A Novel Deep Learning Approach for Diagnosing Sleep Apnea Using Feature Fusion of ECG and SpO2 Signals

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KEYWORDS

Sleep Apnea, Deep learning, CNN, ECG, Blood Oxygen Saturation (SpO2), AHI

ABSTRACT:

Introduction: Frequent disruptions in breathing during sleep also known as Sleep Apnea (SA), is a common sleep disorder, that poses serious health concerns all across the world. Global prevalence of SA is very high, around 936 million adults are suffering from this disorder worldwide. Primary causes of SA include Obesity, old age, being male, high BMI and some other causes are smoking, alcohol, opium consumption etc. If untreated on time, has severe consequences like morning head ache, daytime sleepiness, fatigue, hypertension, diabetes, cognitive impairments and in some cases, it extends to cardiovascular diseases, stokes as well.

Objectives: The aim of this research-study is to identify sleep apnea events through the analysis of Electrocardiogram (ECG / EKG), Blood Oxygen saturation level (SpO2) signals.

Methods: The study employs the PhysioNet Apnea ECG 1.0.0 dataset for training a machine learning/deep learning algorithm. The proposed system processes ECG and SpO2 data concurrently, with machine learning models trained individually for each type of signal. ECG signals offer crucial insights into heart rate variability and arrhythmias, while SpO2 measurements reveal variations in blood oxygenation during sleep. Training models on these individual signals allows for the capture of unique properties significant to sleep apnea identification. A new feature space is formed by concatenating the features extracted from both these signals and then a 1D-CNN model was trained-tested on this new feature set, enhancing the overall accuracy of predictions. Using ECG and SpO2 data, this model accurately identifies apnea occurrences.

Results: The technique yielded promising results, potentially enhancing the early-stage diagnosis and treatment recommendation for sleep-apnea. Our research analysis attained Accuracy, Specificity and AUC of 91%, 92% and 0.93 respectively.

Conclusions: Using multimodal approach like ECG and SpO2, performance of Sleep-apnea predicting models can be increased to a level that physicians can rely on. Future research will explore the integration of additional physiological signals like limb movement, chest and abdomen movement etc. and generate recommendations for sleep apnea patients by building recommender systems on top of these results.

1. Introduction

Sleep apnea (SA) is a type of sleep disorder having very high prevalence rate. SA is defined by breathing pauses during sleep. Patients have either complete cessation (apnea) or diminished airflow (hypopnea) to their lungs for more than 10 seconds [1]. Over 200 million peoples are suffering from this disease worldwide, men are more susceptible than women as per the recent survey. Obstructive Sleep Apnea (OSA) is a type of SA that interferes with the sleep cycle and is linked to numerous negative outcomes, including cardiovascular disease, heart failure diabetes mellitus, impaired cognitive function, mental health issues, depression, diminished quality of life, changes in brain structure, and persistent fatigue, atrial fibrillation [2]–[4]. Sleep-disorders such as Periodic-Limb-Movement during Sleep (PLMS) and OSA are generally linked to each other [5]. The accurate diagnosis of apneac events is crucial for developing successful SA treatment and management method. Polysomnography (PSG), Photoplethysmography, ECG, EEG, SpO2 signals etc. are popular diagnosis tools whereas Epworth Sleepiness Scale (ESS), Stob-Bang Questionnaire (SBQ) help to measure OSA severity level [6]–[9]. While ECG signal provides crucial information about heart which is often associated with apneac events, SpO2 signal provides insights into oxygen saturation/ desaturation levels which is also linked to apneac events.

This research work is based on PhysioNet Apnea-ECG v1.0.0 database for SA classification [10], [11]. The ML algorithms such as SVM, RF, DT can be trained-tested on ECG and SpO2 signals to identify key features for SA detection [12]–[16]. Similarly, DL models such as CNN, HMM, ANN etc. have potential to detect SA and significantly improve treatment for the disease [17]–[20]. This multi-modal analysis aims to provide a more reliable and efficient method for diagnosing sleep apnea, potentially leading to earlier intervention and improved treatment of the condition. Outline of this research paper is as follows; Section-1 introduces the various methods available for SA detection. Section-2 provides a summary of prior research on the identification of sleep-apnea through physiological indicators. Section-3 discusses the dataset used and preprocessing methods required. Section-4 details the ML / DL models and the ensemble learning strategy implemented in this study. Section-5 presents the discussion on results obtained through experimental work. Finally, Section-6 consist of conclusion of the paper and proposed directions for future research.

