · Neural networks
Sleep disorder · Big data

1 Introduction

Sleep apnea is a potentially common sleep disorder in which a person's breathing may have one or more pauses during sleep. These pauses may continue from a few seconds to several minutes, and may occur hundreds of times during the night. If the obstruction to breathing is total and continues for ten or more seconds, then this case is called apnea [1]. Sleep apnea may have long-term effect on the cardiovascular system which makes it a risk factor for increasing mortality rate [2]. Sleep apnea typically is classified into three types; obstructive sleep apnea (OSA), central sleep apnea (CSA) and mixed sleep apnea (MIX). OSA is the more common form of apnea; it is caused by a blockage of the airway and is generally associated with a reduction in blood oxygen saturation [3].

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Traditionally, sleep-related breathing disorders are diagnosed by visual observation of Polysomnography (PSG) signals. PSG is a sleep test that is performed at special laboratories [4]. Even though PSG become the standard diagnostic tool for sleep disorder cases, there are some problems related to its implementation which make it expensive and time consuming. Therefore, the need for a simpler alternative detection method has been arising. Automated methods that use the artificial intelligence algorithms can solve PSG problems. In this light, there have been many algorithms and schemes proposed to address the problem of automatic OSA detection. such solutions used ECG patterns obtained during PSG studies and machine learning techniques to tackle OSA detection.

The dataset of ECG recordings used in this work is obtained from the PhysioNet web site. These recordings were arranged into three classes, as follows: (1) Class A (apnea): the learning and test sets each contain 20 class A recording files, each file contains at least 100 min with apnea; (2) Class B (borderline): recordings in this class contain between 5 and 99 apnea minutes. Each of the learning and test sets contain 5 class B files; and (3) Class C (control): recordings in this class contain fewer than 5 apnea minutes. The learning and test sets each contain 10 files [5].

Deep learning is currently one of the most important active research areas in machine learning. It has attracted extreme attention from researchers due to its potential in wide range of active applications such as object recognition [6]; [7], speech recognition [8]; [9], natural language processing [10], medical science [11]; [12], and other vital fields. Inspired by the biological nature of human brain mechanisms for natural signals processing, deep neural networks are representation learning methods with multiple levels of representation [13]; [14]. The expression “deep” is used because the depth of the network is greater when compared to the more conventional neural networks, which are sometimes called shallow networks. In most conventional learning methods, a simple network with one hidden layer may achieve acceptable performance for performing a specific task but, by applying a deep architecture with more hidden layers; higher efficiency can be achieved. This is because each hidden layer extracts more features from the previous layer and creates its own abstract representation. Therefore, to resolve more complicated features, we have to add more hidden layers, which make deep learning capable of learning latent information [15].

Most of the recent experimental results with deep architecture are obtained with models that can be turned into deep supervised neural networks, but with initialization or training schemes different from the classical feed-forward neural networks [16].

This work proposes a new contribution to the trend of training deep neural network based on topological concepts like weights initialization and activation functions. This is in part inspired by observations obtained from the work proposed by [17] which approved that for those neural networks with the same number of hidden units; deep architectures, with arctangent and polynomial activation functions, can realize maps with a higher complexity with respect to shallow ones. Also the work proposed by [18] approved empirically that deep supervised neural networks can reach their best performance without requiring any unsupervised pre-training. This finding was an attempt to close the performance gap between neural networks learnt with and without unsupervised pre-training.

The aim of this study is to propose a novel scheme for OSA detection based on features of ECG signals. This scheme is a hybrid algorithm that combines the Deep Neural Network (DNN) with the Decision Tree. The classification process in this proposed scheme consists of two phases; the first phase uses DNN for minute-based classification, then the output of this phase is fed into a decision tree model in order to perform the second phase; class identification. In addition to the proposed scheme, a comparative study of the most used classification methods, that have not been used with the same features and dataset, adopted in the literature is done.

The rest of this paper is organized as follows. Section 2 summarizes the related work in the literature. Section 3 contains an overview of the system and details the paper methodology. In Sect. 4, the experimentations and the obtained results are presented. Section 5 concludes the proposed study and lists possible extensions to this work.

