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EEG Feature Engineering for Machine Learning-Based CPAP Titration Optimization in Obstructive Sleep Apnea

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Abstract

Obstructive sleep apnea (OSA) is one of the most prevalent sleep disorders that can lead to serious consequences, including hypertension and/or cardiovascular diseases, if not treated promptly. Continuous positive airway pressure (CPAP) is widely recognized as the most effective treatment for OSA, which needs the proper titration of airway pressure to achieve the most effective treatment results. However, the process of CPAP titration can be time-consuming and cumbersome. There is a growing importance in predicting personalized CPAP pressure before CPAP treatment. The primary objective of this study was to optimize the CPAP titration process for obstructive sleep apnea patients through EEG feature engineering with machine learning techniques. We aimed to identify and utilize the most critical EEG features to forecast key OSA predictive indicators, ultimately facilitating more precise and personalized CPAP treatment strategies. Here, we analyzed 126 OSA patients' PSG datasets before and after the CPAP treatment. We extracted 29 EEG

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features to predict the features that have high importance on the OSA prediction index which are AHI and SpO2 by applying the Shapley Additive exPlanation (SHAP) method. Through extracted EEG features, we confirmed the six EEG features that had high importance in predicting AHI and SpO2 using XGBoost, Support Vector Machine regression, and Random Forest Regression. By utilizing the predictive capabilities of EEG-derived features for AHI and SpO2, we can better understand and evaluate the condition of patients undergoing CPAP treatment. The ability to predict these key indicators accurately provides more immediate insight into the patient's sleep quality and potential disturbances. This not only ensures the efficiency of the diagnostic process but also provides more tailored and effective treatment approach. Consequently, the integration of EEG analysis into the sleep study protocol has the potential to revolutionize sleep diagnostics, offering a time-saving, and ultimately more effective evaluation for patients with sleep-related disorders.

Keywords: *Machine Learning, Artificial Intelligence, Sleep Disorder, Healthcare, Feature Engineering, Polysomnography, Electroencephalography, Obstructive Sleep Apnea, Continuous Positive Airway Pressure*

1. Introduction

Sleep plays a vital role in human health and daily life. The quality and quantity of sleep are influenced by individual circadian rhythms, stress levels, physical health, and various other factors. Notably, sleep disorders are associated with various health problems, leading to a decline in the quality of life [1]. Among sleep disorders, Obstructive Sleep Apnea (OSA) is recognized as a significant concern. OSA is characterized by repeated cessation of breathing during sleep, resulting in symptoms like daytime fatigue, decreased attention, and memory impairment [2].

The primary device used for treating OSA patients is the Continuous Positive Airway Pressure (CPAP). CPAP provides continuous positive pressure through the respiratory system, preventing the collapse of the upper airway and subsequent apneas. Consequently, it enhances the sleep quality of OSA patients and mitigates daytime symptoms [3]. When utilizing a CPAP device, the pivotal aspect is to set the appropriate pressure. For this, CPAP titration which is the procedure of determining the optimal pressure based on the patient's condition and requirements is performed. Proper pressure settings enhance the sleep quality of OSA patients and avert long-term health complications [4, 5].

The Apnea–Hypopnea Index(AHI) and oxygen saturation(SpO2) were the two main indices for indicators of OSA improvement. AHI represents the frequent event of apneas (complete cessations of airflow) and hypopneas (partial cessations of airflow) per hour of sleep. SpO2 is a measure of the amount of oxygen-carrying hemoglobin in the blood relative to the amount of hemoglobin not carrying oxygen. Based on the guidelines of the American Academy of Sleep Medicine(AASM), snoring and low limitation of airflow were not observed at all postures and all sleep stages, and the lowest pressure was considered optimal among pressures with AHI below 5 and SpO2 above 90% [6].

Traditional CPAP titration methods have inherent limitations. Adjusting the pressure manually can be cumbersome and may not consistently provide the most effective results for the patient. With technological advancements and the rising prevalence of OSA, there is an increasing demand to integrate artificial intelligence into CPAP treatment to enhance its efficiency and individualize it according to the patient's needs [7]. Also, relying heavily on expert judgment, manual titration can be challenging due to the varied responses exhibited by patients, making it difficult to determine the optimal pressure [8].

Attention was drawn to the AHI and SpO2 variables, which are important in predicting the optimal pressure for CPAP. From the EEG data, 29 features were extracted. Through modeling, the machine learning model that best predicts AHI and SpO2 was identified. Features with the highest contribution to predicting the optimal CPAP titration were extracted and analyzed.

