

# EEG-based Sleep Deprivation Classification: A Performance Analysis of Channel Selection on Classifier Accuracy

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**Abstract**—This study analyses the effect of electroencephalogram (EEG) channel selection on the classification accuracy of sleep deprivation using four distinct classifiers: Random Forest (RF), k-Nearest Neighbours (k-NN), Support Vector Machine (SVM), and Artificial Neural Network (ANN). In this study, the EEG data from ten male individuals in good health were collected. Two distinct sets of EEG channels—a limited frontal channel set (Fp1, Fp2) and a thorough 19-channel set—were used to compare the performance of the classifiers. According to our findings, the k-NN classifier produced the greatest classification accuracy of 99.7% when applied to the 19-channel EEG signals. In contrast, both SVM and ANN classifiers were able to obtain the greatest accuracy of 94% with the frontal channels. Though there are not many gaps, these results imply that employing a larger range of EEG channels greatly improves the classification accuracy of sleep deprivation. The present study emphasizes the significance of channel selection in EEG-based sleep deprivation investigations by showcasing the significant advantages of full EEG signal capture over minimum channel configurations.

**Keywords**—electroencephalogram (EEG), classification, sleep deprivation

## I. INTRODUCTION

Sleep deprivation is a growing public health concern with significant consequences for cognitive function, physical activity, and overall well-being. Lo et al. [1] emphasizes successive nights of sleep restriction cumulatively impair diverse cognitive functions, including memory, attention, and executive control. Early detection of sleep deprivation is crucial for promoting healthy sleep habits and mitigating its negative effects.

Electroencephalography (EEG) offers a non-invasive method for measuring brain activity and has shown promise in classifying sleep states, including identifying sleep deprivation. Khoo et al. in their research showed that there are notable changes in EEG microstates for subjects with even mild sleep deprivation [2].

In previous research in automatic sleep staging and classification using EEG signals, Jeon et al. [3] demonstrated the effectiveness of machine learning for sleep stage classification using multiple EEG channels. Their study highlighted the potential for accurate sleep state identification even with a reduced number of channels.

Our research extends this work by specifically focusing on sleep deprivation classification and investigating the trade-off between using a comprehensive set of channels and a minimal frontal channel configuration. Several studies explored channel selection algorithms for EEG signal

processing, achieving high classification accuracy with a subset of channels compared to using all available channels [4-6]. This suggests that specific channels may hold more valuable information for sleep deprivation classification. Furthermore, Sen et al. [7] compared the performance of various classifiers for sleep stage classification using feature selection techniques. Their findings emphasize the importance of selecting informative features, which can be linked to choosing informative channels in our context.

In regards to the analysis methods, there are various techniques to analyse EEG data for classification, such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), and so on. SVM was incorporated by Sase et al. in their proposed adaptive feature extraction approach based on EEG theta/beta ratio [8], while Upadhyay et al. studied the effect of heat stress on sleep stages using wavelet-based analysis of SVM and radial basis function neural network [9]. Other than that, an algorithm to automatically classify sleep stages from EEG data was proposed by Liu et al. based on RF and hidden Markov model [10].

This research focuses on studying suitable EEG-based sleep deprivation classification by evaluating the performance of four common machine learning classifiers (SVM, ANN, k-NN, and RF) with varying channel configurations, using resting state EEG. The finding might be valuable for researchers and developers working on

portable and user-friendly EEG devices for sleep monitoring and sleep deprivation detection.

Moreover, in this paper we investigate the effectiveness of channel selection in EEG-based sleep deprivation classification using machine learning algorithms. We analyse the impact of channel number on classifier accuracy by comparing performance between using all 19 available channels and a limited selection of frontal channels (Fp1 and Fp2).