2. Literature survey

Sleep-apnea, a highly-prevalent sleep disorder which is marked by pauses in breathing-in air during sleep. These pauses can be complete stops (apnea) or reductions in airflow (hypopnea) lasting over 10-seconds. Precise diagnosis of sleep apnea is vital for determining effective treatment and management plans (Bahrami et al.) [21].

Researcher Chang et al. [18] developed an approach based on a 1D-CNN-model considering ECG measurements for SA detection. The model demonstrated high accuracy for apnea detection by achieving 87.9% for per-minute, per-segment whereas accuracy of 97.1% for per-recording classification obtained. It outperformed other feature-based strategies. However, the study's limitation was its lower sensitivity, which was 81.1% for per-minute apnea detection. Reduced sensitivity may lead to the misidentification of apnea events as normal, which can lower the estimated Apnea-Hypopnea-Index (AHI) and potentially result in the misclassification of patients during per-recording classifications. Many cases of OSA go undiagnosed and hence untreated because of the cost and practical restrictions of night-long polysomnography (PSG) tests. Researchers Almazaydeh at el. [13] used electrocardiogram (ECG) data with support vector machines to create an automatic categorization algorithm. This approach achieves around 96.5% accuracy in recognizing sleep disturbance epochs and may serve as a foundation for future OSA screening systems. The researchers employed a distinct set of characteristics based on RR-intervals to train a SVM for classification tasks. They evaluated the model using three varying epoch durations: 10 seconds, 15 seconds, and 30 seconds. The SVM, utilizing a linear kernel, attained the highest accuracy with the 15-second epochs. However, the authors did not explore strategies for optimal feature selection. Pombo at el. [22] investigates the efficacy of five classifiers, namely SVM, ANN, PLS, LDA and aNBC for detecting sleep apnea instances using minute-by-minute electrocardiogram (ECG) readings. The article discusses the accuracy comparison of several classifiers. The article evaluates the accuracy of different classifiers. To find out Heart Rate Variability (HRV), ECG-Derived Respiration (EDR), a Savitzky-Golay filter is applied to each ECG signal. These features were utilized for train-test and validation purposes. The results show an accuracy of 82.12%, a specificity of 72.29%, a sensitivity of 88.41%. Furthermore, an extended feature analysis evaluates the significance of all categorized features. Drawback of their study was they did not include feature selection for finding an ideal characteristic set for the identification of sleep-apnea.

Researchers Paul et al. [23] looked for an alternative to the time-consuming and costly PSG-test. They developed a real-time SA detection system, incorporating SpO2 and ECG data. Three models were trained over R-R intervals extracted from raw ECG data, one model for SpO2, another for ECG, and a combined model (ECG + SpO2). The combined model outperformed the separate signal-based models, obtaining an accuracy of 91.83% using the dual-channel approach. Issues with their study was the reduced accuracy of the ECG-based model was related to an inaccurate QRS detector.

Wang et al. [24] utilized a time-window ANN alongside single-lead ECG measurements for the SA detection. This method takes into account temporal relationship between ECG segments. The dataset on which these researchers were working, does not include annotations to discriminate between various forms of respiratory disturbances such as apnea and hypopnea. So, it is difficult to design models to distinguish between two categories.

Varshan et al. [25] aim to create a system that identifies sleep-apnea through analysis of single-lead ECG. They have employed ML and DL methods to detect anomalies associated with SA from ECG data. Researchers achieved a classification accuracy of 79.99% for SVM classifier and 81.77% for hybrid DNN VGG16.

