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RESEARCH ARTICLE

BREATHING NEW LIFE INTO DIAGNOSIS: INTELLIGENT SIGNAL ANALYSIS FOR APNEA- HYPOPNEA AND MEDICAL DATA SECURITY

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ABSTRACT

Obstructive sleep apnea-hypopnea syndrome (OSAHS) is an increasingly significant health concern due to its widespread occurrence, heightened risk factors, and significant mortality rates. To address this issue, researchers have focused on utilizing the blood oxygen saturation (SpO2) signal to analyze the occurrences of apnea or hypoventilation episodes during sleep, resulting in the development of the apnea-hypopnea index (AHI). In order to extract relevant information from the SpO2 signals, 35 Time Domain characteristics have been identified and studied. To enhance the practical application of these features in Industry 5.0 supply chains, a feature selection procedure was implemented, effectively reducing the dimensions from 7 to just 5. This reduction has significantly improved the feasibility of integrating these features into real-world scenarios. To select the most relevant features, a combination of the competitive swarm optimizer algorithm and the Pearson correlation coefficient was utilized in this study. By employing these techniques, the researchers were able to identify the most informative features for analysis and classification. The study achieved promising results using a random forest classifier, reporting an accuracy rate of 86.92% and a specificity rate of 90.7%. These findings highlight the potential of using the selected features for the accurate detection and diagnosis of OSAHS, contributing to the development of effective treatment strategies and improved patient outcomes.

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INTRODUCTION

The study presented in this article explores the connection between Obstructive Sleep Apnea-Hypopnea Syndrome (OSAHS) and COVID-19. It highlights that approximately 27% of the global population experiences sleep disturbances, which can potentially increase the risk of COVID-19 infection. The research indicates that OSAHS is highly prevalent and it is commonly happening sleep disorder. It reveals that up to 25% of individuals with hypertension also have OSAHS. During a follow-up visit, 246 patients with OSAHS were included in the study. It is a medical condition characterized by repetitive episodes of partial or complete obstruction of the upper airway during sleep. These obstructions can lead to a decrease in airflow (hypopnea) or a complete cessation of airflow (apnea) for brief periods. OSAHS often results in disrupted sleep patterns and a decrease in blood oxygen levels, which can have various health consequences, including excessive daytime sleepiness, fatigue, and an increased risk of cardiovascular problems. Treatment for OSAHS may include lifestyle changes, the use of continuous positive airway pressure (CPAP) devices, or surgical interventions to alleviate airway obstructions. Patients with OSAHS often experience a decline in oxygen saturation during sleep, leading to hypoxia in the brain and increased stimulation of sympathetic nerves.

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This can result in complications associated with hypertension, including angina pectoris and myocardial infarction. The condition is also linked to symptoms of arteriosclerosis and an increased risk of cerebral infarction. A PSG device, or Polysomnography device, is a medical tool used to monitor and record a variety of physiological functions during a patient's sleep. It is commonly employed in sleep medicine to diagnose sleep-related disorders, such as sleep apnea, narcolepsy, insomnia, and restless legs syndrome, among others To diagnose OSAHS, polysomnography (PSG) is mentioned as the "gold standard" in the medical field. PSG involves recording various physiological parameters during sleep to evaluate the quality of sleep, detect sleep-related breathing disorders, and determine the severity of OSAHS. However, PSG has certain limitations, including subjective discomfort experienced by some individuals, its limited duration capturing only a single night of sleep data, and its inability to assess certain sleep parameters such as sleep fragmentation and circadian rhythms. PSG is also resource-intensive and time-consuming, requiring specialized equipment, trained personnel, and dedicated facilities.

Some of the limitations include:

- Expensive and Resource-Intensive
- Artificial Sleep Environment
- Limited Testing Time
- Invasive and Discomfort
- Incompatibility with Home Environment

- Time-Consuming
- May Not Capture All Sleep Disorders
- Limited Availability

Polysomnography (PSG) devices and SpO2 (Blood Oxygen Saturation) signals are both used in the field of sleep medicine, but they serve different purposes and provide distinct types of information. Here's a comparison between PSG devices and SpO2 signals:

Purpose

PSG Device: Polysomnography is a comprehensive sleep study that simultaneously monitors various physiological parameters. It is primarily used to diagnose a wide range of sleep disorders, such as sleep apnea, insomnia, narcolepsy, and restless leg syndrome. PSG provides detailed data on sleep stages, respiratory events, brain activity, and muscle movements during sleep.