## II. METHODOLOGY

The methodological approach used to categorize sleep deprivation using EEG signals is described in this chapter. Using a large dataset of EEG recordings from ten healthy male students, the study focuses on the phases of preprocessing, feature extraction, and classification. In addition to a comprehensive 19-channel set, special attention is paid to the examination of frontal EEG channels because of their increased susceptibility to alterations associated with sleep.

### A. Participants

Ten healthy male students' resting-state EEG recordings from an existing dataset were used in the investigation. This dataset is based on the experiment by Kamaruzzaman et. al. who studied the effect of sleep deprivation on driver's mental fatigue [11]. To guarantee a homogeneous and controlled sample and to make it easier to assess the effects of sleep deprivation on EEG signals, these people were chosen. Two sleep conditions were used to gather the EEG recordings: regular sleep and sleep deprivation. The dataset offered a wide range of EEG signals from several channels. This dataset is

### B. Methodology Flow

Four main steps make up the methodological framework for this study as shown in Fig. 1 below: data acquisition, data preprocessing, feature extraction, and classification.

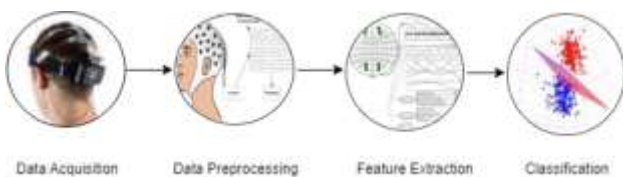


Fig. 1 The methodology flow for the EEG analysis

### C. Data Acquisition

The existing EEG data was recorded using a DABO machine following the international 10-20 system for electrode

placement. A total of 19 channels (Set 1) were used, and for this study, two EEG channels of interest (Set 2) were selected which is Fp1-Cz and Fp2-Cz, representing the voltage difference between the frontal. This selection was based on the suggestion by Fu et al. that the effectiveness of sleep scoring is influenced by the choice of EEG channel, with derivations from the frontal region being the optimal choice due to the voltage difference between the frontal areas [12]. The positions of the channels are shown in Fig. 2.

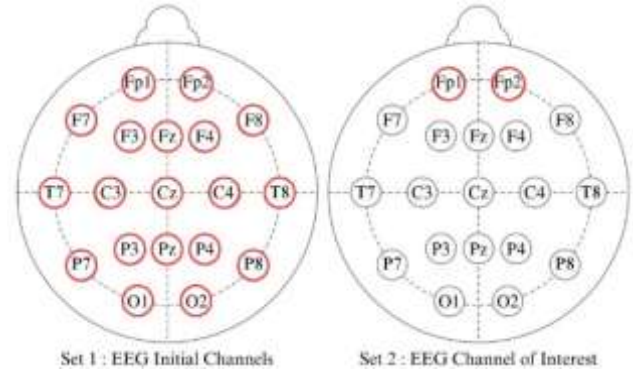


Fig. 2 The selected sets of EEG channels

### D. Data preprocessing

EEG signal preprocessing is essential to eliminate artifacts and noise, guaranteeing that the analysis that follows is founded on accurate and clean data.

Detrending the EEG signals to eliminate slow drifts was the first stage in the preprocessing pipeline. By removing low-frequency trends that can mask the real-signal, this procedure improves the EEG data's clarity for additional analysis. Removing these trends makes the underlying brain activity more visible, which makes feature extraction more precise.

Next, a Butterworth low-pass filter with a 30Hz cutoff frequency was used to filter out high-frequency noise. 30Hz was selected because it is good at keeping the key EEG components that are important for sleep research while removing higher-frequency noise that could deteriorate signal quality. Because of its smooth frequency response, which prevents the signal from becoming distorted, the Butterworth filter is very well-liked. The transfer function of the filter can be expressed as follows:

$$|H(jw)| = \frac{1}{\sqrt{1 + \left(\frac{w}{w_c}\right)^{2n}}}$$

where  $w_c$  symbolizes the frequency cutoff, and the filter's order is denoted by  $n$ . The substantial attenuation of frequencies above 30Hz is guaranteed by this mathematical representation.