Zhang et al. [26] focused on designing an efficient OSA diagnosis and management method. They have employed single-lead ECG data for training a DL model which not only detects SA but also measures its severity. Their work includes signal preprocessing, feature extraction, concatenation of time-domain and frequency-domain features for classification. These authors have tested the model on 375 PSG patients and found it highly effective. They have evaluated models' performance on publicly available dataset proving its feasibility for SA detection.

3. Methods

Our research includes ECG and SpO2 signals for Sleep-Apnea diagnosis.

3.1 ECG based diagnosis: The Apnea-ECG V1.0.0 dataset [10], [11], sourced from https://www.physionet.org/about/database/ under an open-source license, was employed for the SA detection. We developed and evaluated our Deep Learning models using this database. This dataset includes 70 medical-records from 32 subjects (7 females, 25 males, age 44±11 years, weight 86±22 kg, height 175±6 cm) categories into 4-classes respectively A, B, C, and X.

Table -1 Apnea-ECG dataset statistical details

Gr.	Sample size	AHI Range	Classification	Reco. Len.	Samp. Rate	Annota-tion Freq.
A	13	0 < AHI ≤ 5	Normal	8.2 ± 0.52 hours	100 Hz	1-min intervals
B	13	AHI > 30	Severe			
C	6	5 < AHI < 30	Mild/ Moderate			
X	35	5 < AHI < 30	Normal, Mild, Severe			

For statistical details please see Table-1. This dataset includes annotations provided by sleep experts for the presence of apnea events. The ECG waveforms were segmented into one-minute intervals for analysis. R-R intervals were extracted from the ECG data using Hamilton R-peak identification method. Analyzing physiological signals is significantly challenged by noise and motion distortions. We mitigated this by applying a median filter to the ECG signals. However, for more reliable apnea diagnosis, it is advisable to employ artifact rejection and correction techniques. These methods involve removing or correcting heavily contaminated data points using autoregressive models. Fig. 1 represents the annotations provided by sleep experts for the ECG signals, where Apneac events were represented by 'A' and normal breathing events represented by 'N'.

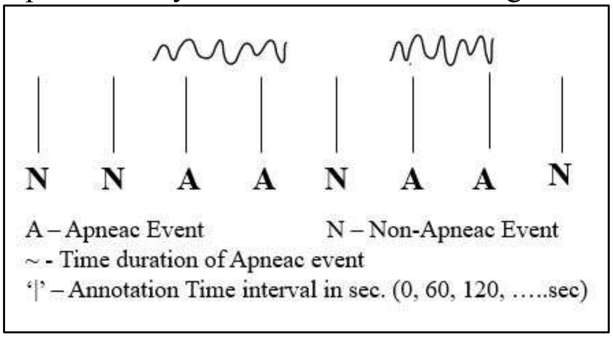


Fig. 1 Annotations for Apneac and Non-Apneac events

Table-2 provides summery of various parameters extracted from ECG signal. Feature Extraction and Processing followed by apnea event detection process as depicted in Fig. 2 below. After performing suitable preprocessing on ECG data, the R-R intervals obtained were inputted into machine learning algorithms. Additionally, the heights of the R-peaks were also obtained. A frequency of 3Hz for Cubic-Interpolation was applied to both the R-peak and the R-R intervals to maintain a consistent sampling rate. Subsequently, these interpolated signals were fed to deep learning model. Electrocardiogram (ECG) data are often used to extract various HRV characteristics. These characteristics reflect the variability in the time intervals between consecutive heartbeats, thus helpful in detection of apneac events.

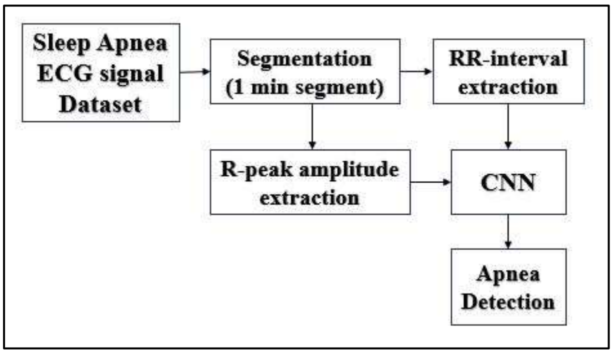


Fig. 2 CNN based architecture for ECG signal analysis

Table – 2 Summary of the key features extracted from ECG signal

Time-Domain Features Extraction	
Feature name	Description
SDSD (Standard Deviation of Successive Differences)	This long-term feature assesses the variability among nearby R-R intervals, which are the durations between consecutive heartbeats.
NN20	NN20 signifies the count of R-R interval differing at-least 20-milliseconds.
NN50	Number of R-R intervals which are more than 50 milliseconds apart.

