Performance Comparison of Various Learning Algorithms for Prediction of CVD Risk among OSA Patients

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ARTICLE INFO

Article history:
Received: 23 December 2023
Revised: 10 May 2024
Accepted: 29 June 2024
Online: 30 June 2025

Keywords:
Obstructive Sleep Apnea (OSA)
Cardiovascular Diseases (CVD)
SHHS data
Learning algorithms Performance metrics

ABSTRACT

Sleep is an essential part of life but if breathing is disturbed while sleeping it may lead to a sleep disorder called sleep apnea which is influenced by factors like obesity, lifestyle, consumption of alcohol age, etc. Inadequate management of sleep apnea can lead to diabetes, hypertension, cardiomyopathy, stroke, loud snoring, and exhaustion throughout the day. OSA is the term for partial or total upper airway blockage that occurs during sleep. When our brain detects that we are not breathing, it briefly wakes us up to reopen our airway. About five to thirty times will occur each hour of sleep. This may lead to CVD and even fatal death. So, we need to design a system to monitor the OSA severity as well as its consequence of CVD risk. To evaluate the current machine and deep learning models, an intelligent model would compare the results to obtain the best-performing models and can be used for classifying CVD risks of apnea patients. Support Vector Machine, Random Forest, Naïve Bayes, Decision Tree (DT), Artificial Neural Networks, 1D-Convolutional Neural Networks, VGG16, ResNet50, ResNet100, and ResNet101were trained for the detection and classification of OSA and CVD using SHHS data. The data need to be pre-processed using Principal Component Analysis to remove unwanted data and the model is trained afterward. Then best-performing model in comparison to other models is selected and used for the three classifications of CVD risk into risk, no risk, and high risk. Under different testing and training data ratios, the ML classifier (DT) achieved 82.625% accuracy, 82.4% in sensitivity, and 81.3% in specificity on average. In the same manner, the DL classifier (ResNet101) achieved 82 % accuracy, 82% in sensitivity, and 81.725% in specificity on average.

1. INTRODUCTION

Obstructive sleep apnea (OSA), the sleep disorder affects thousands of people annually in India alone [1]. Cyclic partial or total shutting of the upper nozzle during sleep is its defining feature. These asphyxia events result in acute physiologic stressors such as arterial oxygen desaturation, acute hypertension and spikes in sympathetic activity. Hundreds of times during night, a patient with moderate-to-severe OSA may experience the mentioned symptoms. Although sleep disorders have been described for almost 200 years, diagnosis and intervention have not been given importance in treatment choices until the last 20 years. Observational studies initially suggested a connection between OSA and cardiovascular illness by associating snoring—a proxy for OSA—with a rise in cardiac events. The existence and severity of OSA are linked to increased cardiovascular disease and systemic hypertension, based on later research. As of right now, OSA is believed to be involved in the pathophysiology of arrhythmias, cerebrovascular events, pulmonary hypertension, acute coronary syndromes, and congestive heart failure [2]. Numerous studies with different algorithms and sleep apnea data were observed. To assess the OSA and CVD risk, several sleep databases were used, including the Sleep Heart Health Study (SHHS), Physio net, as well as Apnea ECG databases. To treat OSA patients at the outset, an earlier estimation of their CVD risk is necessary.

The cardiovascular risk of OSA patients is predicted using a variety of ML and DL methods. 81 guys with stable heart failure underwent polysomnography, and 11% of them had OSA [3]. Random forest model was used on SHHS data and achieved a specificity of 73.94% and sensitivity of 81.82%, respectively but people aged 65+ were considered for the study not the younger population [4]. ANN classifier was used with ECG (Electrocardiogram), and EEG