Muscles artifacts were eliminated using Independent Component Analysis (ICA) after the filtering procedure. A computational technique called ICA divides a multivariate signal into additive parts. Klug et al. [13] emphasizes that ICA can still effectively clean sensor data from eye and muscle activity artifacts, and they also recommend using higher high-pass filter cut-offs than traditionally applied. When it comes to separating and eliminating non-neural aberrations like muscular movements that could taint the EEG data, this method works especially well. The EEG data are cleaned up by using ICA, leaving only the neuronal activity that is relevant to the research.

The EEG signals were then analyzed, cleaned, and stored in a new file. By ensuring that the dataset is prepared for further feature extraction and analysis, this stage protects the preprocessed data's quality and integrity. The study's subsequent phases are based on the saved dataset, which makes it easier to classify sleep conditions accurately and consistently.

#### E. Feature Extraction

The preprocessed EEG signals are transformed into a format appropriate for machine learning through feature extraction. Welch's method was used in this study to calculate Power Spectral Density (PSD), which was the main technique for feature extraction. PSD provides information about the frequency content of the signal by estimating the power distribution of the EEG signal across various frequencies. Using Welch's approach, the signal is divided into overlapping windows, each segment is subjected to a Fourier transform, and the outcomes are averaged. When compared to single-segment approaches, this methodology minimizes variance and provides a robust estimation of the power spectral density of the signal. Each segment's PSD is provided by:

$$P_{xx}(f) = \frac{1}{N} \sum_{n=0}^{N-1} |X_n(f)|^2$$

where  $P_{xx}(f)$  is the power spectral density,  $N$  is the number of data segments, and  $X_n(f)$  is the Fourier transform of the  $n$ -th segment.

In addition, the power within each frequency band—beta, gamma, alpha, theta, and delta—was calculated to examine the signal dispersion among all channels. Since different frequency bands are linked to different cognitive and physiological processes, this band-specific examination is essential. The goal of the study is to identify the distinctive alterations in brain activity brought on by sleep deprivation by measuring the power in these bands. The building of an accurate classification model is facilitated by the comprehensive picture of the EEG signal characteristics under various sleep situations provided by this detailed frequency analysis.

#### F. Classification

To create and assess a model that could differentiate between sleep deprivation and normal sleep based on the variables that were retrieved, the classification process required several crucial phases. Originally, the dataset was structured for machine learning using the features  $X$  and labels  $y$ . The collected PSD values were represented by features, and the labels were binary, designating either regular sleep (0) or sleep deprivation (1). To train the classifier to identify patterns linked to each condition, this configuration was necessary.

The dataset was then divided, usually in an 80-20 or 70-30 ratio, into training and testing sets. We have allocated 80% of the data for training and 20% for testing is used to computed accuracy. This section made sure there was enough data available for the model to be trained and for assessing its performance, which helped to avoid overfitting and guaranteed the model's applicability to fresh data.

Various classification techniques with its algorithms were examined, such as SVM, ANN, k-NN, and RF. SVM for its efficacy in high-dimensional spaces, ANN for its capability to model complex nonlinear relationships and its flexibility in learning from large amounts of data, k-NN for its simplicity and ease of implementation, and RF for its resilience and capacity to handle noisy data were the specific advantages that led to the selection of each algorithm.

The equations for SVM, ANN, k-NN, and RF are shown in equations (1) until (4), respectively. The equation of SVM is provided by:

$$SVM ; K(x_i, x'_i) = \left( 1 + \sum_{j=1}^p x_{ij} x'_{ij} \right)^d \quad (1)$$

where  $K$  is some function called the kernel,  $(x_i, x'_i)$  are the inner products between all pairs of training observations, and  $d$  is the positive degree of polynomial kernel.

Next, NN is depicted by:

$$ANN ; y = f^s(x) \quad (2)$$

where input  $x$  is therefore assigned to category  $y$ , and according to the feed forward model,  $y = f(x; \theta)$ .