2 Literature Review

Since PhysioNet/CinC challenge, many methods using the ECG signal to diagnose OSA have been proposed. The algorithms in this research area were divided into two types; some for apnea classes' identification and others for the minute-by-minute apnea classification.

Regarding the first challenge, several algorithms using different methods were developed to identify apnea class. For example, in [19–21] authors made use of spectral analysis of heart rate variability (HRV) to identify apnea class and achieved 30 correct score out of 30 (without class B consideration). While authors in [22, 23] used the Hilbert transform to extract frequency information from the heart rate signal and achieved a score of (28/30). Authors in [21, 24, 25] achieved the top three ranks in the PhysioNet's challenge on the subject of the minute-by-minute quantification. They reached an accuracy of 89.4%, 92.6%, 92.3%. In addition to HRV, authors made use of different features derived from ECG signals like ECG pulse energy [21], R-wave amplitude using power spectral density (PSD) [24] and T-wave amplitude using the discrete harmonic wavelet transform [25].

Since the challenge, different automated schemes have been proposed to detect OSA on the same PhysioNet Apnea-Ecg dataset. Khandoker et al. [26] employed wavelet based features and K-Nearest-Neighbour (KNN) classifier to achieve an accuracy of 83%. Xie and Minn [27] applied a number of classification algorithms as AdaBoost with Decision Stump and Bagging with REPTree to the extracted features from ECG and saturation of peripheral oxygen (SpO2) signals to obtain classification accuracy of 77.74%.

Different studies demonstrated that detection of obstructive sleep apnea can be achieved through HRV and the ECG signal. Quiceno-Manrique et al. [28] proposed a diagnostic scheme for OSA detection using time-frequency distributions and extracted features from ECG signal. This scheme was able to achieve up to 92.67% accuracy. In addition, authors in [29] proposed a technique that depends on features of the ECG signal and uses a bivariate auto regressive model to evaluate beat-by-beat power spectral density of HRV and R peak area and got classification accuracy higher than

85%. In 2012, Laiali Almazaydeh et al. proposed an automated classification scheme based on support vector machine (SVM) using statistical features extracted from ECG signals explicitly Heart Rate Variability (HRV) and obtained a classification accuracy of 96.5% [30].

Even though the aforementioned studies achieved relative satisfactory performance on apnea detection and quantification, there are some important aspects have to be highlighted. First, the proposed approaches either identify apnea class or detect the presence or absence of each minute of ECG data. To the best of our knowledge, only authors in [31, 32] addressed both apnea detection and quantification for each patient recording but both identify only two class not the three ones (class B is excluded). Second, different features are extracted from the RR intervals without any concern regarding its numbers and impact which implied that prediction of the classification models to be more excessive. Moreover, extracting and selecting features from such high-dimensional feature spaces require large computational resources, that is not reasonable for such wearable devices. As well, it is inadequate for home-based applications that have to aid physicians provide a quick pre-diagnosis for patient status. Therefore, to tackle these issues, this study proposes a novel OSA detection scheme to achieve acceptable performance using less features under limited capacities of wearable devices.

3 Methodology

This work is based on the ECG signal features to detect sleep apnea. Phases of the proposed methodology is discussed in the following subsections (see Fig. 1).

3.1 Data Collection Phase

The experimental data used in this study was obtained from the PhysioNet Apnea-ECG database [33]. The Apnea-ECG database contains ECG recordings for 70 different patients with OSA (classes a, b, c). Recordings vary in duration from slightly less than 7 h to nearly 10 h each. However, only 35 of these recordings contain minute-wise apnea annotations, which indicate the presence or absence of apnea during each minute of ECG data. ECG signals are sampled at 100 Hz with 12-bit resolution.

