International Journal of Research Publication and Reviews, Vol 4, no 8, pp 1619-1623 August 2023

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Sleep APNEA Anomaly Detection Using Machine Learning Algorithms

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ABSTRACT-

Sleep apnea is one of the common sleep disorders caused by continuous disturbances in breathing while sleeping, it leads to the reduction of oxygen saturation in the blood. One of the traditional standards to treat this is by using overnight Polysomnography in an authorized conditional laboratory. Moreover, this test requires more economic availability, fewer beds to treat, require more staff members to record the whole session. So, due to this difficulty, this paper presents the work to detect anomaly detection using oxygen saturation by looking at the patient record. In this paper, we used isolation forest 70.67%, logistic regression, k-nearest neighbor, and support vector machine to detect the anomaly resulting accuracy of 60.27% in logistic regression, 71.67% using k-nearest neighbor, and lastly 60.17% Using support vector machine.

***INDEX TERMS polysomnography, apnea, Isolation Forest, k-nearest neighbor, support vector machine*.**

I. INTRODUCTION

Oxygen saturation is the type 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 asmall 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 of sleep apnea is one of the challenging tasks because it undergoes undiagnosed due to its symptoms that occur during sleeping. That's why it is important to monitor the oxygen saturation levels during sleep will be a useful and helpful approach to detect anomalies. In this paper, we have applied anomaly detection algorithms to oxygen saturation data to identify the patterns which deviate from normal sleep patterns [2]. Treating sleep apnea and managing that from to time and detecting abnormal oxygen saturation is a difficult task. That's why this anomaly detection came into existence. In anomaly detection analyzing the oxygen saturation data collected from the pulse oximeters during sleep to identify the patterns which deviate from the normal values [3]. Anomaly detection algorithms are applied to this data to automatically detect abnormal patterns such as oxygen saturation, which may indicate sleep apnea events such as hypopnea (partial airway blockage) or apneas (complete airway blockage)).

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

[5]. It also has the potential to enable the monitoring of patients suffering from sleep apnea which allows for early detection of sleep apnea events.

However, it is important to know that sleep apnea anomaly detection using oxygen saturation data is not only the solution or treatment tool that should be used in conjunction with other clinical assessments and sleep studies for accurate anomaly detection and management of sleep apnea [6]. In addition to this, detecting it accurately using algorithms requires further research and validation to ensure reliability and clinical utility. Spite, of this emerging field of research, holds promising and improves the treatment and management of sleep apnea, which leads to a better qualityof 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 Varia bility" 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 SaturationUsing 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.

"Sleep Apnea Detection Using Wavelet-Based Analysis of Oxygen Saturation Signals" by Fan etal. (2020):

This work proposed a wavelet-based analysis for sleep apnea detection from oxygen saturation signals. Here authors used wavelet transform to extract the features from oxygen saturation signals. And they trained the support vector machine (SVM) classifier to detect sleep apnea detection. This method showed a good performance in detecting sleep apnea events.

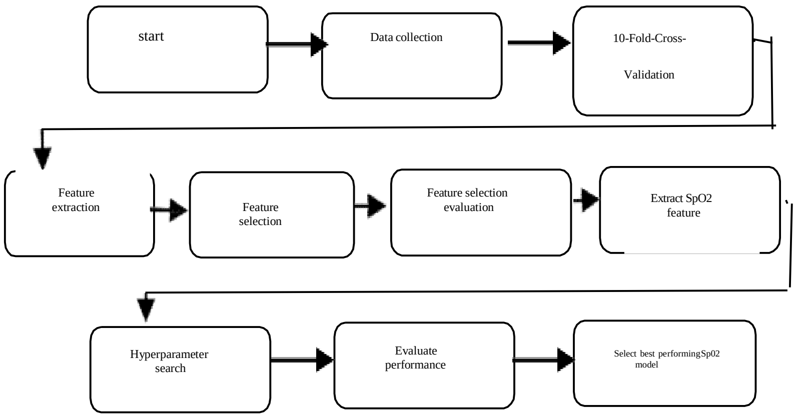
3. "Sleep Apnea Detection Using Ensemble of Classifiers from Oxygen Saturation Signal" by Ramakrishnan et al. (2021):

This work proposed an ensemble-based type to detect sleep apnea using oxygen saturation signals. The authors of this work used multiple c classifiers like k-nearest neighbors (KNN), support vector machine (SVM), and artificial neural networks (ANN), which authors combined their outputs to improve the accuracy of sleep apnea detection. This ensemble work showed improved performances when compared to individual classifiers.