SpO2 Signal: SpO2 signals, on the other hand, specifically measure blood oxygen levels. They are often used to monitor a patient's oxygen saturation during sleep, primarily to diagnose or assess sleep apnea and other respiratory disorders. Low SpO2 levels can be indicative of oxygen desaturation events during sleep.

Data Collected

PSG Device: PSG devices collect a wide range of data, including EEG (brain waves), EOG (eye movements), EMG (muscle activity), ECG (heart rate), respiratory effort, airflow, and more. This data is used to comprehensively analyze sleep patterns and diagnose sleep disorders.

SpO2 Signal: SpO2 monitors measure oxygen saturation in the blood. This is typically done using a non-invasive finger probe or a similar sensor. SpO2 data specifically reflects changes in oxygen levels throughout the night.

Invasiveness

PSG Device: PSG is an invasive and complex sleep study that requires a patient to spend a night in a sleep laboratory or clinic. It involves attaching numerous sensors to the body, including electrodes on the scalp and body, which may affect sleep quality.

SpO2 Signal: Monitoring SpO2 levels is non-invasive and usually done at home using a simple and comfortable finger probe. This makes it more convenient for many patients and less disruptive to their natural sleep patterns.

Cost and Accessibility:

PSG Device: PSG studies are costly and require access to a specialized sleep clinic or laboratory. They are not readily accessible to everyone.

SpO2 Signal: SpO2 monitoring is relatively affordable, and portable devices are available for home use. This makes it more accessible to a wider range of individuals.

Diagnostic Capability

PSG Device: PSG is the gold standard for diagnosing a wide range of sleep disorders and provides comprehensive data for healthcare professionals to make accurate diagnoses.

SpO2 Signal: While SpO2 data can be indicative of certain sleep disorders, such as sleep apnea, it is not as comprehensive as PSG and may not diagnose other sleep conditions accurately. In summary, PSG devices and SpO2 signals serve different roles in the field of sleep medicine. PSG is the more comprehensive tool for diagnosing a wide range of sleep disorders, while SpO2 monitoring is primarily used to assess oxygen levels, especially in the context of sleep apnea. Therefore, here used SpO2 signal instead of using this PSG device

Based on the Apnea Hypopnea Index (AHI), The American Academy of sleep research has introduced four levels of Obstructive Sleep Apnea to initiate the diagnosis of Obstructive Sleep Apnea Hypopnea Syndrome (OSAHS). The variation of AHI from normal to severe is caused due to the deviation in the frequency of Apnea events. Commonly AHI is a measure used in sleep medicine, to measure the Apnea severity. Sleep Apnea is basically a sleep disorder caused due to continuous interruptions in breathing, mainly due to complete cessation of breathing or partial reduction in airflow. AHI is measured every hours during sleep to calculate the severity range.

The formula to calculate the AHI is as follows:

AHI = (Number of complete cessation of breathing + Number of partial reduction in airflow) / Total Sleep Hours.
The AHI is typically expressed as events per hour. It provides a way to categorize the severity of sleep apnea as follows:
AHI events less than 5 per hour is considered as normal patient.
AHI events between 5 and 15 per hour is considered as patients with Mild Sleep Apnea.
AHI events between 15 and 30 per hour is considered as patients with Moderate Sleep Apnea.
AHI events greater than 30 per hour is considered as patients with Severe Sleep Apnea.

The AHI is a critical diagnostic tool for healthcare or medical professionals to use the severity of a patient's sleep apnea and to analyze the suitable course of treatment. It helps in deciding whether lifestyle changes, the use of continuous positive airway pressure (CPAP) therapy or operation may be needed to manage the condition effectively. Monitoring the AHI over time is also essential for tracking the effectiveness of treatment interventions and ensuring that the patient's sleep apnea is well managed. The article proposes an intelligent classification diagnosis workflow that analyzes the relationship between SpO2 signals and OSAHS. This workflow aims to enhance the efficiency and accuracy of OSAHS diagnosis by incorporating feature extraction techniques and ensuring data security.

SpO2, or Blood Oxygen Saturation, is a vital physiological parameter that measures the percentage of oxygen-bound hemoglobin in a person's blood. It serves as an essential indicator of the oxygen levels in the bloodstream.