In our research, we conducted an analysis employing the predictive power of EEG-derived features for AHI and SpO2 to enhance our understanding of patients undergoing CPAP treatment. This innovative approach streamlines the evaluation process, offering the potential for more tailored treatment strategies. By integrating EEG analysis, we aim to provide deeper insights into patient conditions, facilitating more effective therapeutic interventions for those with sleep-related disorders.

2. Related work

2.1 Medical Techniques for OSA Treatment

The primary therapeutic intervention for OSA patients is the CPAP which works by delivering a continuous stream of air preventing the upper airway from collapsing, thereby averting apneas. As a result, it significantly improves the sleep quality of OSA patients and alleviates their daytime symptoms. [3].

There are several types of PAP devices available, including CPAP, BiPAP (Bilevel Positive Airway Pressure), and APAP (Automatic Positive Airway Pressure). Each device has its unique mechanism and application. While CPAP provides a consistent air pressure, BiPAP offers two distinct pressures: one for inhalation and another for exhalation. In contrast, APAP devices adjust the pressure automatically based on the patient’s breathing patterns throughout the night. However, APAP has its limitations that frequent pressure fluctuations can cause discomfort to the patient, unlike the steady pressure provided by CPAP besides the higher costs and increased complexity. BiPAP also has its challenges that some patients may find it difficult to adjust to the changing pressures, leading to discomfort.

CPAP is not a perfect alternative either because the process of CPAP titration can be labor-intensive since It often involves an overnight sleep study in a lab where the patient’s breathing patterns are monitored, and the pressure settings are adjusted accordingly. This can be inconvenient for the patient and may require multiple visits to get the settings just right. Despite the challenges, medical professionals emphasize the importance of accurate CPAP titration. Without proper titration, the therapy may not be as effective, and the patient might experience discomfort or even discontinue the treatment.

2.2 OSA Prediction in Sleep Data Using Machine Learning

A large body of prior work has investigated on diagnosing OSA by analyzing EEG signals through classification methods. Earlier works primarily focused on using machine learning classifiers to analyze EEG signals related to OSA [9, 10, 11, 12]. Vimala et al. demonstrated the utility of EEG analysis for OSA diagnosis by utilizing Decomposed EEG signals and employing Support Vector Machine (SVM), Kernel Functions, K-Nearest Neighbor (KNN), and Artificial Neural Network (ANN) for classification [9]. Additionally, Almuhammad et al. analyzed EEG signals using SVM, ANN, Linear Discriminant Analysis (LDA), and Naive Bayes (NB), achieving a high accuracy of 97.4% with SVM [10]. Furthermore, Zhao et al. performed EEG signal analysis based on EEG sub-band signal characteristics using random forest, K-nearest neighbor, and support vector machine classifiers [12]. Khursheed et al. analyzed EEG signals using Decision Tree and Random Forest ML classifiers, with the most accurate being the Random Forest method, a type of bagging, achieving an accuracy of 99.68% and performing effective classification [11]. Moreover, Our previous study has shown that OSA screening may be feasible using a model that trained only EEG characteristics in REM and NREM without any respiration-related measures [13]. While prior studies have focused on machine learning classification for OSA diagnosis, our research aims to focus on predicting AHI and SpO2 which are crucial assessment variables for OSA by applying machine learning mechanisms.

On the other hand, there has been a growing body of research that explores predicting AHI and SpO2. Ludwig et al. conducted a study using a support vector regressor (SVR) to predict AHI and also predicted arousal index and hypoxic burden extracted from the Polysomnography dataset [14]. Furthermore, Lee et al. divided patients into two groups, young and elderly, and predicted the AHI index using linear regression analysis, observing significant differences between the sleep EEG of these two groups [15]. In particular, there has been research on applying machine learning techniques to predict EEG signals of participants undergoing CPAP treatment. Kim and Yang developed a predictive model using machine learning to determine the optimal CPAP pressure for obese patients with obstructive sleep apnea. By analyzing the medical records of 162 OSA patients, they employed both a random forest model and a LASSO regression model. The study highlights the effectiveness of machine learning techniques in medical predictions, specifically for CPAP pressure optimization [16]. This paper further created a new variable that could be used to view the AHI after baseline as a starting point to compare the subject's AHI before and after CPAP treatment and also attempted to predict SpO2.