The equation of k-NN is shown by:

$$k-NN ; Pr(Y=j|X=x_0) = \frac{1}{K} \sum_{i \in N_0} I(y_i=j) \quad (3)$$

where  $I(y_i=j)$  is an indicator variable that equals 1 if  $y_i=j$  and zero if  $y_i \neq j$ .

Lastly, Random Forest is calculated as the following:

$$Random\ Forest ; Gini\ Index = 1 - \sum_{i=1}^n (P_i)^2 \quad (4)$$

where *Gini index* is for knowing how impure or pure the splitting will be when selecting a feature to split further. A pure sub-split means either we should be getting ‘yes’ or ‘no’.  $P_+$  represents the probability of a class whereby  $P_-$  is the probability of a positive class and  $P$  is the probability of a negative class.

Using the collected features, the selected classification model was trained on the training set to identify patterns related to different sleep states. The model’s parameters were fine-tuned during training to maximize classification accuracy.

SVM-with a radial basis function (RBF) kernel is selected for classification tasks. ANN-comprises, including two hidden layers with 64 and 32 neurons, respectively, and an output layer with a single neuron using a sigmoid activation function for binary classification and the training process iterates over multiple epochs (10 in this case) with a batch size of 32, KNN-with the number of neighbors set to 5 ( $n\_neighbors=5$ ), RF-with 100 decision trees ( $n\_estimators=100$ ) and a fixed random state for reproducibility ( $random\_state=42$ ).

Following training, several metrics were used to assess the model’s performance, including precision, recall, F1-score, and accuracy. These metrics offered a thorough evaluation of the model’s accuracy in classifying sleep environments. These metrics’ formulas are as follows:

$$Precision = \frac{TP}{TP + FP}$$

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

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

where  $TP$  represents true positives,  $TN$  represents true negatives,  $FP$  represents false positives, and  $FN$  represents false negatives. With the help of these measurements, the model’s performance was thoroughly assessed, enabling modifications and enhancements to reach the maximum level of accuracy in categorizing sleep deficiency.

### III. RESULTS

The results of the EEG-based sleep deprivation categorization study are presented in this section, with an emphasis on the examination of EEG signals obtained from subjects who were sleep deprived as well as those who were not. Using various EEG channel configurations, the study assessed the effectiveness of numerous machines learning classifiers, including SVM, ANN, k-NN, and RF. Several figures

and tables that give a thorough and objective depiction of the data gathered, and the accuracy attained by each classifier under different circumstances are used to illustrate the results.

#### A. Varying EEG Signals

Brain activity is dramatically affected by sleep deprivation, as EEG measurements show. The raw EEG signals of participants who were sleep deprived are shown in Fig. 4. The graphic shows a time-series graph that illustrates the EEG signal amplitudes recorded from various channels over a predetermined amount of time. A distinct EEG channel is shown by each subplot, which depicts the electrical activity of the brain during sleep deprivation. The amplitude variations show how the brain reacts to sleep loss; there are discernible patterns and fluctuations that may be connected to the subject’s sleep deprivation. Before any preprocessing or feature extraction, the raw data is shown graphically in this figure.

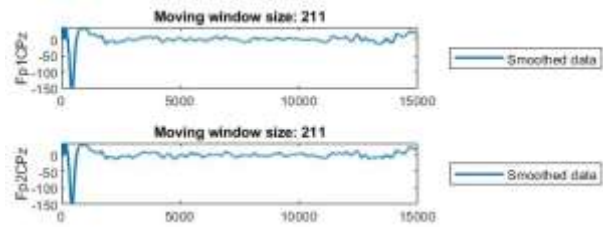


Fig. 3 Sleep deprived raw signals

EEG signals are crucial for comprehending brain activity in a variety of situations, such as diagnosing neurological disorders, monitoring cognitive states, and studying the effects of sleep deprivation on brain function. The raw EEG signals of participants who did not have sleep deprivation are displayed in Fig. 5. This image, like image 2, has several subplots that show various EEG channels over time. These signals’ amplitude changes indicate typical brain activity when people are not sleep deprived. We can visually identify the changes in brain activity between sleep-deprived and non-sleep-deprived states by comparing Figures 1 and 2, which highlight potential features that could be used for classification.

