



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 10, October 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

Innovative Approaches to Sleep Apnea Anomaly Detection Utilizing Machine Learning Techniques

Ranjan V, Pradeep K

Assistant Professor, Department of AIML, JNN College of Engineering College, Shivamogga, Karnataka, India

Assistant Professor, Department of CSE, PESITM, Shivamogga, Karnataka, India

ABSTRACT: The other common sleep disorders are sleep apnea, caused by continuous disturbances of breathing while sleeping. It leads to a reduction in the level of oxygen saturation in the blood. To treat it, one may use overnight Polysomnography in an authorized conditional laboratory. However, this test demands more economic availability, fewer beds in order to treat, and require more staff members to record the whole session. Thus, this paper is presenting work to detect anomaly detection using oxygen saturation by looking at the patient record. In this paper, we used GMM70.67%, and Principal Component analysis detect anomaly resulting accuracy of 70.27% in logistic regression, 71.67% using DBSCAN, and lastly 65.17%

KEYWORDS: Sleep apnea, Isolation Forest, k-nearest neighbor, support vector machine, polysomnography,...

I.INTRODUCTION

Oxygen saturation is the kind of measuring the amount of oxygen, which is carried by the red blood cells in the body [1]. It is measured meddling using an oximeter, oximeter is a small device that is attached to the fingertip or the other parts of the body. SpO2 levels provide information about a person's overall health and respiratory problems. Detection Sleep apnea is one of the challenging tasks because it undergoes undiagnosed due to its symptoms that occur during sleeping. This is why the levels of oxygen saturation during sleep must be monitored, and this will serve as an approach that will help detect any anomalies. In this paper, we applied anomaly detection algorithms to oxygen saturation data to identify the patterns that depart from normal sleep patterns [2]. Managing sleep apnea and controlling that from time and detecting abnormal oxygen saturation is a big task. That's why this anomaly detection came into existence. In anomaly detection, analyzing the oxygen saturation data collected from pulse oximeters during sleep to identify the patterns which deviate from the normal values [3]. Therefore, anomaly detection algorithms applied to these data would automatically detect abnormal patterns such as oxygen saturation indicating sleep apnea events such as hypopnea, partial airway blockage or apneas, complete airway blockage).

Detection of sleep apnea anomaly from oxygen saturation has so many applications in sleep medicine. It can cure the treatment of sleep apnea by giving objective and quantitative measurements of oxygen saturation levels during sleep [4]. It can also use to monitor the effectiveness of the treatments for sleep apnea, that is continuous positive airway pressure (CPAP) therapy, by tracking changes in the patterns over time.

[5]. It also has the potential to be able to monitor patients with sleep apnea so early detection of sleep apnea events can be done.

But most importantly, sleep apnea anomaly detection through oxygen saturation data is not only the As such, a solution or treatment tool to be used along with other clinical assessment and sleep studies will be required for the true detection of anomalies and thus will help in management of sleep apnea [6]. Moreover, accuracy using algorithms for the detection requires more research and verification in aspects of reliability and clinical utility. Despite this new area of research, there is much hope in spite of improvement, which will be there for the better treatment and management of sleep apnea and thereby quality life..

II. RELATED WORK

As we told before in the last sections when it comes to oxygen saturation, which is the amount of oxygen carried by the red blood cells and is frequently used in sleep apnea treatment and patient monitoring, sleep apnea is a disorder that occurs during sleep and causes repeated pauses in breathing while a person is sleeping. This decreases the oxygen saturation level in the blood. Over the years there are so much significant and related research on sleep apnea anomaly detection using oxygen saturation. Here in this section, we are going to look at some related works:

1. “Automatic Detection of Sleep Apnea using Oxygen Saturation and Heart Rate Variability” by Khedr et al. (2022)

This work proposed an automated detection of sleep apnea using oxygen saturation and heart rate variability. The authors used statistical features which are extracted from the oxygen saturation and heart rate variability signals to train a model for detecting sleep apnea. This proposed work achieved high accuracy in detecting sleep apnea events.

2. “Detection of Sleep Apnea from Oxygen Saturation Using Convolutional Neural Networks” by Patnaik et al. (2019): This work proposed a deep learning-based approach using CNNs for detecting sleep apnea from oxygen saturation signals. Here authors used a large dataset of oxygen saturation recordings to train a CNN-based approach which showed promising results to detect sleep apnea events.

Step Description Tools/Techniques

1. Data Acquisition	Collect physiological signals related to sleep (EEG, ECG, SpO2, respiratory effort, airflow, etc.).	Polysomnography (PSG), Sleep monitoring devices.
2. Preprocessing	Clean the raw data by removing noise, normalizing signals, and segmenting data into windows.	Filters (bandpass, low-pass), normalization techniques, signal windowing.
3. Feature Extraction	Extract relevant features from the data to highlight important patterns like respiratory cycles.	Time-domain, frequency-domain, morphological, and statistical features.
4. Feature Selection	Reduce dimensionality by selecting the most relevant features. This step is optional.	PCA (Principal Component Analysis), correlation analysis.
5. Anomaly Detection	Use machine learning algorithms to detect anomalies (apnea events).	KNN, SVM, Random Forest, Isolation Forest, LOF, PCA-based detection.
6. Evaluation & Classification	Evaluate the model’s performance using metrics like accuracy, sensitivity, and specificity.	Accuracy, sensitivity, specificity, F1 Score.
7. Diagnosis and Reporting	Provide a final report on detected apnea events, including severity (AHI score).	Apnea-Hypopnea Index (AHI), sleep study reporting.