pNN50	The pNN50 is the % of successive R-R intervals that vary by 50-milliseconds from each other.
pNN20	The term pNN20 refers to the % of consecutive R-R intervals that vary by 20-milliseconds from each other.
RMSSD (RMS value of Successive-Differences)	This short-term feature describes the range of normal heartbeat variations.
Nonlinear Features	
SD1 and SD2	Poincare plot attributes.
(SD2/SD1)	Ratio of attributes.
CVI	The cardiovagal index.
CSI	The cardio sympathetic index.
Frequency-Domain Features	
VLF	The thermoregulatory systems are associated with the VLF band, ranging from 0.0033 to 0.04 Hz.
LF	The low-frequency range (0.04–0.15 Hz) is primarily associated with sympathetic activation.
HF	The high-frequency range (0.15 to 0.4 Hz), is indicative of parasympathetic-activity.
VLF power, LF power, HF power	The analysis includes total power for each ECG segment.

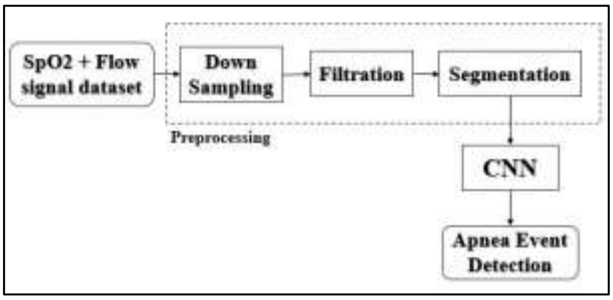


Fig. 3 CNN based architecture for Sleep Apnea detection from SpO2 signal

Each ECG segment typically yields 13 characteristics in the time domain. Our research utilized the *PhysioNet Apnea-ECG Database v1.0.0*. Nevertheless, this database has limitations, such as a limited number of patients with mild and severe OSA and a dearth of CSA events. Future studies should aim to compile a more comprehensive dataset encompassing various types of apneas.

3.2 SpO2 based diagnosis:

For SA-detection using SpO2 signals, our research utilizes the sleep-apnea database Apnea-ECG V1.0.0 dataset [10], [11], containing polysomnogram records of 35 patients over 7-10 hours with second-by-second annotations. The medical-records namely a01…. a04, b01 and c01…… c03, include four extra signals: Resp-C and Resp-A where Inductance plethysmography was employed to collect chest and abdomen breathing effort signals, Resp-N: Nasal thermistors are used to measure nasal airflow, SpO2 serves as an indicator of saturation. The network employs peripheral oxygen saturation (SpO2) signals recorded at an 8-Hz sampling rate. Experimental results clearly show lower SpO2 values during the Apneac event. The data is divided in train-test and validation. SpO2 measurements, taken at one-minute intervals, formed a crucial subset of characteristic data. The attributes of these intervals, such as the maximum, minimum, and other variables detailed in Table-3, were utilized to diagnose apnea. Characteristics of SpO2 were extracted post-preprocessing, and 1D-CNN was employed for SA-diagnosis.

Fig. 3 illustrates the overall methodology which includes downsampling of signals followed by filtration stage to remove noise and artifacts and segmentation stage to divide signal into segments of 1-minute duration. Each segment is identified as either an apneac event or a non-apneac event. Segments shorter than one minute, like 30-second intervals, were not considered. Consequently, the data in this study was annotated in one-minute intervals. These characteristics help in detecting patterns and anomalies in oxygen-saturation.

Table-3 highlights critical aspects extracted. These metrics help identify patterns and anomalies in sleep-cycles.