This paper conducts Quantitative EEG Analysis, emphasizing the significance of EEG features. Previous research has also analyzed the importance of EEG features using various approaches. Adams et al. employed Principal Component Analysis to scrutinize EEG features and demographic factors associated with depression using EEG data from patients with OSA. The study concluded that AHI, financial stress, partner, and medication were related, while insomnia with age and BMI were not correlated [17]. Additionally, Khursheed et al. analyzed the EEG subband by extracting four features which were energy, kurtosis, Mean Absolute Deviation, and skewness from EEG signals resulting in the enhancement of the performance of ML classifiers [11]. Based on the prior research, our study extracted variables with high impact, such as energy, kurtosis, deviation, and skewness, from EEG signals.

3. Method

3.1 Data Acquisition

Data were collected from Ewha Womans University Mokdong Hospital spanning the years 2018 to 2021. A Grass telefactor (USA) was used for conducting polysomnography (PSG). This comprehensive system included: Six-channel electroencephalography (EEG) to monitor brain activity, bilateral electrooculography for tracking eye movements, electromyography leads placed on the submentalis and tibialis anterior muscles to monitor muscle activity, and electrocardiography for recording heart activity. To assess respiratory events, various sensors were utilized, including a nasal thermistor, nasal airflow pressure transducer, thoracic and abdominal strain gauges, a position sensor, and finger pulse oximetry (SpO2). Synchronized audio and video recordings were made throughout the PSG procedure. Sleep stages were scored in 30-second epochs following the guidelines outlined by the American Academy of Sleep Medicine (AASM) manual. The presence of OSA was determined with an AHI value of ≥5/h. The severity of OSA is determined by AHI: mild (5-14.9/h), moderate (15-29.9/h), and severe (≥30/h). However, other parameters reflect the severity of OSA other than AHI. The Oxygen Desaturation Index (ODI) quantifies how often SpO2 drops below a specific threshold. Time spent below SpO2 of 90% represents the amount of exposure to hypoxemia. Lowest SpO2 or mean durations of apnea/hypopnea events are other parameters representing the severity of OSA. In this study, SpO2 in addition to AHI was utilized to assess the severity of OSA.

Table 1. Demographic characteristics of all participants

Characteristics		All Participants (n=211)
Sex	Male	109 (87%)
	Female	17 (13%)
Age		54.69 ± 13.35
BMI		27.86 ± 5.53

3.2 Study Population

A total of 153 paired datasets from patients diagnosed with OSA were initially gathered, representing data before treatment and during the pressure titration phase. However, datasets were excluded if they lacked PSG data or CPAP records, if only half-day PSG measurements were taken, or if the majority of rows in the dataset were marked as N/A due to input errors. After these exclusions, the final dataset comprised 126 patients, of which 17 were female and 109 were male. The age distribution of the patients ranged from their 20s to their 80s.

3.3 Data Preprocessing

AHI and SpO2 are significant indicators in CPAP therapy, each bearing its unique significance. AHI represents the number of apneas and hypopneas per hour during sleep. An apnea indicates a complete cessation of breathing, while a hypopnea signifies a partial reduction in breath. The primary purpose of CPAP treatment is to prevent these interruptions in breathing. A high AHI suggests that the current pressure settings might not be optimal, making it a pivotal metric in evaluating CPAP treatment outcomes. On the other hand, SpO2 denotes the percentage of oxygen saturation in the blood, reflecting how well oxygen is being transported. During sleep interruptions, the cessation of breathing can lead to a drop in SpO2 levels. The CPAP device aids in preventing these interruptions, ensuring a stable SpO2 level. A consistent SpO2 level is an indicator of effective treatment.

If only the AHI is satisfactory (low AHI but SpO2 not within the normal range), it indicates that while the frequency of breathing interruptions has decreased, the oxygen saturation in the blood remains insufficient. This could suggest issues with the depth or quality of breathing. Conversely, if only SpO2 is satisfactory (AHI not within the normal range but high SpO2), it means that despite frequent short breathing interruptions, overall oxygen supply remains stable. In such a scenario, breathing interruptions, though brief, could be frequent. Thus, achieving only one of these metrics suggests an imbalance between respiratory stability and oxygen supply, with the goal of CPAP therapy being to satisfy both.

The decision to set each as a separate predictive value was driven by the desire to pinpoint features that most influence each metric and enhance the model's predictive accuracy. This approach potentially reduces the complexity compared to a composite model predicting both metrics simultaneously.