3.2 Data Pre-processing Phase

RR Intervals Extraction

The features used in our experimentation were all metrics based around RR intervals. An RR interval is defined as the time between two consecutive R peaks (see Fig. 2), which in turn are defined as the maximum amplitude of a given QRS complex. QRS is the combination of the Q wave, R wave and S wave and represents ventricular depolarization. The normal duration of the QRS complex is 0.08 and 0.10 s [34]. These metrics were chosen because RR intervals have been shown to be a telling indicator of HRV, which is a known byproduct of sleep apnea [35].

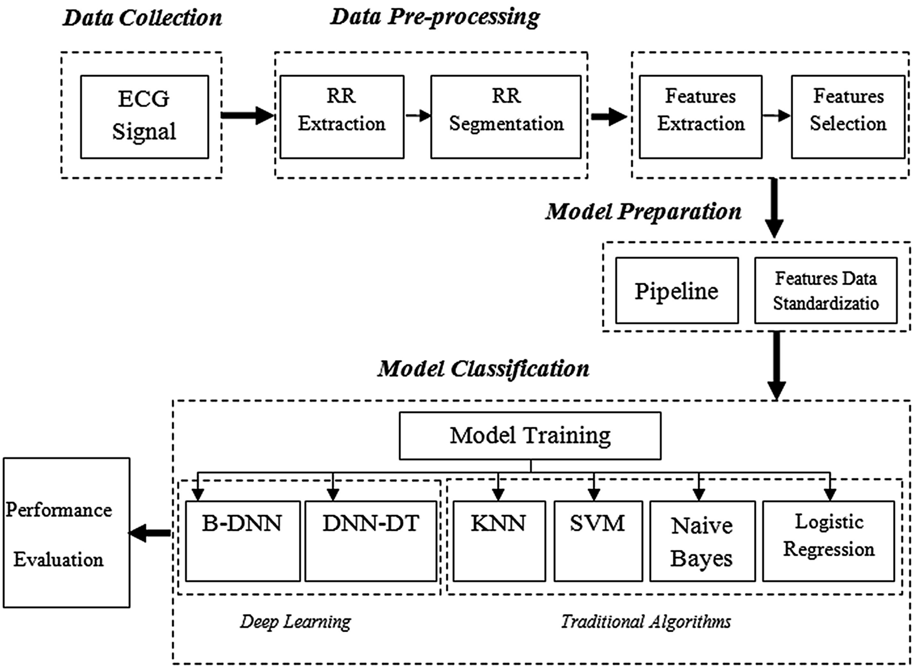

Fig. 1. Block diagram of the proposed methodology

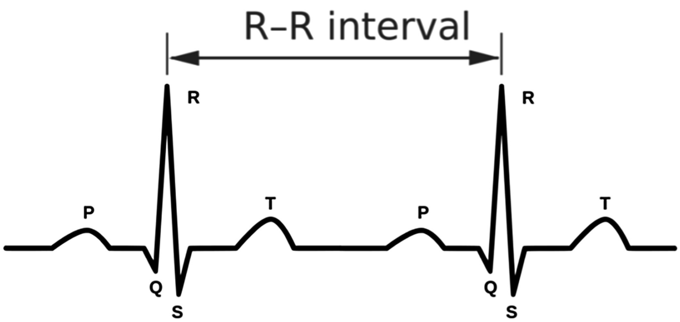

Fig. 2. Calculations of RR interval

RR Intervals Segmentation

As each ECG recording in the PhysioNet database was annotated per minute, the extracted RR intervals are segmented on a minute-by-minute basis according to the annotations. Therefore, RR intervals was calculated for each minute at each file; which implies that we have about 17003 RR records (35 file * file length (450–550 min)). Figure 3 presents the extracted RR values for one of the data set files (a01 file).