Table 3 - The statistical features of - SpO2 signal (over 1-minute segment)

Feature Name	**Feature Description**
S_{min}	Minimum value SpO2 level
S_{max}	Maximum SpO2 level
S_{mean}	Average SpO2 level
S_{vari}	SpO2 Variance
C_{orrec}	Correlation-factor of SpO2 data
D_{mean}	Average of the absolute differences between two adjacent mean-values of SpO2-signal.
ODI	Measures the count of (per hour of sleep) blood-oxygen-level drops by a certain amount from the baseline
CT90	The percentage of time during which the SpO2 level is below 90%
Desaturation Events	The frequency and duration of significant drops in SpO2 levels, typically 3-4% drop or more from the baseline.

SpO2 characteristics combined with characteristics of ECG-signals can increase the accuracy of SA detection.

4. Proposed System

The Fig. 4 shows proposed method for sleep-apnea detection. Initially, features were extracted independently from both ECG and SpO2 signals, collecting key physiological signs associated with sleep apnea. The next step is to combine these features into a unified dataset in order to provide a more comprehensive depiction of the patient's status by merging the temporal and spectral properties of both signals. This integrated dataset used to train/test a DL algorithm, which was chosen based on its capacity to handle multi-modal data and properly detect sleep apnea occurrences. The integration of ECG and SpO2 characteristics is anticipated to enhance the robustness and dependability of the system. This approach can enhance the accuracy and reliability of the diagnosis. Fig. 5 shows process flow for the same.

Preprocessing stage of SpO2 Signal filters out noise by using low-pass filters and normalize the signal. Whereas for ECG Signal removal of baseline wander and noise using bandpass filters were performed followed by normalization of the signal. In feature extraction stage from SpO2 signal Time-domain & Frequency-domain features were extracted like Mean, standard deviation, minimum, maximum, desaturation events, and duration, Power spectral density, dominant frequencies, and spectral entropy.

From ECG signal following features were extracted RR intervals, HRV metrics, Power spectral density of HRV, LF/HF ratio etc.

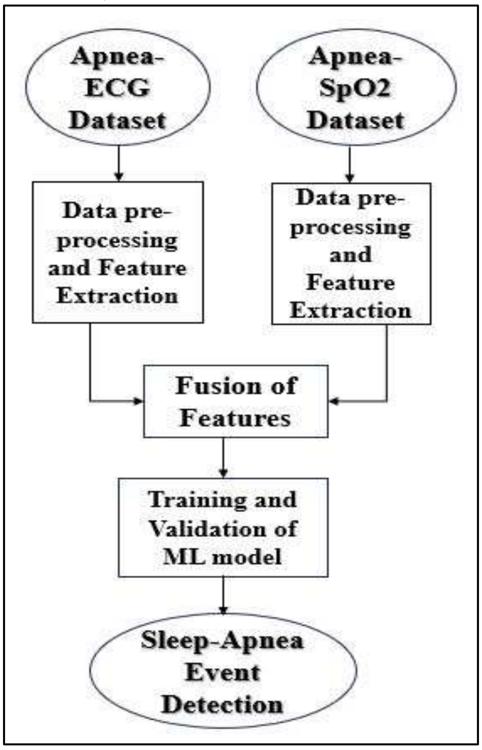
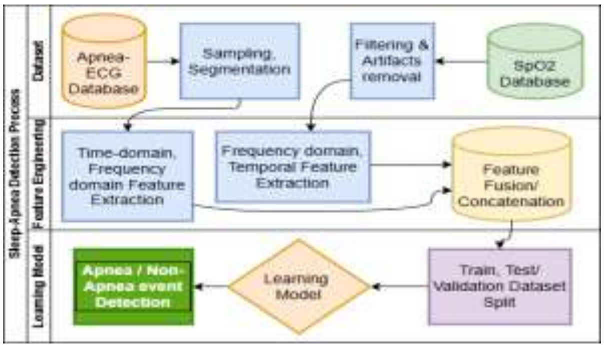


Fig. 4 Proposed system for Sleep-Apnea prediction from ECG and SpO2 signals
Fig. 5 Process-flow for Sleep-Apnea detection from ECG and SpO2 signal
In Feature Fusion stage we have concatenated features from both SpO2 and ECG signals. This can be done by concatenating the feature vectors from both signals. For feature selection stage we used techniques like Recursive Feature Elimination with Cross-Validation (RFECV). Finaly in model training stage we trained a 1D CNN using these combined features set to classify apnea events.