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(Electroencephalogram) signal and achieved 99.97% accuracy but it requires more resources for processing [5]. The same ANN model with an ECG signal achieved 92.3% accuracy but energy consumption is high [6]. Support Vector Machine (SVM) and Stacked auto encoder-based deep neural network (SAE-DNN) were employed on the Apnea ECG database, University College Dublin (UCD) database, and Physio net challenge database and achieved 94.3% accuracy for per-recording-based sleep apnea classification and 72% accuracy for normal patients, but the computational complexity of a real-time scenario is not considered [7]. KNN (K Nearest Neighbor), SVM, MLPNN (Multilayer Perceptron Neural Network), and least-square support vector machine (LS-SVM) classifiers were employed on the Apnea-ECG dataset results in 97.14% accuracy for SVM and LS-SVM classifiers [8]. SVM model on the Apnea-ECG database with ECG, HRV (Heart Rate Variability), and EDR (ECG Derived Respiration) signals achieved 90.52% accuracy and specificity of 93.4% but the model requires more attributes for the classification [9]. The SVM classifier on the SHHS database achieved 90% accuracy but performance is affected by bio-signals quality [10]. The same SVM classifier with ECG Signals on the Apnea-ECG database achieved 95.57% accuracy, 98.64% sensitivity, and 92.51% specificity but there will be a high processing delay [11]. Carolina Varon et al., 2015 used an SVM classifier with single-lead ECG signals and achieved an accuracy of 85-90% but suffers from communication overhead [12]. Haitham M. et al., 2012 used an SVM classifier on the SHHS dataset and achieved an 82.4% accuracy but more training time is needed for a large dataset [13].

Decision tree classifier for MIT-BIH (Massachusetts Institute of Technology- Beth Israel Hospital) Polysomnographic data (18 ECG signals) achieved 90% precision, 98.53% accuracy, 96.86% specificity, 98.39% sensitivity, and an overall 93.2% F-score results in high processing delay under real-time scenarios [14]. The decision tree classifier and data from the type III Cadwell Apnea Trak TM HSAT system allowed sensors placed under mattresses as a substitute for obtrusive regular sensors to achieve 86.96% accuracy with 81.82% sensitivity and 91.67% specificity correspondingly. However, the sensors consume a lot of energy [15]. The University of California Irvine Machine Learning (UCI-ML) dataset using an ANN model optimizes execution time, however, it does not include performance evaluations for crucial QoS metrics like power consumption and latency [16]. ANN model with a database of 8 subjects with one-minute annotation from the Apnea-ECG database achieved 97.7% accuracy but suffered from high computational complexity and required more time for training [17]. CNN (Convolutional Neural Network) model based on ECG signal on Apnea-ECG database produced 94% accuracy and 88% sensitivity but requires more attributes for training the network [18]. An accuracy of 99.56% and sensitivity of 96.05% were attained by the CNN model using ECG signals from wearable devices; however, performance was not stable as the data size scaled [19]. In the instance of per-minute apnea detection, the CNN model with the single-lead 1D ECG signals on MIT Physio Net Apnea-ECG Database achieved accuracy of 87.9%, specificity of 92.0%, and sensitivity of 81.1% in other cases, however, communication overhead rose [20]. UCI-ML Cleveland dataset with CNN model and achieved an accuracy of 94.78% but it is not suitable for large-scale datasets [21]. CNN model with single lead ECG signals on Apnea-ECG Database in which classification accuracy in increased by 9% suffers from high computational burden [22]. CNN model using Sleep Health Heart Study (SHHS) single-channel EEG recordings A higher accuracy of 69.9% was obtained with the MIT-BIH Polysomnographic Database, Visit 2 database, and St. Vincent's University Hospital / University College Dublin Sleep Apnea Database [23]. However, training the model took longer. It is necessary to move the study in future directions to develop deeper learning classifiers, which will result in more reliable OSA and CVD diagnosis tools.

The novelty in this research work is only a few authors considered a single CVD risk level of patients in the literature, but our work is based on classifying multiple risk levels of patients with sleep apnea into no risk, risk, and high risk. This paper covers existing techniques undertaken for classifying and detecting CVD-OSA risk. The paper takes SHHS polysomnography data was used as input, and ten powerful and popular Machine Learning and Deep Learning algorithms like Decision tree, Random Forest, Naïve Bayes, VGG 16, SVM, 1D-CNN, ANN, ResNet50, ResNet100 and ResNet101 were tried to predict CVD risk of OSA patients. Each model was validated with an increased test data set (20%, 30%, 40%, and 50%), and performance metrics were calculated. From the performance metrics under different test data sets, two best-performing models were selected. The work's restriction is Popular machine learning methods can predict heart-related problems only in sleep apnea patients. The model does not predict every other cardiac condition.

The article is structured in the following order: Section 1 details Introduction to OSA and CVD, along with a list of some publications describing the risks of CVD associated with OSA. Section 2 provides a detailed explanation of dataset used for model training and analysing different powerful deep and machine learning models. At last, Section 3 concludes the research work with which models are performing better and how the future work can be enhanced.