III. EXPERIMENTAL SETTINGS

Data set

This experiments Sleep apnea anomaly detection datasets can be collected in the 25000 patients into datasets that can detect anomalies this dataset feature can be spo2, weight, heart pulse, temperature, muscle mass, hydration, bone mass, pulse wave velocity from the patients with and without sleep apnea and the data sets training and testing process of some machine algorithms implemented to the based accuracy score which algorithm can be the better performance of the algorithm.

Gaussian Mixture Models (GMM)

GMM is a probabilistic model that assumes the data is generated from a mixture of several Gaussian distributions. Each data point is assigned a probability of belonging to one of these distributions, and points with low probabilities are considered anomalies.

1. Key Points: Effective for detecting anomalies when the data follows or can be approximated by a Gaussian distribution. However, it may not perform well if this assumption is violated.
2. Average path length in sleep apnea is determined using `average_path_length`
3. $(n)=2*(\log(n1)+0.5772156649)$

In this equation, n stands for the number of samples in the dataset.

4. Anomaly score in sleep apnea is determined using $\text{anomaly_score}(x)=2(-\text{average_path_length}(x)/c(n))$ where n is the dataset's sample count, and $c(n)$ is a normalizing constant.

Principal Component Analysis (PCA)

PCA is a dimensionality reduction technique that transforms data into a new coordinate system based on its principal components (directions of maximum variance). For anomaly detection, data points that deviate significantly from the low-dimensional space formed by the principal components are considered anomalies.

Key Points: Particularly useful in high-dimensional data. However, PCA assumes that the majority of variance in the data is meaningful, PCA requires that the data be standardized so that each feature has a mean of 0 and a standard deviation of

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}$$

Where:

- X is the original data matrix.
- μ is the mean of each feature.
- σ is the standard deviation of each feature.
- X_{scaled} is the standardized data.

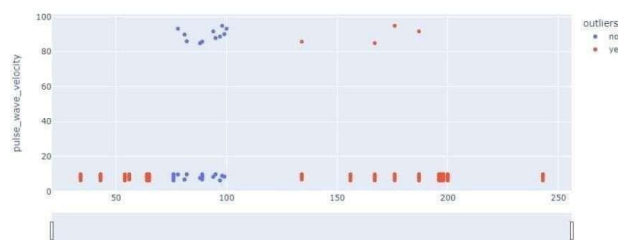
DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

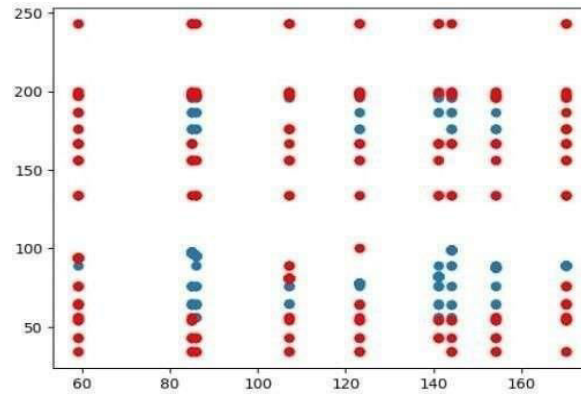
DBSCAN is a clustering algorithm that groups together closely packed points based on density and treats points that are not in a dense region as outliers. It does not require specifying the number of clusters in advance.

Key Points: Works well with datasets that contain noise and clusters of arbitrary shape. The results are sensitive to the choice of parameters like the radius (epsilon) and minimum number of points in a cluster

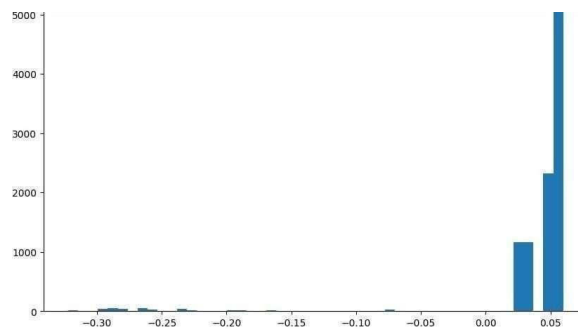
IV. RESULTS AND DISCUSSIONS

In this below, we are using plot express to plot anomalies using oxygen saturation as an x-axis and pulse wave velocity as a y-axis where red color indicates the outliers and blue color indicates no outliers in this we are using the slider to vie and to get a better point of view.