5. Result and Discussion

Experimental analysis shows improving in sleep-Apnea diagnosis using combined features of ECG and SpO2 signals in contrast to SA-diagnosis using individual signals. Table-7 below shows diagnostic accuracy of 91% against accuracies of 89% and 90% for ECG and SpO2 signals based diagnosis respectively.

We build CNN model with the help of 3-convolution layers each followed by a Max-pooling layer. These Convolution layers extract hidden patterns among data with the help of small size filters, activation function used is "ReLU" to add non-linearity to the model. Pool size of 2 used for downsampling data to reduce the dimensionality. After Convolutional and Pooling layers, we have used 2-dense fully connected layers with 128 neurons each to flatten the data and produce final

classification. At the output we have used a single neuron with sigmoid activation function to make final classification. We set binary cross-entropy as loss function and Adam-optimizer is used to reduce this loss function. Table-7 bellow discuss the performance of CNN model.
Table-4 gives comparative view of SA-diagnosis methods proposed earlier by various researchers and our proposed Cardiorespiratory method. The CNN model underwent training followed by validation process on a desktop computer with configuration as Processor - Intel(R) Core (TM) i5-1035G1 CPU at 1.00GHz - 1.19GHz, Operating System: Windows-10 Professional and a GeForce(R) RTX 2080 Super (TM) 8GB graphics card.
The first epoch, including weight initialization, took 61 seconds, while subsequent epochs from the second to the fifth took 57 seconds each. Completing one experiment required roughly 48 - 50 minutes. The trained model is capable of classifying a 1-minute ECG signal as normal or indicative of apnea in just 0.3 seconds.
OSA as per definition of the American Academy of Sleep Medicine (AASM) is characterized by an Apnea-Hypopnea-Index (AHI) of five or more [24]. The AHI can be determined by the equation-(1) shown below:

$$AHI = \left(\frac{60}{Len}\right) \times Num \ldots\ldots (1)$$

Here, 'Len' denotes the total count of 1-minute ECG segments, 'Len/60' is the duration of the recording in hours, and 'Num' represents the number of 1-minute apneas observed.
Table-5 shows results obtained by HRV-analysis of 3-different categories of ECG signals. One with normal ECG-signal, another one is T-wave distorted signal and a ECG-signal with Sleep-Apneac events.
Table-5 Results obtained for ECG signal analysis using HRV-analysis function

Param-eters	**ECG signal with T-wave distortion**	**Normal ECG signal**	**ECG signal with Apneac events**
bpm:	57.843	59.697	74.642
ibi:	1037.29	1005.075	803.834
sdnn:	60.907	45.612	25.854
sdsd:	20.513	17.278	8.060
rmssd:	33.059	30.487	13.118
pnn20:	0.493	0.483	0.104
pnn50:	0.135	0.118	0.000
hr_mad:	36.000	28.000	16.000
sd1:	23.285	21.545	9.273
sd2:	84.306	59.912	35.471
s:	6167.32	4055.16	1033.31
sd1/sd2:	0.2762	0.359	0.261
breathing rate:	0.133	0.1667	0.300

Various features extracted and their values were shown for the purpose of comparison. Table-6 shows the Sleep-Apnea events and Desaturation events detected from SpO2 signal by our proposed method. Only 8-petients data has been shown here.