2. METHODS

2.1 Dataset

SHHS, a public dataset obtained as requested from NSRR (National Sleep Research Resource) is used [24]. The

National Heart, Lung, and Blood Institute first developed SHHS dataset to identify any CVD and related events related to sleep-breathing dysfunction. Sleep-associated breathing disorders are strongly linked to higher mortality rates, hypertension, stroke, and coronary heart disease.

The SHHS dataset includes information from 6441 individuals' initial and follow-up check-up visits, which were conducted between 1995 and 1998. Nine current epidemiological research types were used to find subjects; these studies have previously gathered data on cardiovascular risk factors. The Framingham Offspring Cohort, The Strong Heart Study sites in South Dakota, Arizona, and Oklahoma, The Cardiovascular Health Study (CHS) sites in Hagerstown, Sacramento, and Pittsburgh, The Atherosclerosis Risk in Communities (ARIC) study sites in Minneapolis/St. Paul, Hagerstown, and Studies of respiratory illness in Tucson and hypertension in New York were among the parent group studies.

The experimented issues met the necessary criteria of being at least 40 years old, having never had a sleep apnea treatment history, not having a recent home oxygen remedy, and not having a tracheostomy. They were asked to take part in the first polysomnogram as part of the SHHS baseline survey. Oversampled snorers were included in a few cohorts, which increased research into the prevalence of respiratory dysfunction-related sleep disorders. The demography details of SHHS-1 are depicted in Table 1.

Table 1: Demography details of SHHS-1

Gender	Male			Female		
	2765			3039		
Age	35-44	45-54	55-64	65-74	75-84	>85
	342	1017	1769	1617	955	104
Ethnicity	Hispanic or Latino			Non-Hispanic or Latino		
	280			5524		
Education (years)	<10	11-15	16-20	>20		
	435	2750	1913	223		
Statistics of Age	N	Mean	SD	Median	Min	Max
SHHS	5,804	63.1	± 11.2	63	39	90
Outcomes of CVD	10,641	66.2	± 10.8	67	39	90

The PSG recording table comprised of,

- The EEG of C3/A2 and C4/A1 was tested at 125 Hz.
- The electrooculograms (EOGs) in both eyes were tested at 50 Hz.
- The bipolar submental electromyogram (EMG) was tested at 125 Hz.
- The Plethysmography bands were sampled at 10 Hz to record thoracic and abdominal excursions by induction.
- The Protec nasal-oral thermocouple was tested at 10 Hz.
- The Nonin fingertip pulse oximetry was tested at 1 Hz.
- The ECG with bipolar leads was tested at 125 Hz for SHHS. Heart rate (PR Interval), which is recorded at 1 Hz, from the ECG.
- The mercury gauge sensor for different body positions (e.g., supine and non-supine), and
- The ambient light detected by the light sensor
- The bipolar submental electromyogram (EMG), which tested at 125 Hz.
- Blood pressure, blood, ECG, sleep architecture, and HRV are employed as goal variables, whereas lung function, oxygen parameters, hypopnea, OSA respiratory episodes, and sleep architecture are used as causal factors. Sleep arousals and CVD outcomes are used as labels. The details of the SHHS Polysomnography data that were used in this investigation are listed below. Heart Rate with Arousal for REM and NREM, all oxy, deoxy sat Supine, Average, Minimum, Maximum feature with size of 6, Apnea-Hypopnea Index (AHI), with no distinction and Obstructive feature with size of 8, and >=3% oxygen desaturation feature with variable type of 2. Number of REM, NREM, >=3% oxygen desaturation feature cases with and without arousals, with a variable type of 9, and similarly a total of 73 features with 316 variables were used for the study.

2.2 Investigation of ML and DL Methods for Prediction of OSA and CVD

The algorithms: Support Vector Machine(SVM) [25], Decision Tree (DT) [14], Random Forest(RF)[26], Naïve Bayes(NB) [27], Artificial Neural Networks(ANN) [28],1D-Convolutional Neural Network(1D-CNN)[29], VGG16[30], ResNet50[31], ResNet100 [31] and ResNet101[31] were trained for the detection and classification of CVD and OSA using SHHS data (https:// sleepdata.org/datasets/shhs/files). From the results, it was found that DT and ResNet101 performed better. Figure 1 shows the proposed framework analysis. Raw SHHS data is pre-processed for removing unwanted data necessary features were extracted and trained by the proposed model (Decision Tree and Resnet101) and performances were compared with existing models. The trained model is tested with different ratios of test datasets to categorize different CVD risk levels of OSA [31-36].