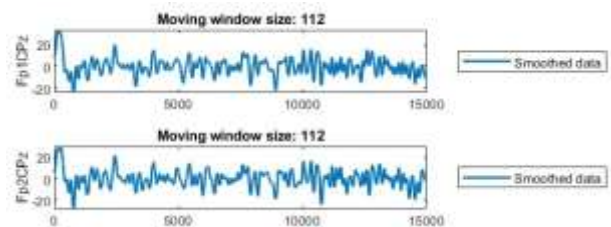


Fig. 4 Non-sleep deprived raw signals

In this study, we use MATLAB’s “smoothdata” function with the “movmean” method and a smoothing factor of 0.65. It was observed that sleep-deprived subjects exhibit slow wave activity, whereas non-sleep deprived subjects display active wave patterns.

**B. Classifiers Average Accuracy**

The average accuracy rates of SVM, ANN, k-NN, and RF classifiers under various situations are summarized in Table 1. The table has distinct columns for each classifier’s accuracy when utilizing all 19 EEG channels and when restricted to frontal channels. For instance, when employing 19-channel set, k-NN demonstrates the greatest accuracy of 99.7%. However, when limited to frontal channels, all classifiers show decreased accuracy, highlighting the significance of complete EEG data for precise classification.

TABLE 1  
 THE AVERAGE ACCURACY TABLE OF SLEEP DEPRIVATION CLASSIFICATION

Subject	Accuracy (%) for 19-channels				Accuracy (%) for frontal channels			
	SVM	ANN	KNN	RF	SVM	ANN	KNN	RF
S1	98	99	100	98	94	94	93	93
S2	99	99	100	97	94	94	93	93
S3	98	99	100	98	94	94	93	93
S4	96	97	99	95	94	94	93	93
S5	98	98	99	96	94	94	93	93
S6	96	98	100	96	94	94	93	93
S7	99	99	100	98	94	94	93	93
S8	96	98	99	96	94	94	93	93
S9	98	99	100	98	94	94	93	93
S10	97	99	100	97	94	94	93	93
<b>Average</b>	<b>97.5</b>	<b>98.5</b>	<b>99.7</b>	<b>96.9</b>	<b>94.0</b>	<b>94.0</b>	<b>93.0</b>	<b>93.0</b>

For the average performance of classifiers on non-sleep deprived data—19 channel, KNN achieved the highest accuracy at 99.8%, and for the frontal channel set, the highest accuracy for non-sleep deprived data was achieved by SVM and ANN at 94%.

TABLE 2  
 THE AVERAGE ACCURACY TABLE OF NON-SLEEP DEPRIVATION CLASSIFICATION

Subject	Accuracy (%) for 19-channels				Accuracy (%) for frontal channels			
	SVM	ANN	KNN	RF	SVM	ANN	KNN	RF
S1	98	99	100	98	94	94	93	93
S2	99	100	100	99	94	94	93	93
S3	99	99	100	98	94	94	93	93
S4	95	99	99	96	94	94	93	94
S5	95	97	99	94	94	93	94	93
S6	100	100	100	100	94	93	94	93
S7	97	99	100	97	94	94	93	93
S8	99	99	100	98	94	94	93	93
S9	98	100	100	98	94	94	93	93
S10	95	99	100	98	94	94	93	93
<b>Average</b>	<b>98.3</b>	<b>99.1</b>	<b>99.8</b>	<b>97.8</b>	<b>94</b>	<b>93.8</b>	<b>93.2</b>	<b>93.1</b>