SpO2 stands for Peripheral Capillary Oxygen Saturation. It is a non-invasive measurement that quantifies the percentage of oxygen saturation in the hemoglobin within red blood cells SpO2 is typically measured using a pulse oximeter, a healthcare device that is placed onto a finger, earlobe, or other peripheral parts of the body. The SpO2 reading indicates how well oxygen is being transported to the body's tissues and organs. A normal SpO2 level is typically around 95-100%, while levels below 90% may indicate hypoxemia, a condition characterized by low O2 levels in the blood and strong respiratory issues. SpO2 is a critical parameter in healthcare, particularly for monitoring patients' respiratory and cardiovascular health, as well as in the diagnosis of conditions like sleep apnea and chronic obstructive pulmonary disease (COPD). The article concludes by presenting an overview of related research, addressing the detection issue of OSAHS, providing insights into the processing of SpO2 signals, and presenting the classification findings and performance evaluation. This study lays the groundwork for future developments in intelligent diagnosis methods for OSAHS and contributes to the understanding of the relationship between OSAHS and SpO2 signals, ultimately aiming to improve diagnosis and treatment outcomes.

Factors that increases the risk are mentioned below:

Excess weight*:* This Excess weight obstruct the breathing of the apnea patients. Majority of patients with apnea are overweight.

Hypothyroidism and polycystic ovary syndrome are the conditions in obesity that causes sleep apnea.

Older age: As the age increases apnea syndrome also increases. It happens around the age of 60 to 70.

Narrowed airway: It is the passed down trait in our family. It blocks our airway when tonsils or adenoids became enlarged.

High blood pressure: this also known as hypertension. And thus it is related to sleep apnea patients.

Chronic nasal congestion: When one has consistent nasal congestion during night time, there is more likely to happen sleep apnea for two times.

Smoking: Patients with sleep apnea are most probably a smokers.

Diabetes*:* It is common for diabetes patients. Lack of memory power, high headaches, mood swings are some of the major complain. People with OSAHS often suffers from memory issues, sinus problems and mood swings. They often urinate at dawn. It is a highest risk factor for corona. Compared to other patients they need better care.

Proposed System Design: This proposed system design aims to leverage advanced technologies, data security measures, and healthcare expertise to provide intelligent classification and diagnosis of medical conditions, including COVID-19, within the context of Industry 5.0, where data-driven insights and automation play a significant role in enhancing healthcare outcomes. It's essential to work closely with healthcare professionals, data security experts, and technology specialists to implement and continually improve such a system. *The proposed system design for the apnea hypopnea diagnosis system involves several steps for feature extraction from the SpO2 signal segments. This section identifies the process of apnea hypopnea diagnosis system as shown below:*

System Model

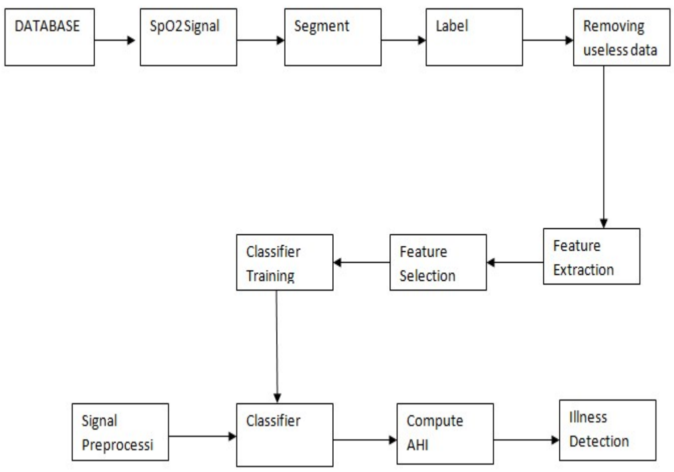

Fig. 1. Proposed System design

Dataset Description: The article makes use of two databases, namely the University College Dublin Sleep Apnea Database (UCD database) and the Apnea-ECG database [19]. The UCD database, which is constantly updated, consists of a wide range of subjects, totaling 25+8 in the most recent version. These databases provide a rich and comprehensive collection of data for the study and analysis of sleep apnea and its correlation with electrocardiograms (ECG). By leveraging these datasets, researchers have access to a diverse set of subjects, enabling them to gain valuable insights into the relationship between sleep apnea and ECG patterns. 1.

Data Preprocessing: Data preprocessing plays a pivotal role in the realm data analysis and machine learning, particularly in healthcare applications. It encompasses the tasks of refining, transforming, and structuring raw data to render it suitable for analytical purposes and model development. The core objective of data preprocessing in healthcare is to enhance data quality, reduce noise, manage missing data, and ensure data is prepared for a spectrum of analytical tasks. The following are key elements of data preprocessing in the context of healthcare data, specifically focusing on SpO2 (blood oxygen saturation) data:

Data Collection and Privacy*:* It is imperative to ensure that the collection of SpO2 data adheres to stringent privacy standards. This may necessitate procedures like anonymization of patient identifiers and encryption of sensitive medical information to safeguard patient privacy.