These are some of the few examples of related work on sleep apnea anomaly detection using oxygen saturation. Researchers in this field continued toexplore and discover new methods to improve the accuracy of sleep apnea anomaly detection using oxygen saturation signals, which aids in the early treatment and management of sleep apnea, a serious sleep disorder that has significant health consequences if left untreated.

III. METHODOLOGY

The sleep apnea anomaly detection system is implemented using the following steps



Data Collection: Collect spo2, weight, heart pulse, temperature, muscle mass, hydration, bone mass, and pulse wave velocity from the patients with and without sleep apnea.

10-fold-cross validation: one data set divide randomly into ten parts, nine of those parts for training, and reserve one path for testing perform this action ten times each time reserving a different tenth for testing.

Feature Extraction: the action of transforming raw data into numerical features.

Feature Selection: The method for reducing the input variables to our modules by using only relevant data and getting rid of sound in data.

Feature Selection Evaluation: Area under the curve(AUC), F1-score is a measure of modules accuracy and datasets(1- perfect,0-fail).

Extract Spo2 features: Within this section we used 90- second windows. One characteristic of the Spo2 signal is extracted,desaturation drops within 45 seconds.

Hyperparameter Search: the process of finding the hyperparameter by training modules with different values of a parameter can classification.

Evolution Performance: Utilize relevant measures, such as accuracy, sensitivity, specificity, and area under the curve (AUC), to assess the effectiveness of the anomaly detection algorithm. and select the best-performing spo2 model

IV. EXPERIMENTAL SETTINGS

Data set

This experiments Sleep apnea anomaly detection datasets can be collected in the 15000 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.

A. Isolation Forest

The Isolation Forest method is used for sleep apnea diagnosis to find unusual breathing patterns that can point to the condition. For each tree in the forest, the algorithm randomly chooses a feature and a split value, and then it divides the data recursively into smaller sections until each data point is isolated in its own subset. The data points with shorter path lengths in the tree are the anomalies or those that require fewer splits to isolate. The possible existence of sleep apnea therefore indicated by these abnormalities.

- Average path length in sleep apnea is determined using average_path_length(n)=2*(log(n- 1)+0.5772156649)

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

- Anomaly score in sleep apnea is determined using anomaly score(x)=2(-average_path_length(x)/c(n)) where n is the dataset's sample count, andc(n) is a normalizing constant.

B. K-NEAREST NEIGHBOR (KNN)

The K-nearest neighbors (KNN) method analyses and categorizes sleep patterns based on their resemblance to previously labeled patterns, which can be used to detect sleep apnea anomalies. This method uses the KNN algorithm to locate the closes neighbors of a particular sleep pattern based on characteristics including the length of various sleep phases, the frequency of breathing pauses, and the blood's oxygen saturation level.

- Euclidian distance in sleep apnea anomaly detection is calculated using the equation

distance (x, y) = sqrt ((x1 - y1)^2 + (x2 - y2)^2 + ... + (xn - yn)^2)

Where x1, x2,...,xn and y1,y2,.....,yn are the values of the relevant features and n is the quantity of features in each vector.

C. SUPPORT VECTOR MACHINE

The Support Vector Machines (SVM) technique for machine learning can be utilized for sleep apnea anomaly identification. As a way to distinguish between normal and abnormal data points in a high-dimensional space, SVM searches for the ideal border, also known as a hyperplane. The margin, or the separation between the hyperplane and the nearest data points of each class, is maximized by this hyperplane. A dataset of sleep study recordings which has been classified as normal or abnormal based on clinical standards used for training SVM in the setting of sleep apnea. The SVM algorithm learns a decision border that distinguishes between normal and pathological behavior using the data retrieved from the sleep records, such as the length and frequency of apnea occurrences.