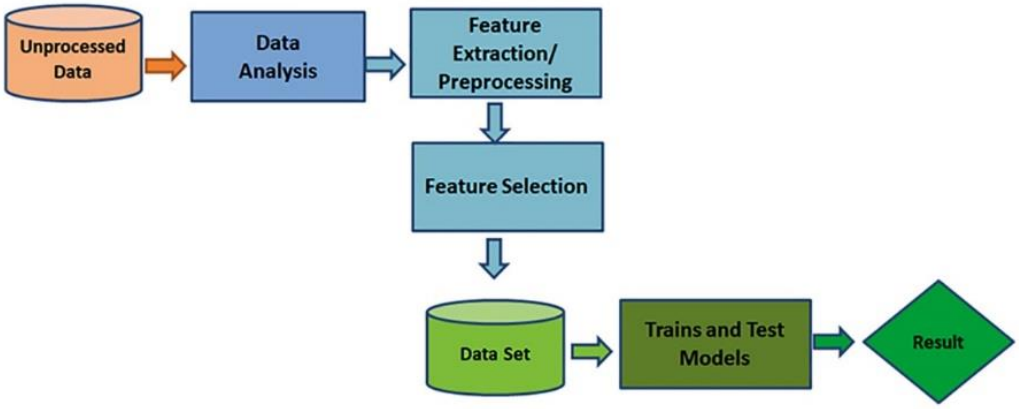

Fig. 1. Schematic representation of the proposed analysis.

3. CONCLUSIONS AND DISCUSSION

Using the mathematical equation shown in Table 2 below, depicts performance evaluation of suggested model with various datasets was determined.

Table 2: Validation metrics formulas

Performance Measures	Expression	Notes
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	How often classifier makes correct prediction
Specificity	$\frac{TN}{TN+FP}$	Exact negative predictions out of observed true negatives
Recall (Sensitivity)	$\frac{TP}{T\,P+FN} * 100$	Classifier's ability to predict correct class
TP – True Positive, TN- True Negative, FP- False Positive, FN- False Negative		

Table 3: ML classifiers in OSA and CVD detection and classification under a testing scenario of 50% testing data and 50% training data comparison

Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)	Reference
SVM	70	70	75.3	[25]
DT	80	82.4	81.3	[14]
RF	78.3	75.2	74.2	[26]
NB	75	75.3	75.4	[27]
ANN	72.5	72.2	74.4	[28]
1D-CNN	76.5	74.3	72.6	[29]
VGG16	69	70	71	[30]
ResNet50	77	74.5	72.7	[31]
ResNet100	78	78	79	[31]
ResNet101	80	80.5	80.4	[31]

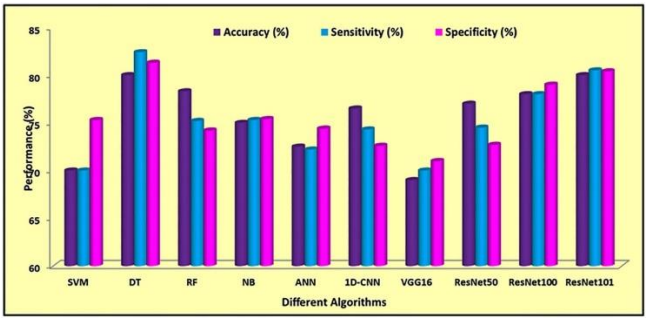

Fig. 2. Comparison of ML classifiers in OSA and CVD detection and classification under a testing scenario of 50% testing data and 50% training data.

Table 3 and Figure 2 illustrate the overall performance obtained for the 50:50 ratio data (50% data under testing and 50% data under training). Among all machine learning classifiers, the DT model achieved better compared to other models with a high accuracy of 80%, high sensitivity of 82.4%, and high specificity of 81.3%. Similarly, among all deep learning classifiers, the ResNet101 classifier achieved a higher accuracy of 80%, high sensitivity of 80.5%, and high specificity of 80.4% than other classifiers.