Data Cleaning and Quality Assurance: Rigorous data cleaning procedures are essential to address issues like missing values and outliers in SpO2 data. High-quality data is a fundamental prerequisite for obtaining reliable results in classification and diagnosis tasks.

Feature Engineering: Feature engineering is a critical step in healthcare data preprocessing. It involves creating domain-specific features that can provide insights into specific medical conditions. For instance, features related to oxygen desaturation events can be highly relevant for the diagnosis of conditions like sleep apnea.

Data Transformation: The normalization or standardization of SpO2 data is crucial to ensure that the features are brought to a consistent scale. This is particularly important when employing machine learning algorithms, as it aids in their effectiveness.

Dimensionality Reduction: In cases where you are dealing with high-dimensional datasets, it's prudent to explore dimensionality reduction techniques. These methods can enhance model efficiency without compromising accuracy.

Imbalanced Data Handling: Should your dataset exhibit class imbalance, especially in scenarios with a disparate distribution of COVID-19 cases and non-COVID-19 cases, it is essential to employ strategies to rectify this imbalance.

Data Splitting: The data should be methodically divided into training, validation, and test sets. This separation is fundamental for purposes such as model training, hyper parameter optimization, and evaluation.

Data Security and Privacy: Particular emphasis should be placed on data security and privacy, particularly when working with sensitive medical data. Comprehensive documentation is essential to record the security measures applied to protect patient information. These steps are vital in ensuring that healthcare data, especially SpO2 data, is processed and prepared in a manner that is not only compliant with privacy regulations but also conducive to generating valuable insights and accurate medical diagnoses.

Feature extraction: Feature extraction is the process of selecting, transforming, or creating relevant features from the raw data to improve the performance of machine learning models or to facilitate data analysis. For each one-minute segment of the SpO2 signal, time-domain characteristics are extracted. The feature values of each individual SpO2 signal segment are represented by a row in a new matrix.

The following features are extracted for each segment:

Basic Statistics

Minimum Value*:* The minimum value of each SpO2 signal segment is captured in the first column of the feature matrix.

Average: The average value of each SpO2 signal segment is reflected in the second column of the feature matrix. This average value represents the overall mean SpO2 level during the segment, offering a measure of the general oxygen saturation during that period.

Variance: The third column of the feature matrix represents the variance of each SpO2 signal segment. This value indicates the degree of variability or dispersion in the SpO2 levels within the segment. A higher variance suggests more significant fluctuations in oxygen saturation, while a lower variance indicates more stability.

Number of Baselines Crossed*:* In this experiment, the mean value is chosen as the baseline. The count of SpO2 curve crossings over this baseline is recorded in the feature matrix. This information provides insights into the extent to which the SpO2 levels deviate from the average value, highlighting potential abnormalities or fluctuations in oxygen saturation.

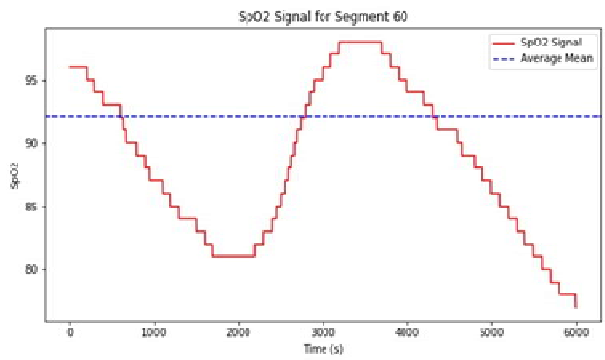

Fig. 2. Baseline count

Linear Fitting: Linear fitting is performed for each one-minute SpO2 signal segment. Mild trend can be shown during the stable SPO2 signal segment, with the intercept of the linear fit nearer to the average SpO2 signal for that segment and the slope nearer to zero. A segment which has "complete cessation breathing-partial reductioning airflow" events will have a comparatively larger slope or absolute value in the linear fit. A segment that contains "apnea-hypopnea" episodes will have a relatively large slope or absolute value in the linear fit.