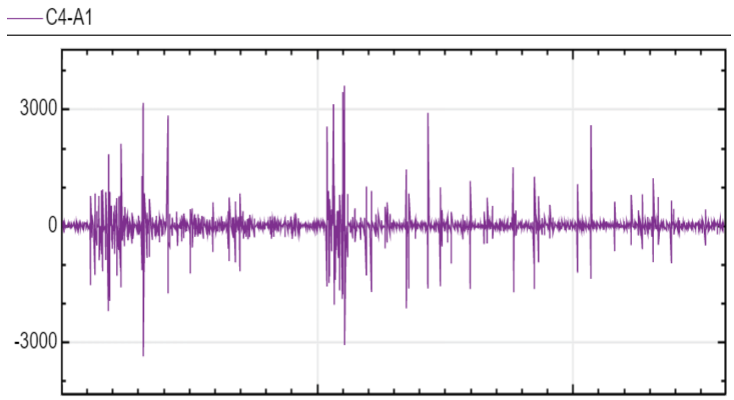

Figure 1. C4-A1 EEG raw data

Furthermore, given the emphasis on feature engineering, interpretability was prioritized. Training via separate models for each metric allows for a clearer understanding of which features significantly impact the prediction of each indicator. This clarity aids in interpreting the model's results, subsequently assisting in formulating more effective diagnostic and therapeutic strategies. From the six available EEG channels, the C4-A1 channel was selected due to its central location in the brain as you can see in Figure 1. Data processing and feature extraction were carried out using MATLAB and Python tools. Specifically, the "eeg extraction tool" available on GitHub was utilized to extract 29 distinct features.

$$\frac{(BaselineAHI - PressureAHI)}{Baseline\ AHI} \tag{1}$$

In equation (1), $BaselineAHI$ variable is the AHI measured by PSG before CPAP treatment, and $PressureAHI$ variable represents the AHI value per CPAP pressure.

$$HjorthActivity = \frac{1}{N}\sum_{n=1}^{N}(x(n) - \bar{x})^2 \tag{2}$$

In equation (2), $x(n)$ is the EEG time series, $\bar{x}$ is the average signal frequency, and N is the number of items

$$MeanTeagerEnergy[k] = \frac{1}{N}\sum_{m=k-N+3}^{k}(x[m-1]^2 - x[m] \times [m-2]) \tag{3}$$

In equation (3), $x[m]$ is an EEG time series, N is the window length and k is the last sample in the epoch

$$RatioBandPowerAlphaBeta = \frac{BandPowerBeta}{BandPowerAlpha} \tag{4}$$

In equation (4), $BandPowerAlpha$ and $BandPowerBeta$ are time that patients showed alpha signal and beta signal

$$ArithmeticMean = \frac{1}{N}\sum_{n=1} x_n \tag{5}$$

In equation (5), x_n is a time series, N is the number of data points

If the number of values is odd then (where N=number of items)

$$MedianValue = \left(\frac{N+1}{2}\right)^{th} \tag{6}$$

In equation (6), N is the number of items

If number of values is even

$$MedianValue = \frac{\frac{N}{2}^{th} value + \left(\frac{N}{2}+1\right) value}{2} \tag{7}$$

In equation (7), N is the number of items

$$Skewness = \frac{1}{N}\sum\left(\frac{X_k - m}{\sigma}\right)^3 \tag{8}$$

In equation (8), N is the length of the signal X, m is the mean and σ is the standard deviation of X

We calculated the correlation of all 29 variables. Figure 2 reveals the visualization result of 29 variables correlation. 18 Variables that have more than 0.7 correlation were dropped to avoid the curse of dimensionality [18], caused by the unnecessary increase in the number of parameters. Moreover, we analyzed 11 variables by leveraging the Variance Inflation Factor (VIF), a traditional multi-collinearity measurement method. Multi-collinearity is a phenomenon when independent variables are not fully independent of other independent variables. Table 3 shows the VIF values of variables. According to the rules of thumb in the VIF method, VIF values more than 10, Mean Curve Length, Hjorth Mobility and Normalized First Difference, and RenyiEntropy were excluded. As you can see in Figure 3, the final variables based on the correlation process and VIF method are Hjorth Activity, Mean Teager Energy, Arithmetic Mean, Median Value, Skewness, Band Power Delta, and Ratio of Band Power Alpha to Beta.