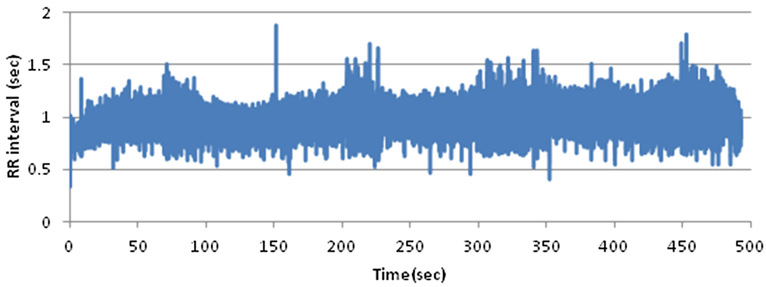

Fig. 3. Extracted RR intervals from (a01) file

3.3 Features Extraction Phase

Four each segment of the RR intervals obtained from the previous preprocessing phases, statistical features could be extracted and fed into the classification model for the possible classification of apnea events. Each feature vector was computed based on 60 s of ECG data; as each minute-wise annotation indicates the presence or absence of apnea at the beginning of the following minute. The following ECG features, which are the most common features used in the literature [4, 16] for apnea detection, are calculated:

1. Mean of the RR-interval.
2. Median of RR-intervals.
3. Standard deviation SD, of the RR-interval.
4. The NN50 measure (Variant 1), is the number of pairs of neighboring RR-intervals such that the first RR-interval exceeds the second RR-interval by more than 50 ms.
5. The NN50 measure (Variant 2), is the number of pairs of neighboring RR-intervals where the second RR-interval exceeds the first RR-interval by more than 50 ms.
6. The PNN50_1 measures, defined as NN50 (variant 1) measure divided by the total number of RR intervals.
7. The PNN50_2 measures, defined as NN50 (variant 2) measure divided by the total number of RR intervals.
8. The SDSD measures, defined as the standard deviation (SD) of the differences between neighboring RR-intervals.
9. The RMSSD measures, defined as the square root of the mean of the sum of the squares of differences between adjacent RR-intervals.
10. Inter-quartile range, defined as difference between 75th and 25th percentiles of the RR interval value distribution.
11. Mean absolute deviation values, defined as mean of absolute values by the subtraction of the mean RR-interval values from all the RR interval values in an epoch.

3.4 Features Selection Phase

In this phase, the features, that have the strongest effect on prediction, are selected. This stage scores the attributes according to their correlation with the classified apnea class.

It selects the most informative attributes. In total, 11 features were extracted from each ECG minute. In order to determine the discriminative power of each feature, ANOVA [36] statistical tests was adopted. After applying ANOVA test to features vector (see Fig. 4); it was induced that NN50_1, NN50_2, pNN50_1, pNN50_2 are the less relevant features and does not contribute highly in the classification results; so they are eliminated from the features set to have 7 features instead of 11.

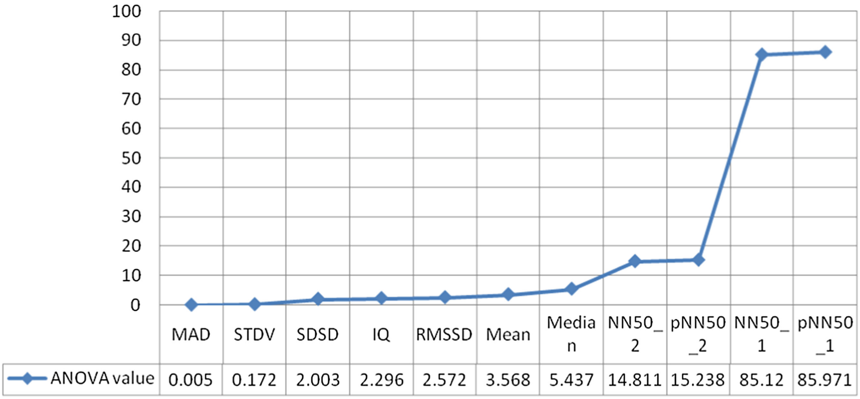

Fig. 4. Values of ANOVA test for features set

3.5 Model Classification

In the classification process, the extracted and selected features have to be fed into the training model to classify each minute of ECG data. In this work; two approaches were proposed for model training process. The first approach is based on the concept of deep learning and the other one is done using the traditional classification algorithms particularly Logistic Regression, KNN, SVM and Naïve Bayes models. In the rest of this section, detailed description of the proposed approaches is provided.