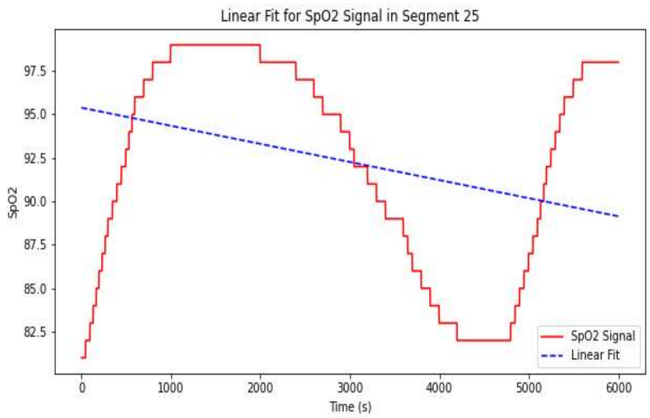

Fig. 3. Linear Fitting

Δ Index: The Δ index is a characteristic parameter that is computed by partitioning the SpO2 signal segment into 12-second windows. The average SpO2 value within each window is calculated, and the absolute difference between adjacent windows is determined. The mean of the absolute differences throughout the segment is calculated to obtain the Δ index.

Central Tendency Measure (CTM): The CTM is a nonlinear feature. The change in One-D time signal of the SpO2 segment into a Two-D coordinate system is carried out by CTM. The CTM provides a graphical representation of the amount of change or complication in the time series. A larger CTM value implies a projection into two dimensions, indicating a smaller variation and greater stability in the SpO2 signal segment.

Oxygen Desaturation Index (ODI): ODI is used to evaluate blood oxygen levels during sleep. It focuses on oxygen desaturation which indicates insufficient oxygen supply to the body during sleep. During an ODI test, the number and intensity of oxygen level drops observed throughout each hour of sleep are recorded and analyzed. he ODI test results provide a quantitative measure of the severity of oxygen desaturation, allowing for an objective evaluation of the condition.

Total length of the signal length (TSA): The TSA index, also known as the Total Signal Area index, is a metric used to assess the proportion of low-level signals in a specific segment of an SpO2 (blood oxygen saturation) signal. It measures the ratio of the total length of the signal segment below a certain threshold to the total length of the segment. The TSA index is extracted as a feature because it provides valuable information about the presence and proportion of low-level signals in the SpO2 segment being analyzed. By quantifying the extent of low-level signals, the TSA index helps in understanding the characteristics of the SpO2 signal and can be used in various applications, such as the diagnosis and monitoring of sleep disorders or respiratory conditions.

Feature Selection

Algorithm	**Competitive feature selection via swarm optimization**
	Features of original SpO2 signals.
Input:	Selected features
Output:	Set the swarm set $s^t = \{s^t_1, s_2^t \dots s_m^t\}$.
1	Iteration time is Ng, and the group size is nP.
	Initialization is done for the position x_l^0 and speed v_l^0.
2	Splitting up the swarm group s^t is return written
3	into $s^t = \{set^t_1, set_2^t, \dots, set_m^t\}$.
	Calculate the fitness values for s^t_{i1}, s^t_{i2} .
	If fitness value $f(s^t_{i1}) < f(s^t_{i2})$,
	$s^t_w = s^t_{i1}, s^t_1 = s^t_{i2}$.
	else,
4	$s^t_w = s^t_{i2}, s^t_1 == s^t_{i1}$.
5	Put s^t_w into the subsequent swarm s^{t+1} .
6	Calculate the subsequent swarm for s_l^t .
	$u_l^{t+1} = R_1^t u_l^t + R_2^t(x_w^t - x_l^t) + jR_3^t(\bar{x}^t - x_l^t)$
	$x_l^{t+1} = x_l^t + u_l^{t+1}$
	t=t+1, till t=n, go back to step 2.

This algorithm helps in feature distillation. Using this algorithm no of features selected is reduced from 35 to 17.