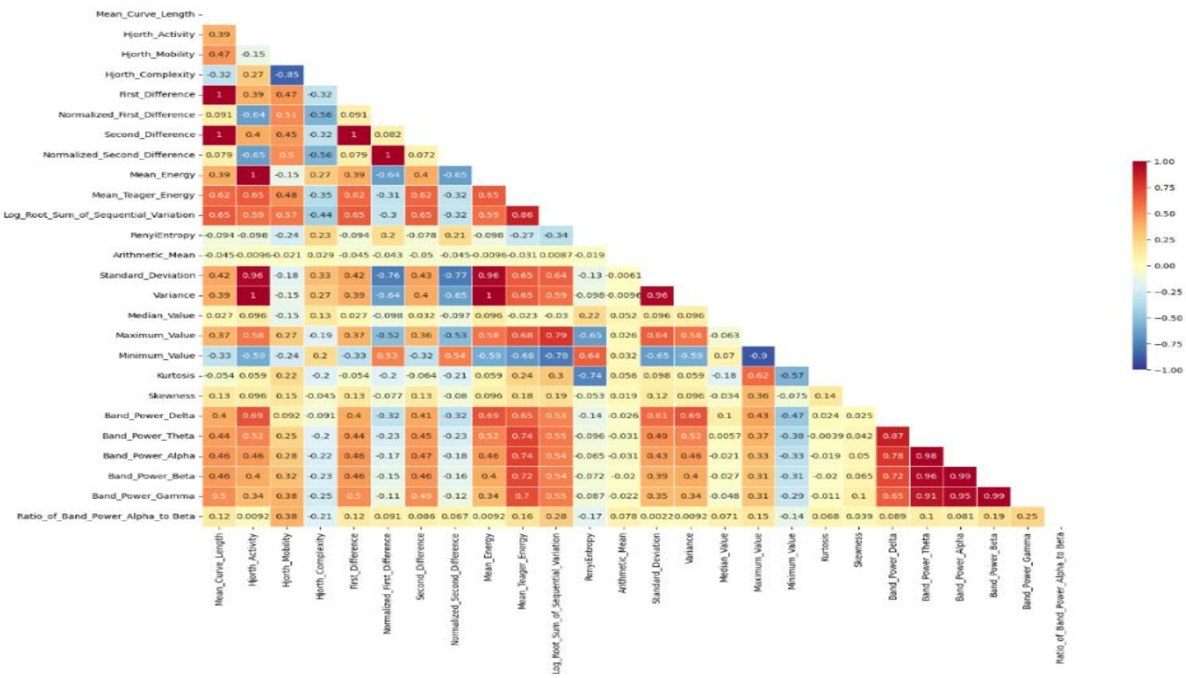

Figure 2. Correlation

First of all, Hjorth Activity is one of the Hjorth parameters (2). Hjorth parameters are used to determine the EEG activity [19]. The Hjorth parameters can be determined using the first and second derivatives. Activity quantifies the EEG signal's mean power, while mobility computes the average signal frequency [20]. Complexity offers an estimate of the signal's bandwidth. Hjorth parameters offer a statistical measure of EEG signal variance, which is why this method is computationally more efficient than others. In this research, three Hjorth parameters were utilized for extracting features from EEG signals [21]. Secondly, Mean Teager Energy (3) MTE is a feature that is highly used in EEG analysis. MTE was first proposed in [22] and is defined as; where x[m] is an EEG time series, N is the window length and k is the last sample in the epoch [23]. Next, Arithmetic Mean (5) Arithmetic Mean is the average of the EEG signal data points. n=1,2,3...n is a time series, N is the number of data points, and AM is the mean of the sample [23, 24]. In addition, Median Value (6),(7) Median value is a calculated median of the time series data points which have different equations based on N (number of items). If N is odd, use this formula (6); if N is even, use this formula (7). Also, the Ratio of Band Power Alpha to Beta (4) The EEG patterns, encompassing delta, theta, alpha, sigma, beta, and gamma waves, exhibit distinct characteristics across different sleep stages. Please refer to Table 4. In stage 1 of sleep, both theta waves (4-8 Hz) and alpha waves (8-12 Hz) are present. Stage 2 sees an increase in EEG signal amplitude along with the appearance of K-complexes, with theta waves becoming more prominent. Stage 3 highlights the prevalence of theta and delta waves (0-4 Hz), while in stage 4, the EEG signal frequency typically ranges from 0.5 to 2 Hz. During the REM period, sigma waves (12-15 Hz), beta waves (15-30 Hz), and gamma waves (30 Hz) dominate, resulting in an EEG signal with a frequency exceeding 12 Hz. Beta waves are also more prominent during wakefulness [20]. Especially, Ratio of Band Power Alpha to Beta implies the ratio of the time that patients had beta signal and alpha signal while they were asleep. Lastly, Skewness (8) of the EEG signal in the time domain is calculated with the (8) as the following: where N is the length of the signal x, x m is the mean and x std is the standard deviation of x [25].