- Kernel function used in sleep apnea anomaly

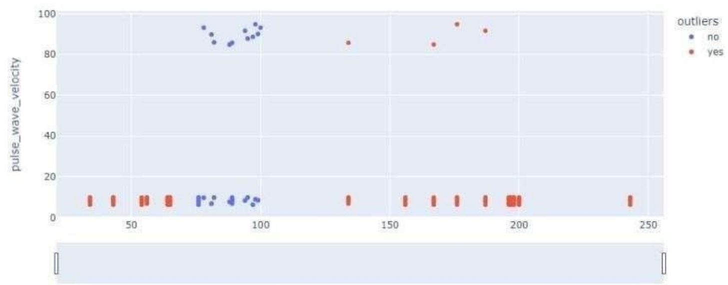
detection

K(x_i, x_j) = exp(-gamma ||x_i - x_j||^2)

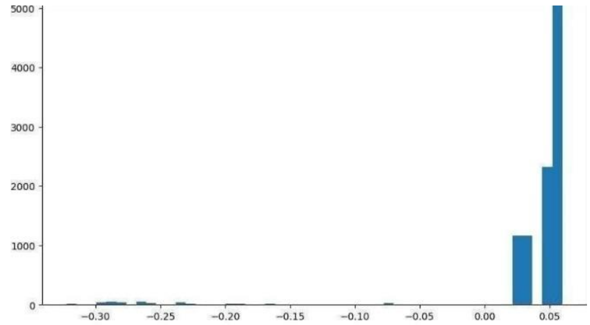
where gamma is a hyperparameter that regulates how smooth the decision boundary is, x_i and x_j are two feature vectors, and ||x_i - x_j||2 is their Euclidean distance.

V. RESULTS

A. ISOLATION FOREST CLASSIFIER

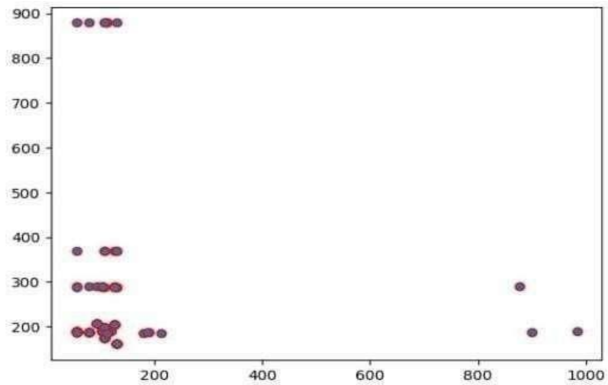


In this, we are using plot express to plot anomalies using oxygen saturation as an x-axis and pulse wave velocity as a y-axis where red color indicates the outliers and blue color indicates no outliers in this we are using the slider to view the anomalies and to get a better point of view.

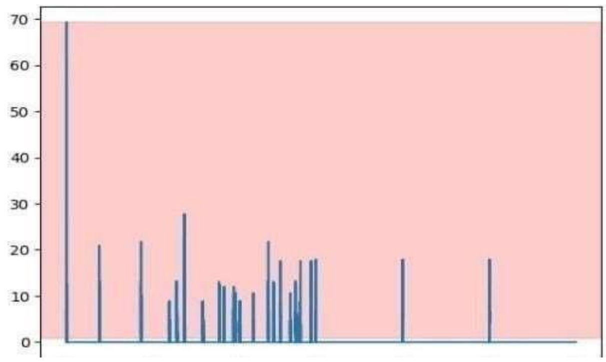


In this figure, we are using the model. The decision function is to get a score by passing a data frame as oxygen saturation and in the score we will get both positive and negative values. Here is a histogram plot, using bins=50 where we evaluate the score less than -0.05 as an outlier.

B. K-NEAREST NEIGHBOR (KNN)

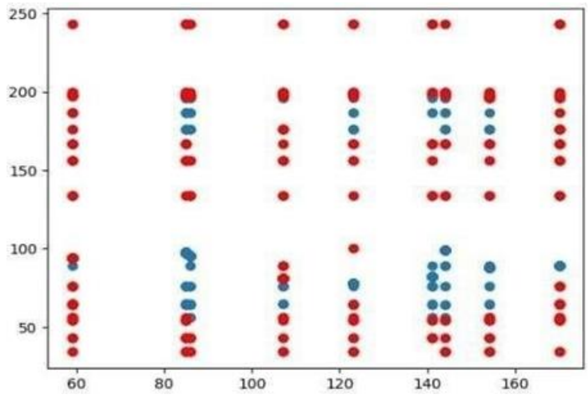


In this figure, we are using a scatter plot where we are plotting all the abnormal points with red color and this is been applied to the function called abn_index where distance and mean are used with an axis equal to 1.



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 is balltree.

C. SUPPORT VECTOR MACHINE (SVM)



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.

VI. 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.

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