Deep Learning Approach

The proposed deep learning model passes two phases. In the first phase; a baseline deep neural network (B-DNN) model is proposed. This model is mainly used for the stage of minute-based classification. While in the second phase; a hybrid model is designed by the fusion of deep neural network model and decision tree model. This hybrid model is used for the stage of minute-class-based classification. Keras [37] library was used for building the proposed deep models.

Phase 1: Baseline Deep Neural Network Model (B-DNN)

The proposed Baseline Deep Neural Network (B-DNN) model uses feed-forward neural network architecture which is called a Multi-Layer Perceptron (MLP). It consists of 4 layers; the input layer, two hidden layers and output layer. A neural network topology with more hidden layers have the potential to extract better representations and features from the raw data to create much better classification models.

The first hidden layer has the same number of nodes as input parameters (7 neurons). While the second one was added to force a type of feature extraction by the network by restricting the representational space, since it take an input of 7 neurons (same number as of selected features) and reduce it to 5 (a new representation of the input features). This will enforce the model during training to select the most important representation of the input data.

Figure 5 presents the architecture of the proposed B-DNN model. It shows that the model consists of 4 layers; the first is the input layer with 7 neuron (same number as selected features), the second in the first hidden layer with 7 neuron which in turn passes the values to the second hidden layer that squeezes the representational space of the network to have 5 neurons, that is then fed to the output layer which have one neuron that presents the prediction result (Apnea or Non-apnea).

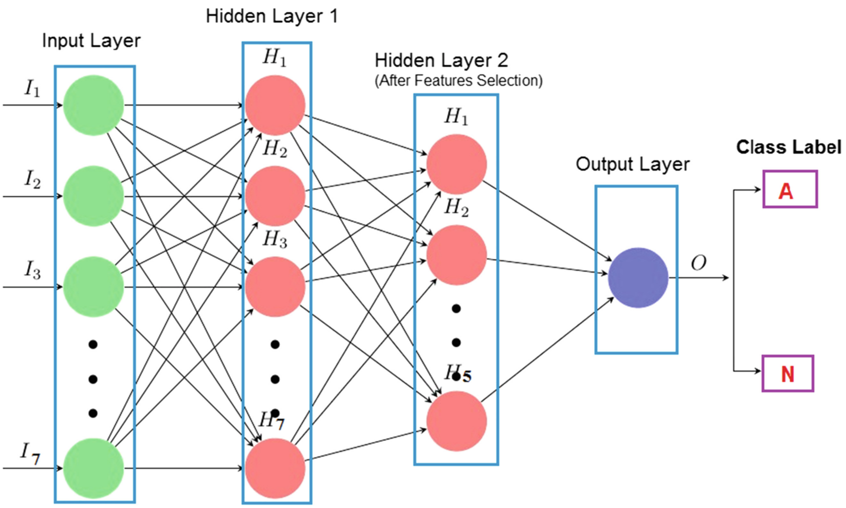

Fig. 5. DNN classification model architecture

As shown by Bengio and Glorot in [16]; units with more incoming connections should have relatively smaller weights; so that weights of the proposed DNN model are initialized using a small Gaussian random number. Rectified Linear Unit (RELU) activation is used as a transfer function for the weights to the net input value, which is then fed to the output layer that uses the sigmoid activation function to produce a probability output in the range of 0 to 1 which will then be converted to crisp class values. The used loss function during DNN training is Cross entropy, also referred to as logarithmic loss, is one of the most favourite loss functions that improve the performance of the DNN training. Once all the derivatives are computed, parameters are updated using the efficient Adaptive Moment Estimation (Adam) optimization algorithm [38] for gradient descent. Figure 6 shows the structure of the B-DNN model. This B-DNN model is used for achieving the first phase of the proposed scheme, which is minute-based classification.