Table 2. Extracted Features

Extracted Feature	Meaning
Mean Curve Length	Mean length of the signal curve
Hjorth Activity	Signal strength of the EEG can indicate the overall activity
Hjorth Mobility	Measure representing the average frequency of the signal
Hjorth Complexity	Measure indicating the complexity or changes in the signal shape
First Difference	First difference of the signal
Normalized First Difference	Normalized first difference
Second Difference	Second difference of the signal
Normalized Second Difference	Normalized second difference
Mean Energy	Average energy of the signal
Mean Teager Energy	Average energy of the signal calculated using the Teager energy operator
Log Root Sum of Sequential Variation	Log root sum of sequential variation
Tsallis Entropy	Complexity measurement of the signal using Tsallis entropy
Shannon Entropy	Measure indicating the information content of the signal
Log Energy Entropy	Measurement of the energy distribution of the signal using log energy entropy
Renyi Entropy	Complexity measurement of the signal using Renyi entropy
Arithmetic Mean	Arithmetic mean of the signal
Standard deviation	Measure indicating the variability of the signal values
Variance	Variance of the signal values
Median Value	Median value of the signal
Maximum Value	Maximum value of the signal
Minimum Value	Minimum value of the signal
Auto Regressive Model	Statistical characteristics of the signal extracted using the auto-regressive model - Excludes 4 data points
Kurtosis	Measure indicating the kurtosis (how concentrated the data is around the mean) of the signal
Skewness	Measure indicating the asymmetry of the signal
Band Power Beta	Power of the signal in the beta frequency band
Band Power Alpha	Power of the signal in the alpha frequency band
Band Power Theta	Power of the signal in the theta frequency band

Band Power Delta	Power of the signal in the delta frequency band
Band Power Gamma	Power of the signal in the gamma frequency band
Ratio of Band Power Alpha to Beta	Ratio of the signal's power in the alpha frequency band to that in the beta frequency band

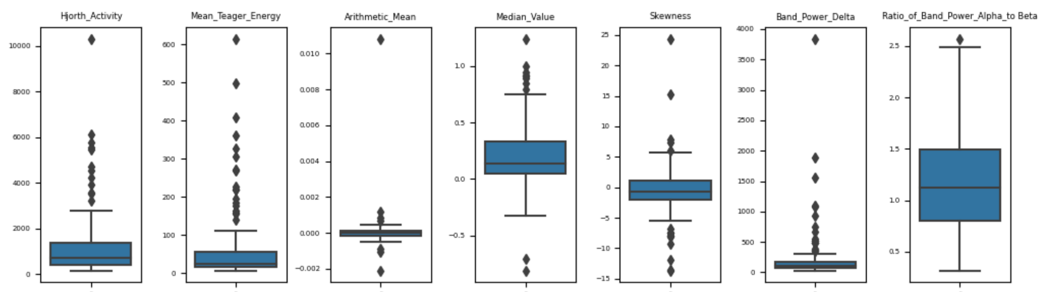

Figure 3. Feature Engineering

Table 3. Variable Inflation Factor results of Independent variables

Variables	Variance Inflation Factor
Arithmetic Mean	1.020373
Skewness	1.078505
Median Value	1.651945
Band Power Delta	3.040622
Hjorth Activity	7.431442
Mean Teager Energy	8.875246
Ratio of Band Power Alpha to Beta	9.379438
RenyiEntropy	**23.715299**
Mean Curve Length	**33.508472**
Normalized First Difference	**34.020277**
Hjorth Mobility	**40.316386**

3.3 Modeling

The variables were selected based on the data preprocessing process and fed into three machine-learning regression models (Random Forest Regression, Support Vector Regression, and XGBoost Regression). The train and test datasets were split randomly into an 8:2 ratio. As model performance varies concerning data, we applied three different machine-learning models to compare model performance and feature importance results. A Random Forest is a type of machine learning with ensemble learning used for tasks such as classification and regression analysis. During the training process, the Random Forest regressor operates by generating multiple decision trees and outputs an average prediction value based on the collective outputs of these constructed decision trees [26]. Support Vector Machines (SVM) are designed for classification and Regression problem-based optimal hyperplanes, convolution of the dot product, and the soft margins [27]. As this paper aims to build a regression model, we use Support Vector Regression Machines (SVR), which focus on solving regression problems. XGBoost is a tree-boosting algorithm that shows remarkable capability to address sparse data by utilizing a weighted quantile sketch algorithm [28]. SHapley Additive exPlanations(SHAP) is an outstanding feature importance analysis method, which is based on game theory and local explanations [29]. We analyzed the feature importance of the three machine learning models by using the SHAP method. Figure 4 shows the overall process from data preprocessing to evaluation and interpretation [30].