**C. Average Accuracy Plots**

The classification accuracy of the four methods (SVM, ANN, k-NN, and RF) is shown in Fig. 6. The graph contrasts each

classifier’s performance while employing 19 EEG channels against just frontal channels. To differentiate between sleep-deprived and non-sleep-deprived settings, the bars are color-coded and categorized according to the classifier. The data in Table 1 and Table 2 is graphically supported by this figure, which also demonstrates that k-NN obtains the maximum overall accuracy, and that the accuracy decreases dramatically when utilizing only frontal channels for all classifiers.

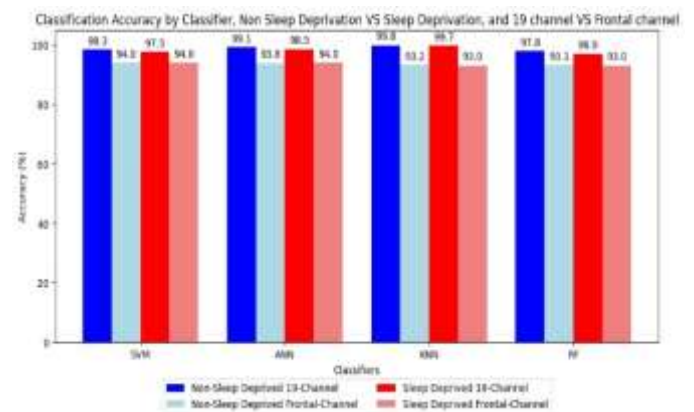


Fig. 5 The overall classification accuracies between four classification algorithms of sleep-deprived and non-sleep-deprived data for 19-channel and frontal-channel sets

**IV. DISCUSSIONS**

**A. Impact of EEG Signal Consistency**

Normal cognitive function and attentiveness are reflected in the consistent EEG signal patterns seen in persons who are not sleep deprived. Because it stands in stark contrast to the increased variability observed in sleep-deprived people, the brain’s attempt to make up for the lack of sleep is shown in the more irregular and less smooth theta and delta wave patterns. This contrast emphasizes how fundamentally different sleep deprivation induces different states of brain activity, underscoring the significance of regular sleep in maintaining normal brain function.

**B. Importance of Channel Selection**

Classifying sleep deprivation data is more accurately achieved when a full set of 19 EEG channels is used. On the other hand, while still useful, employing exclusively frontal channels results in marginally less accuracy. This result highlights the benefit of using a wider range of channels to achieve a more precise classification. Multiple channels are anticipated to record a larger range of brain activity, which gives the classifiers a more robust dataset to work with and ultimately improves their performance. In contrast, it also can be said that 2 frontal channels are enough to detect

sleep deprivation in normal subjects in this study, although with lesser accuracy but still higher than 90% accuracy.

### C. Classifier Accuracy

The k-NN classifier's better performance when using all 19 channels of EEG signals indicates that this algorithm is especially good at processing the high-dimensional data that comes with extensive EEG recordings. The efficacy of the k-NN classifier in differentiating between sleep-deprived and non-sleep-deprived states is demonstrated by its 99.7% accuracy rate. In contrast, the SVM and ANN classifiers' performance, which achieved a 94% accuracy rate employing frontal channels, shows their durability and dependability, even though their accuracy was marginally lower than that of the k-NN classifier. These findings imply that although ANN and SVM are good competitors for classification tasks, k-NN is especially well-suited for this case due to its ability to use the entire spectrum of EEG data.