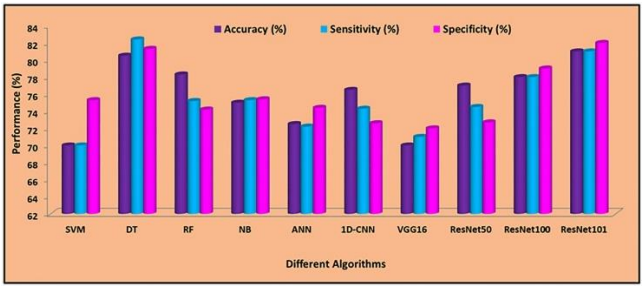

Fig. 3. Comparison of ML classifiers in OSA and CVD detection and classification under a testing scenario of 60% testing data and 40% training data

Figure 3 illustrates the overall performance obtained for the 60:60 data ratio (60% data under testing and 40% data under training). Among all machine classifiers, the DT model achieved 80.5% accuracy, 82.4% sensitivity, and

81.3% specificity compared to other classifiers. Similarly, among all deep learning classifiers, the ResNet101 classifier achieved 81% accuracy, 81% sensitivity, and 82% specificity compared to other classifiers.

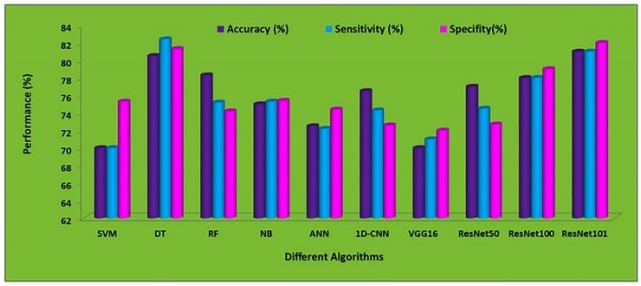

Fig. 4. Comparison of ML classifiers in OSA and CVD detection and classification under a testing scenario of 70% testing data and 30% training data

Figure 4 illustrates the overall performance obtained for the 70:30 ratio data (70% data under testing and 30% data under training). Among all machine classifiers, the DT model achieved 84.5% accuracy, 81.4% sensitivity, and 80.3% specificity compared to other classifiers. Similarly, among all deep learning classifiers, the ResNet101 classifier achieved 83% accuracy, 82% sensitivity, and 81% specificity compared to other classifiers.

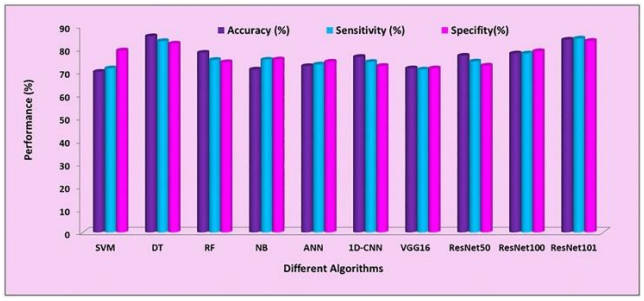

Fig. 5. Comparison of ML classifiers in OSA and CVD detection and classification under a testing scenario of 80% testing data and 20% training data

Figure 5 illustrates the overall performance obtained for the 80:20 ratio data (80% data under testing and 20% data under training). Among all machine classifiers, the DT model achieved an increased accuracy of 85.5%, 83.4% high sensitivity, and 82.3% specificity relative to other classifiers. In a similar vein, the ResNet101 classifier outperformed all previous deep learning classifiers, achieving better accuracy (84%), high sensitivity (84.5%), and high specificity (83.5%).

4. CONCLUSION AND FUTURE WORK

PSG data from SHHS is used to determine the best-fit learning algorithm for CVD risk prediction of OSA individuals. The utilization of ML and DL modules on endurance improvement has been illustrated. As per the comprehensive study of these modules, OSA and CVD detection and classification performance can be improved more in terms of performance metrics. Under different testing and training data ratios, the ML classifier (DT) achieved 82.625% accuracy, 82.4% in sensitivity, and 81.3% in specificity on average. In the same manner, the DL classifier (ResNet101) achieved 82 % accuracy, 82% in sensitivity, and 81.725% in specificity on average. So, among all the 10 models that were tried with the SHHS dataset, Decision Tree and Resnet101 are the best-performing models for classifying CVD risk levels of patients having sleep apnea. However, the model can only predict heart-related problems in patients with sleep apnea. The model cannot predict all other heart-related disorders. To improve the performance further, these two model algorithms can be ensemble into the hybrid model and the performance can be compared with other hybrid models as a future study.

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