Table 4. EEG Band

Rhythm	Frequency Band (Hz)
Delta (δ)	0-4
Theta (θ)	4-8
Alpha (α)	8-12
Sigma (σ)	12-15
Beta 1 (β_1)	15-22
Beta 2 ($\beta 2$)	22-30
Gamma 1 (γ_1)	30-40
Gamma 2 (γ_2)	40-49.5

4. Results and discussion

After training machine-learning models (Random Forest, SVR, XGBoost), the performance of three models was evaluated with the metrics MAE and RMSE. Performance results of two predictable variables (AHI score, SpO2 score) are shown in Table 5. All three machine-learning models show better performance in predicting the AHI score than the SpO2 score. As an aspect of predicting the AHI score, XGBoost Regressor shows the best performance and SVR shows the worst performance. Moreover, the performance results of predicting SpO2 reveal that the MAE of SVR is the smallest and the MAE of XGBoost is the largest among the three machine-learning algorithms. Random Forest has the lowest RMSE results of predicting SpO2 score. Besides model performance evaluation, this study analyzed the feature importance of three machine-learning algorithms. Feature importance results indicate the level of variables that we have to highly focus on optimal pressure prediction. The most notable features are Arithmetic Mean and Mean Teager Energy in AHI score prediction and, Ratio of Band Power Alpha to Beta in SpO2 score prediction.

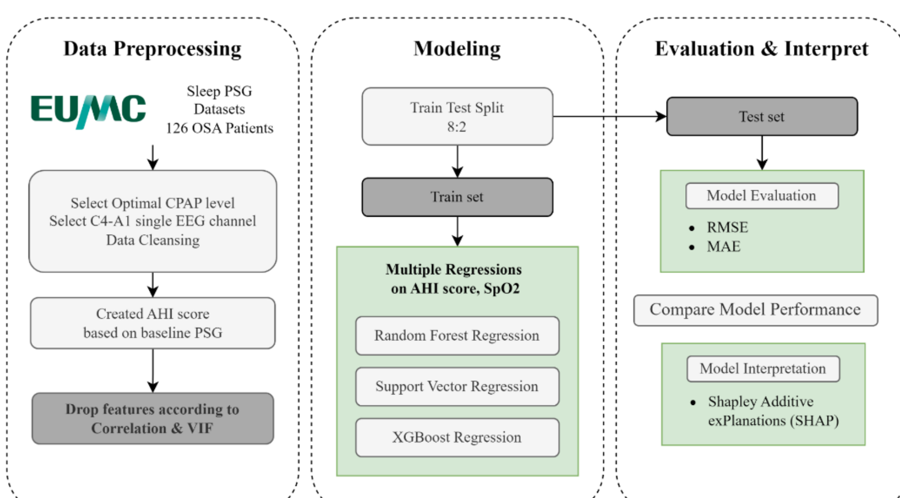

Figure 4. Flowchart

Table 5. Performance Comparison of Random Forest, SVR, XGBoost

	Model	MAE	RMSE
AHI Score	Random Forest	0.0583	0.0851
	SVR	0.1309	0.1743
	XGBoost	0.0534	0.0749
SpO2 Score	Random Forest	2.2375	3.2057
	SVR	2.1204	3.2338
	XGBoost	2.4901	3.4682

In our study, we have meticulously selected several EEG-derived features, each holding specific significance in understanding sleep-related disturbances. The Hjorth Activity, which captures the variability of the EEG signal, becomes particularly relevant as the variability in brain activity tends to increase during awakenings or apnea events. Similarly, the Mean Teager Energy, representing the energy of the EEG signal, is pivotal. A high energy value is indicative of active brain activity, and its fluctuations during sleep interruptions or apnea events can be insightful. The Arithmetic Mean provides insights into the overall activity level of the brain, and its pertinence is underscored when considering events like apnea, where the brain's oxygen supply is momentarily compromised. The Median Value, reflecting the central tendency of the EEG signal, can change with disturbances in breathing or sleep, making it a valuable metric. Another crucial feature is the Ratio of Band Power Alpha to Beta. This ratio, which juxtaposes the resting state-associated alpha band with the active state-associated beta band, offers a window into the brain's activity state. Its emphasis in our study stems from its ability to reflect the stark differences in brain activity states, especially during transitions between light and deep sleep. Lastly, Skewness, which denotes the asymmetry in the EEG signal distribution, becomes particularly telling in scenarios where there's a sudden change in brainwaves due to respiratory disturbances. Each of these features, in its unique way, contributes to a more nuanced and comprehensive understanding of sleep-related disorders, enhancing the robustness of our predictive models.