### D. Proposed Protocol

In this section, we propose a protocol to detect sleep deprivation, for future work. This suggested procedure in Fig. 7 below uses EEG readings in a step-by-step manner to methodically investigate sensory and cognitive functioning. Initially, subjects would rest for four minutes, two of which would be spent with their eyes open and two with them closed, to establish baseline EEG activity both with and without visual input. Subsequently, auditory situations involving both noise and no noise scenarios would be presented to the subjects to evaluate the brain's reaction to auditory stimuli. After that, tests of visual conditions with and without lighting would be conducted to assess how well the brain processes visual data. Lastly, participants would engage in a Go/No-go task that tests reaction inhibition and cognitive control. For 'Go' trial (yellow square), they would click a button; for 'no-go' trials (blue square), they would restrain their answer.

With the use of this extensive methodology, it would be possible to analyze EEG data from a variety of sensory and cognitive states, offering new perspectives on the brain processes that underlie response inhibition and sensory processing. However, in our current study, we used pre-existing data from earlier research subjects for our current investigation. Our method enabled us to concentrate on examining the impact of channel selection performance on classifier accuracy within the framework of EEG-based sleep deprivation categorization. The suggested approach considers how various sensory and cognitive states affect EEG recordings, emphasizing how crucial it is to choose the right EEG channels to improve classifier performance for identifying hypoxia. Khan et al. [14] summarized the negative effects of SD on behavior as a whole and cognitive

function as the neural pathways slow down, resulting in a lower mental state and reaction time.

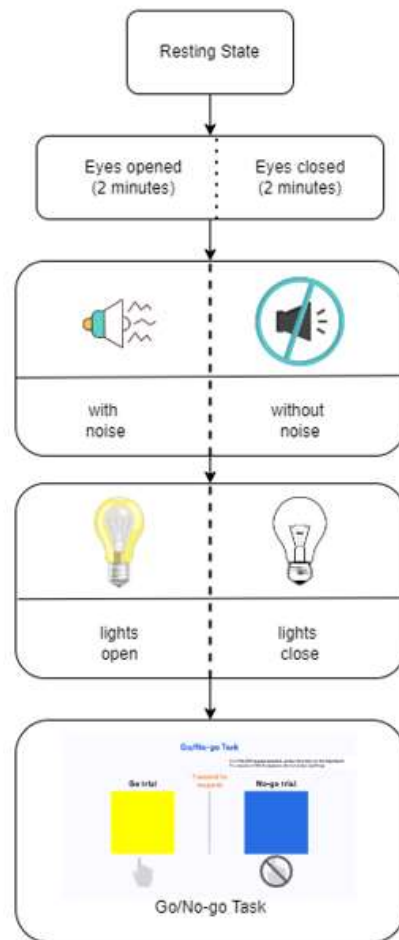


Fig. 6 The proposed protocol for the EEG experiment to detect sleep deprivation

### E. Suggestion for Classification Algorithms

Based on the classification accuracy from the bar plots, the k-NN is the optimal option for 19-channel, demonstrating the maximum accuracy for both non-sleep-deprived (99.8%) and sleep deprived (99.7%) stages. The SVM, which obtains the maximum accuracy for both non-sleep-deprived and sleep deprived (94.0%), is advised for frontal channel data. These findings show that SVM is more successful with frontal-channel data while k-NN performs better with 19-channel data, indicating that k-NN and SVM are the recommended classifiers for these specific configurations.

### V. CONCLUSION

This study shows that choosing the right EEG channel is essential for correctly categorizing sleep deprivation. Significant changes in brain activity are observed when EEG signals from sleep-deprived persons are analysed. The non-

sleep-deprived state shows more stable and consistent patterns than the erratic and fluctuating signals observed in sleep-deprived subjects in certain signals when observed. The results indicate that the k-Nearest Neighbours (k-NN) algorithms is robust when handling high-dimensional data, as evidenced by its maximum classification accuracy among the investigated classifiers, especially when using a comprehensive set of 19 EEG channels. Although they had somewhat less accuracy than k-NN, support vector machine (SVM) and artificial neural network (ANN) classifiers also fared well, particularly when used with frontal channels (Fp1 and Fp2).