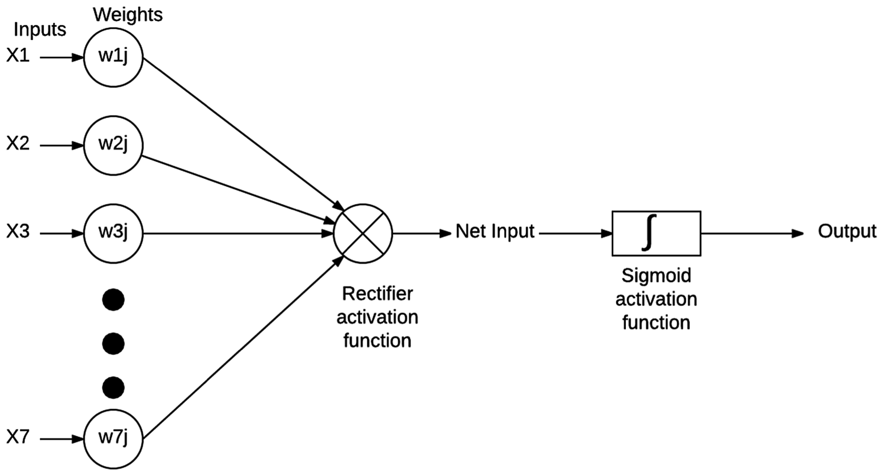

Fig. 6. DNN structure of B-DNN model

Phase 2: Hybrid Deep Neural Network and Decision Tree Model (DNN-DT)
This model is a hybrid algorithm that combines the Deep Neural Network (DNN) classifier with the Decision Tree classifier. The output of the first phase that is performed using B-DNN model (classified minutes as apnea on non-apnea) is fed into a decision tree model in order to perform class identification (Class A, B or C). Totally, the result is used for the fully minute-class-based classification phase. Figure 7 shows the architecture of the proposed DNN-DT.

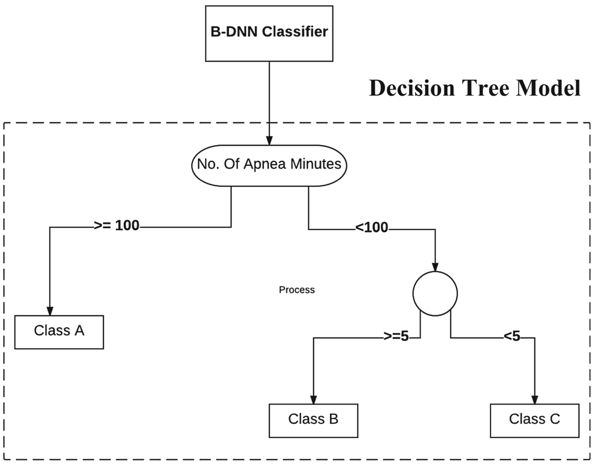

Fig. 7. DNN-DT classification model architecture

Traditional Classification Approaches

In addition to the proposed classification model, the extracted and selected features are applied to traditional classifiers being used previously in the literature for the same dataset and compared the results. The explored classifiers are: Logistic Regression, KNN, SVM and Naïve Bayes Classifier. Table 1 summarizes parameters for these classification models. Regarding the KNN model; Euclidean distance function is used to find the nearest neighbours. The model assigns uniform weights to each neighbour. In regards to the SVM model; the classification types is C-SVM, where C is chosen to be 1.0. The model uses the RBF Kernel with numerical tolerance equals to 0.001 and iterations can reach maximum of 100 iteration.

Table 1. Model parameters for the applied classifiers

Logistic Regression	KNN	SVM
Regularization: Ridge (L2), C = 1	Number of neighbours: 20 Metric: Euclidean Weight: Uniform	SVM type: C-SVM, C = 1.0 Kernel: RBF, $\exp(-1.0\|x - y\|^2)$ Numerical tolerance: 0.001 Iteration limit: 100

Orange Data Mining toolset [39] was used to simulate the traditional classifiers and compare results.

4 Experimental Results

4.1 Minute-Based Classification

Since only the training set (35 ECG recording) of PhysioNet Apnea-ECG database contain minute-wise apnea annotations; given the necessity of annotated test data to evaluate the classifier's performance, we were forced to use only these 35 recordings in the experiment. As aforementioned, we evaluated our approach using 10-fold cross validation technique.