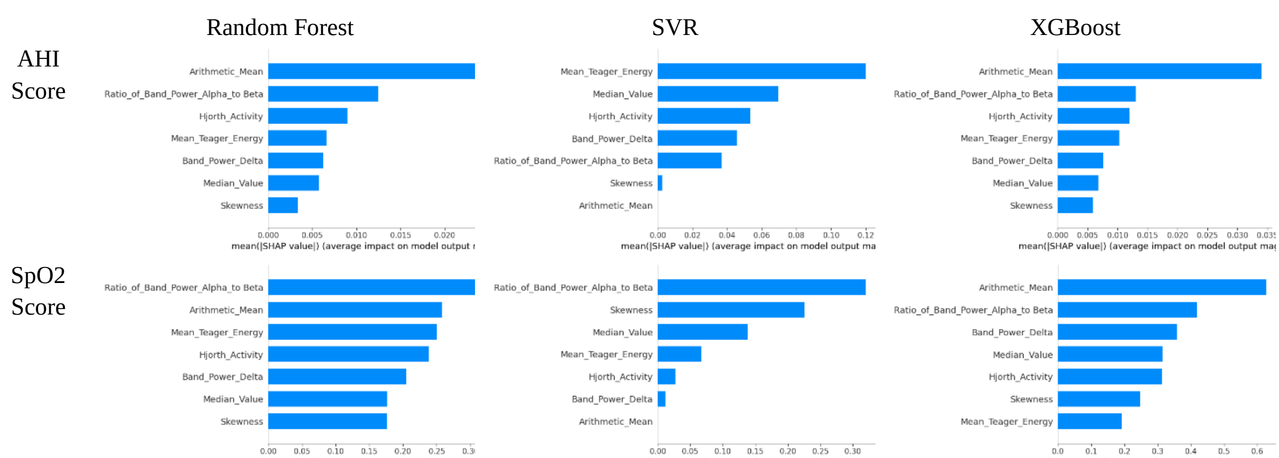

Figure 5. Feature Importance of Shapley Additive exPlanations Method

By utilizing the predictive capabilities of EEG-derived features for AHI and SpO2, we can better understand and evaluate the condition of patients undergoing CPAP treatment. The ability to efficiently predict these key indicators provides more immediate insight into the patient's sleep quality and potential disturbances. This not only streamlines the diagnostic process but also ensures a more tailored and effective treatment approach.

Consequently, the integration of EEG analysis into the sleep study protocol has the potential to revolutionize sleep diagnostics, offering a faster, more precise, and ultimately more effective evaluation for patients with sleep-related disorders.

Given the inherent characteristics of OSA, where it is more prevalent in males, two primary limitations of our study include gender imbalance in the dataset and an overall scarcity of data. These factors may impact the generalizability and robustness of our findings. As the amount of data is very small, it is hard to build good machine-learning models. Moreover, since our final goal is predicting appropriate pressure for patients, we can use these results to develop to predict pressure in future work.

By incorporating EKG data from PSG [31] into a multimodal research approach, especially within the constraints of limited time, we expect to maximize the use of diverse biometric signals to overcome data shortage and achieve a more holistic understanding of sleep-related disorders.

5. Conclusion

This paper contributes by confirming the predictive potential of EEG features for AHI and SpO2. Utilizing the Shapley Additive exPlanation (SHAP) method, a robust analytical tool, we delved into PSG data from 126 OSA patients both before and after CPAP treatment. This analysis facilitated the identification of 29 pivotal EEG features that have a significant impact on predicting OSA indicators, notably AHI and SpO2.

The incorporation of machine learning algorithms and the SHAP technique not only augmented the efficiency of data processing but also enhanced the precision in evaluating patients' sleep quality. This method has the potential to reduce the time patients need to spend in sleep studies to find the optimal EEG parameters, thereby simplifying diagnostic procedures.

Out of the 29 identified features, six EEG features stood out as particularly significant in predicting AHI and SpO2, affirming the potential of integrating EEG analysis into sleep study protocols. Our findings underscore the transformative potential this approach holds, paving the way for more nuanced and effective evaluations in managing sleep-related disorders.

In this research, we have laid a foundation that encourages further exploration and integration of machine learning to better understand sleep dynamics, promising a future where diagnostics are not only more efficient but also patient-friendly, steering towards a landscape that accommodates tailored approaches to handle sleep-related disorders.

6. Acknowledgement

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7. Ethics statement

The research procedure involving human participants was scrutinized and approved by the Institutional Review Board at Ewha Womans University Mokdong Hospital, as documented by the approval reference number EUMC 2018–10-008. Given the retrospective and anonymized manner of utilizing the standard PSG database, the board excused the need for informed consent from the involved participants.

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