These results highlight the value of using a wide variety of EEG channels to improve classification accuracy and imply that obtaining complete EEG data is necessary to create dependable and efficient sleep deprivation monitoring systems. To further enhance classification performance and resilience, future studies should investigate the application of sophisticated machine learning algorithms and the integration of new physiological information.

In addition, we also have proposed a procedure to methodically examine sensory and cognitive performance for sleep deprivation for future work. This technique emphasizes the significance of good EEG channel selection. It also intends to provide extensive insights into brain activities across a range of sensory and cognitive states.

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#### CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

#### REFERENCES

- [1] J. C. Lo and M. W. Chee, "Cognitive effects of multi-night adolescent sleep restriction: current data and future possibilities," *Current Opinion in Behavioral Sciences*, vol. 33, pp. 34-41, Jun. 2020, doi: <https://doi.org/10.1016/j.cobeha.2019.12.005>.
- [2] K. Sing E. Yee. "Resting-state electroencephalography (EEG) microstates of healthy individuals following mild sleep deprivation." *Scientific Reports* 14.1 (2024): 16820.
- [3] Y. Jeon, S. Jo, and H. Kim, "Sleep Stage Classification Using Multiple EEG Channels: A Machine Learning Approach," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 6, pp. 1320-1323, June 2019.
- [4] E. Eldele et al., "An Attention-Based Deep Learning Approach for Sleep Stage Classification With Single-Channel EEG," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 809-818, 2021, doi: 10.1109/TNSRE.2021.3076234.
- [5] M. Kamrunnahar, T. Ahmed, and F. Rabbi, "Channel Selection Algorithms for EEG Signal Processing: A Review," *EURASIP Journal on Advances in Signal Processing*, vol. 2015, no. 1, pp. 1-19, Dec. 2015.
- [6] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," *EURASIP Journal on Advances in Signal Processing*, vol. 2015, no. 1, Aug. 2015, doi: <https://doi.org/10.1186/s13634-015-0251-9>.
- [7] B. Sen.; M. Peker.; A. Çavuşoğlu.; F.V. Çelebi. A comparative study on classification of sleep stage based on EEG signals using feature selection and classification algorithms. *J. Med. Syst.* 2014, 38, 1-21.
- [8] S. Takumi, and M.i Othman. "Prediction of ADHD from a Small Dataset Using an Adaptive EEG Theta/Beta Ratio and PCA Feature Extraction." *International Conference on Soft Computing and Data Mining*. Cham: Springer International Publishing, 2022.
- [9] U. P. Kumar, and C. Nagpal. "Wavelet based performance analysis of SVM and RBF kernel for classifying stress conditions of sleep EEG." *Science and Technology* 23.3 (2020): 292-310.
- [10] Li. Junbiao. "Automatic sleep staging algorithm based on random forest and hidden Markov model." *Computer Modeling in Engineering & Sciences* 123.1 (2020): 401-426.
- [11] K. Muhammad 'A. Ammar., "EEG Features for Driver's Mental Fatigue Detection: A Preliminary Work." *International Journal on Perceptive and Cognitive Computing* 9.1 (2023): 88-94.
- [12] M. Fu et al., "Deep Learning in Automatic Sleep Staging With a Single Channel Electroencephalography," *Frontiers in Physiology*, vol. 12, Mar. 2021, doi: <https://doi.org/10.3389/fphys.2021.628502>.
- [13] M. Klug and K. Gramann, "Identifying key factors for improving ICA - based decomposition of EEG data in mobile and stationary experiments," *European Journal of Neuroscience*, vol. 54, no. 12, pp. 8406 - 8420, Oct. 2020, doi: <https://doi.org/10.1111/ejn.14992>.
- [14] M. Khan and H. Al-Jahdali, "The consequences of sleep deprivation on cognitive performance," *King Abdullah International Medical Research Center*, vol. 28, no. 2, pp. 91-99, Apr. 2023, doi: <https://doi.org/10.17712/nsj.2023.2.20220108>.