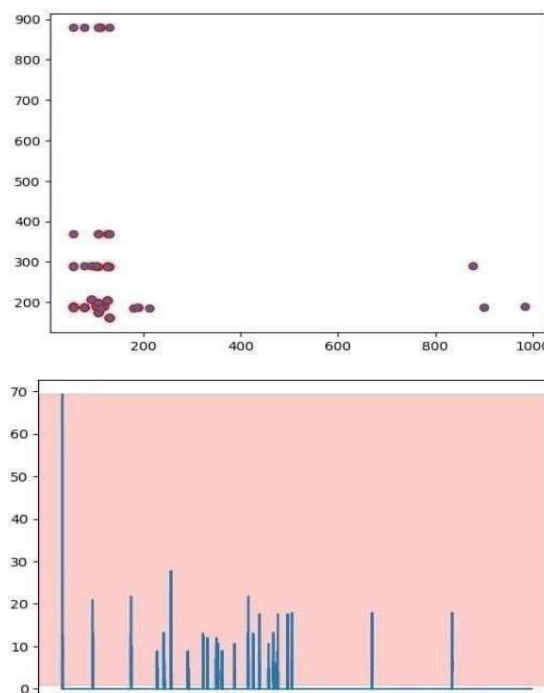




In this below figure, we are using the model. The decision function is to get a score by passing a data frame as oxygen saturation and in the score we will get both positive and negative values. Here is a histogram plot, using bins=50 where we evaluate the score less than -0.05 as an outlier.



Principal Component Analysis(PCA)

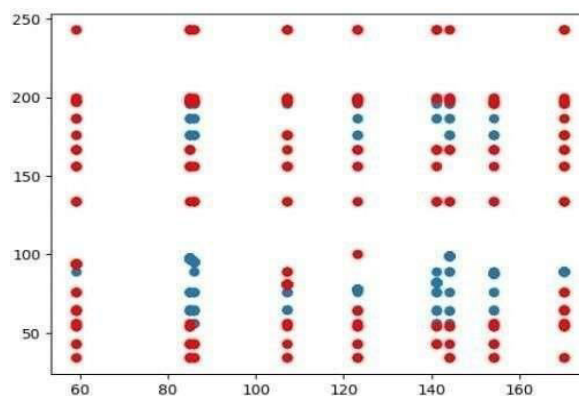


In this figure, we are using a scatter plot where we are plotting all the abnormal points with red color and this is been applied to the function called `abn_index` where distance and mean are used with an axis equal to 1.

In this figure we are using the unsupervised method to detect anomalies using the KNN algorithm where we are using the `axhspan` function which comes under `matplotlib` with `alpha` equal to 2 and fitting the nearest neighboring algorithm with `neighbors` equal to 5 and the algorithm used is in this `isballtree`.

DBSCAN

In this figure, we are visualizing the anomalies using a scatter plot by considering the data and data frame as `heartbeat`, `oxygen saturation`, and showing all the outlier values in red color.



V. FUTURE SCOPE AND CONCLUSION

One of the promising processes is the potential for detecting sleep apnea anomalies using machine learning algorithms. There exists a huge growing interest in this field among clinicians and researchers and with continued research and development in this field.

We can expect further improvements in the occurrence and effectiveness of the algorithms that we used in this work. To this, in addition it will also be helpful for patients to assume their sleep apnea events. In conclusion employing machine learning algorithms for sleep apnea anomaly detection is one the prominent way that might potentially significantly enhance the identification and treatment of sleep apnea. While there is much work to be done, the current research shows the effect. The liveness of machine learning algorithms in detecting sleep apnea and anomalies from the dataset

REFERENCES

1. Revels SL, Cameron BH, Cameron RB (2021) Obstructive sleep apnea and perioperative delirium among thoracic surgery intensive care unit patients: a perspective on the STOP-BANG questionnaire and postoperative outcomes. *J Thorac Dis* 11:S1292–S1295
2. Detection of Sleep Apnea from Oxygen Saturation Using Convolutional Neural Networks” by Patnaik et al. (2019).
3. (2020) `mghecdac/respiratory_event_detection_wearable`. MGH ClinicalData Animation Center
4. Welcome to Neuro. In: Natus. <https://neuro.natus.com/>. Accessed 6 Apr 2020
5. MyAir LLC. In: AirGoTM. <https://www.myairgo.com>. Accessed 6 Apr 2020
6. Automatic Detection of Sleep Apnea using Saturation of Oxygen and Heart Rate Variability” by Khedr et al
7. Vallat R (2020) `raphaelvallat/entropy`. Accessed 6 Apr 2020
8. Deviaene M, Testelmans D, Borzée P, et al (2019) Feature Selection Algorithm based on Random Forest applied to Sleep Apnea Detection. In: 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). pp 2580– 2583
9. Welcome to Neuro. In: Natus. <https://neuro.natus.com/>. Accessed 6 Apr 2020
10. N. Banluesombatkul, P. Ouppaphan, P. Leelaarporn, et al., “MetaSleepLearner: a pilot study on fast adaptation of biosignals- based sleep stage classifier to a new individual subject using meta- learning,” *IEEE Journal of Biomedical and Health Informatics*, p. 1, 2020



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details