Features selected are

1] Minimum value
2] Average value
3] ODI3,ODI5,ODIxy(x=2,y=3)
4] TSA80,TSA85.
5] Absolute value of slope

RESULTS

Classification Result Comparison

	Accuracy (%)	Sensitivity (%)	Specificity (%)
L- LS-SVM	82.74	75.80	86.56
RBF LS-SVM	84.48	76.62	90.53
K-NN(K=5)	78.65	66.90	88.4
RF	94	72.85	90.7
LDA	80.60	63.52	87.55

These results demonstrate the performance of the classifiers in accurately identifying "apnea-hypopnea" occurrences. This study assessed the performance of various classifiers, including an improved least squares support vector machine (LS SVM) classifier with an RBF kernel, k-nearest neighbor (kNN) classifier, random forest (RF) using a decision tree-based ensemble learning method, and linear discriminant analysis (LDA). The evaluation of these classifiers focused on recognizing "apnea-hypopnea" events, using accuracy (Acc), sensitivity (Se), and specificity (Sp) as evaluation metrics. The definitions of these metrics are outlined in the following equations:

$$ACCURACY = \frac{TP + TN}{P + N}$$

$$SENSITIVITY = \frac{TP}{TP + FN}$$

$$SPECIFICITY = \frac{TN}{TN + FP}$$

From the above table, we can say that

1) The Random Forest classifier works well in the 1-minute sequence of period.
2) The accuracy of whether the SpO2 contains the “complete cessation breathing-partial reductioning airflow” event is the highest, reaching 94%.
3) The Random Forest classifier has the highest specificity in the evaluation of classification results.

Table II compares the results of this experiment and other experiments in identifying “complete cessation breathing-partial reductioning airflow” events, shows this experiment has better results than other experiments.

AHI Index: The complete cessation breathing-partial reductioning airflow is calculated with the help of AHI. The data is splitted into 25 parts each includes the extracted parameters of SpO2 signals. The AHI index is calculated for every subject in the database. To classify the subject, one subject's data is used for testing and another subject's data for training using Random Forest classifier. The total number of subjects classified as "1" by the Random Forest classifier in the subject's data is divided by the subject's sample size, as 25+8 persons must be categorized and tested sequentially.

Analysis of the subjects' prevalence evaluation results in comparison

The prevalence evaluation results of the subjects in comparison with other studies are as follows:

	Database	Accuracy
[21]	UCD	84
[15]	UCD	88
[22]	UCD	88
[3]	UCD	92
Our approach	UCD+AED	94

The approach used in this experiment achieved an accuracy of 94% in evaluating the prevalence of OSAHS.

Related Works: Several alternative approaches for detecting and identifying OSAHS have been suggested in previous investigations. These approaches include snoring, ECG, SpO2, and oronasal breathing airflow. One study focused on using patient-provided snoring characteristic data to identify OSAHS. The researchers removed acoustic information features from the snoring noises and trained a Gaussian mixture model using the retrieved features.

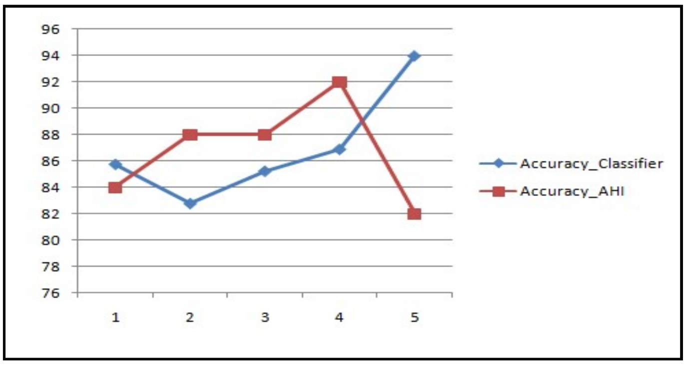

Fig. 4.Comparison of Accuracy from PSG and Classifier

Another investigation focused on using SpO2 signals for OSAHS detection and identification. The researchers preprocessed the SpO2 signal, marked it manually, and extracted temporal domain features for classification [[15]]. A remote patient monitoring system capable of real-time tracking was introduced in another study. The system used a classifier to identify "apnea-hypopnea" events based on feature values extracted from SpO2 signals [[17]]. Other studies have explored the use of different features and signal processing techniques to detect and identify OSAHS, such as analyzing snoring noises and computing energy ratios 1. These studies aim to make the testing procedure more user-friendly and comfortable for testers while accurately identifying and treating OSAHS patients early on [[15]] [[17]].

CONCLUSION

In summary, this article conducted a comprehensive analysis of SpO2 signals from a medical database. Data preprocessing improved its resilience, and feature extraction was performed based on blood ODI principles. Feature selection reduced the set from 35 to 7 dimensions, benefiting classification and computational speed. The Random Forest classifier demonstrated strong accuracy and specificity, showing promise for industrial deployment. Furthermore, this method offers a rapid and effective means of diagnosing OSAHS, facilitating timely treatment coordination with healthcare providers. This can potentially enhance the treatment of OSAHS and improve the recovery rates of COVID-19 patients.

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