The performance of the proposed classifier is compared to those of the state-of-the-art classifiers employing Apnea-ECG data-set at the same statistical features. This comparison is presented in Table 2. It is clear that the proposed B-DNN emerges as the classifier with the highest performance.

Table 2. Summary of various classifiers performance for minute-based classification.

Classifier	**# Features = 11**					**# Features = 7**				
	CA	Prec.	Rec.	Sens.	Spec.	CA	Prec.	Rec.	Sens.	Spec.
Logistic Regression	60.3	67.3	94.2	94.2	26.4	67.9	66.9	94.9	94.9	23.9
KNN	76.8	80.0	83.2	83.2	66.4	80.5	84.8	83.3	83.3	76.0
SVM	52.3	64.6	50.2	97.1	5.6	62.0	62.3	97.1	97.1	5.6
Naive Bays	63.2	66.0	57.8	57.8	71.8	67.2	76.0	61.5	61.5	68.7
Proposed B-DNN	79.0	80.0	79.0	79.7	77.7	92.7	95.3	92.8	92.8	92.6

4.2 Minute-Class-Based Classification

The second phase of the proposed approach is both detection of apnea class and quantification of apnea minutes. The number of the classified minutes for each recording is used to determine whether a patient recording belongs to class A, B or C unlike start-of-art methods that were able to classify only two classes instead of three. As mentioned before, the PhysioNet database for the training set contains 20 recording of class A, 5 of class B and 10 of class B.

In more details, the minutes of each files in classified to apnea or non-apnea minute using D-BNN classifier. At the same time, each recording file is classified to its corresponding class (using decision tree classifier) based on the number of classified apnea minutes.

The performance of the DNN-DT scheme for class-based classification is presented in Fig. 8. Hybrid scheme performed well in all performance metrics. Figure 9 views the confusion matrix of the scheme. It is also clear that the most misclassified classes are from class B which is a misleading class as induced from other schemes.

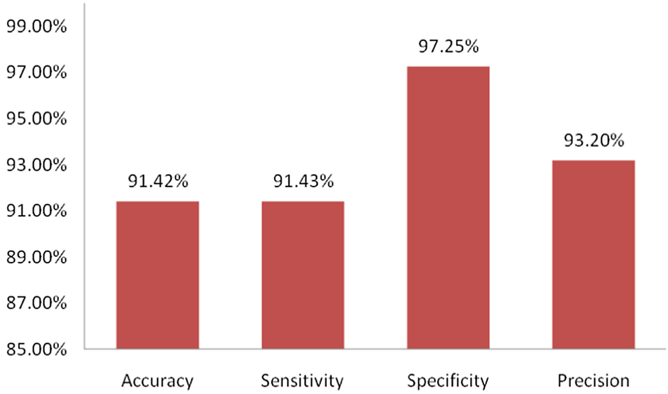

Fig. 8. Performance of the class-based classification using DNN-DT scheme

	A	B	C	∑
A	19	1	0	20
B	0	3	2	5
C	0	0	10	10
∑				35

Fig. 9. Confusion matrix for the class-based classification using DNN-DT scheme

5 Conclusion

In this work, a hybrid approach is proposed that includes deep neural networks and decision trees, for detection and quantification of sleep apnea using features of ECG signals. Statistical features were extracted from the RR interval and serves as training and testing data for the applied classifiers. Deep architectures have benefited much more from the pre-training stage in terms of training efficiency and test performance. Deep learning can adapt all the weights parameters in the network with respect to the tasks they solve. The success of this approach inspired further research to go in depth and perform an investigation into other scenarios of deep learning.

The proposed approach treated, with novelty, the following points: (i) identifies both apnea classes and detects minute-by-minute classification unlike state-of-the-art methods which either identify apnea class or detect its presence, (ii) identifies the three apnea classes (A, B and C) while other papers only identifies two classes (A and C), (iii) and makes a comparative study of the most used classification methods adopted in the literature but using the same features and the same dataset. The experimental results showed that this approach is robust and computationally efficient and clearly outperforms state-of-the-art methods.

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