Table-6 Analysis of SpO2 signals for SA-detection

Patient name/ Patient ID	**Total Samples scanned**	**Count of Apnea events detected**	**Count of Desaturation events detected**
a01	2956796	11751.0	6904.0
a02	3181796	12661.0	9378.0
a03	3134796	12501.0	9112.0
a04	2979796	11885.0	7864.0
b01	2916796	11633.0	11371.0
c01	2898796	11561.0	11476.0
c02	3006796	11993.0	11813.0
c03	2719796	10845.0	10771.0

We utilized accuracy, sensitivity and specificity as metrics for performance measures as shown in equation - 2,3,4 below:

$$Sensitivity = \frac{TP}{(TP+FN)} \text{ .... } (2)$$

$$Specificity = \frac{TN}{(TN+FP)} \text{ .... } (3)$$

$$Accuracy = \frac{(TP+TN)}{(P+N)} \text{ .... } (4)$$

In this context, ‘FN’ and ‘FP’ represent the number of normal and Apneac segments that have been wrongly classified, respectively. ‘TP’ represents number of Apneac segments and ‘TN’ represents the normal segments correctly identified. The terms in equation – (4) negative (N) and positive (P) indicate the count of segments without and with Apneac events, respectively. Sensitivity measures the fraction of apnea epochs accurately identified, specificity measures the fraction of normal epochs accurately identified, and accuracy reflects the fraction of all segments accurately classified.

6. Conclusion

The article outlines a new method for identifying sleep apnea events by integrating features from ECG and SpO2 signals. The CNN model implemented in this research work successfully detects apneac events and oxygen desaturation associated, with an accuracy up to 91%. The results also highlighted that multi-signal approach has enhanced SA detection performance as compared to individual signal approach where accuracies up to 89% for ECG and 90% for SpO2 signal is achieved. An AUC of 0.93 suggest our model’s effectiveness in providing insights into disease identification. Our research highlights the relation between Sleep Apnea and Heart diseases but we could not establish relation between Sleep-Apnea and brain strokes. Future research work could explore incorporating more physiological indicators and advance computational intelligence to establish this relation. Our research work provides valuable insights for effective management and treatment of the sleep-disorder that will help to improve patient outcomes.

7. Statements and Declarations

Funding Source: The authors declare that the present study did not receive any funding or grants from any organisation.

Conflict of Interest: All authors of this manuscript declare no conflict of interest.

Consent for publication: All authors have given their consent for publication of this research paper.

Author contribution: All authors have equal contribution to carry out this research work.

Table - 4 Comparative study of proposed method with existing methods.

Authors	**Signal Processing**	**Classifier used**	**Performance measures**			
			Acc.	**Sens.**	**Spec.**	**AUC**
Varon et al. [12]	RR interval Calculation; EDR Derivation; R-peaks Detection/Correction	LS-SVM	84.7%	84.7	84.7	0.88
Chang et al. [18]	Bandpass Filtering; Z-score Normalization	Deep CNN	87.9%	81.1	92.0	0.94
Song et al. [19]	R-peaks Detection using Filter-Bank; Median Filtering; RR Interval Calculation	HMM-SVM	86.2%	82.6	88.4	0.94
Singh et al. [20]	Bandpass Filtering; Continuous Wavelet Transform	Pre-trained AlexNet CNN + Decision Fusion	86.2%	90.0	83.8	0.88
Wang et al. [24]	Median Filtering /FIR Filtering + R-peaks Detection	LeNet-5 CNN	87.6%	83.1	90.3	0.95
Sharma et al. [27]	Bandpass Filtering; QRS Complex, R-peaks Extraction; Zero Padding	LS-SVM	83.8%	79.5	88.4	0.83
Li et al. [28]	R-peaks Detection; RR Interval Calculation; Bandpass Filtering; Median Filtering; Interpolation	Artificial Neural Network (ANN)	97.8%	98.6%	93.9%	0.97
Proposed method	Segmentation; R-R interval detection; Filtering; Sampling	1D -CNN	91%	87.6%	92%	0.93

Table-7 Performance analysis of 1D-CNN with combined features of ECG, SpO2 signals

Signal	**Classifier**	**Accuracy**	**Precession**	**Recall**	**F-1 score**	**Specificit y**	**AuC**
ECG	1D-CNN	89%	88%	90%	89%	88%	0.9
SpO2	1D-CNN	90%	89%	91%	90%	94.1%	0.9
Combined Features of ECG + SpO2	CNN	91%	88%	91%	90%	92%	0.93

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