# A Review of EEG-based Prediction of Microsleep

Abdul Baseer Buriro[1,*], Ghulam Mujtaba[2], Suresh Kumar[3], Abdul Aziz[1], Nabeel Siddiqui[1],

[1]Department of Electrical Engineering, Sukkur-IBA University, Sukkur, Pakistan
[2]Department of Computer Science, Sukkur-IBA University, Sukkur, Pakistan
[3]Department of Computer System Engineering, Sukkur-IBA University, Sukkur, Pakistan
[*]Corresponding author: abdul.baseer@iba-suk.edu.pk

**Abstract**

Microsleep is a brief, complete, and unintentional sleep-related loss of consciousness. The duration of microsleeps and the probability of accidents are highly correlated. In extended monotonous activities, the consequences of microsleeps are therefore often catastrophic. Electroencephalogram (EEG) signals have widely been used for the early detection of microsleeps. This paper comprehensively reviews several EEG-based microsleep detection/prediction techniques published in academic conferences and journal articles published between January 2005 and January 2023. The review specifically discusses the preprocessing, feature extraction, and feature selection techniques collectively known as feature engineering, machine learning algorithms, and overall performance metrics. The review finally presents future directions that could help improve the overall EEG-based microsleep prediction systems.

**Keywords**—Microsleep, EEG, machine learning, deep learning, ANN

## 1 Introduction

Microsleeps are brief, complete, and involuntary sleep-related loss of consciousness, and can last for 15 s [1], [2]. Generally, behavioral signs like eye closure, droopy eyes, head nodding, and total loss of visuomotor responsiveness are indicators of microsleeps [3]. Such behavioral signs are, however, phasic and quite distinctive from the more tonic states of drowsiness (tendency to fall asleep), and mental fatigue (disinclination to responsiveness) [4]. A phasic state refers to a transient performance measured on a shorter time scale (in seconds or a fraction of a second). Whereas, tonic states refer to average performance over longer time scales (minutes) [5]. Microsleeps are generally harmless and part of everyday life. Many individuals, who momentarily fall asleep, can't recognize that they have microsleeps. Active and attention-demanding tasks, like driving, on the other hand, are everyday norms and are done easily. The propensity to microsleep, interestingly, increases with a decrease in the complexity of the task [6], which suggests that microsleeps are more likely to occur in routinely performed active tasks like driving, trucking, aviation, navigation, maritime, and process control. Loss of sleep-related consciousness during an extended-attention monotonous task can lead to an erroneous (impaired), delayed (increased reaction time), or completely failed (absent) response, the consequences of which are often catastrophic. Like sleep-deprived, healthy and non-sleep-deprived individuals are equally vulnerable to microsleeps [4], [7]. A high correlation exists between the duration of microsleeps and the probability of accidents [8]. Therefore, there arise major safety concerns, especially for high-risk occupations that demand extended and unimpaired visuomotor performance such as driving, aviation, and process control. Imminent microsleep predicted accurately and non-invasively can potentially prevent catastrophic accidents and save lives.

Electroencephalogram (EEG) is a brain imaging technique, used to non-invasively record electrical activity from different spatial locations on the scalp of the human brain. To record brain activity, EEG electrodes are generally placed on the scalp per the internationally recognized 10–20 or 10–10 systems. Besides high temporal (i.e., events occurring at milliseconds time scale) and adequate spatial resolutions, EEG recordings are relatively inexpensive and convenient in real-time applications. However,

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due to their low signal-to-noise ratio (SNR), non-stationarity, and intra- and inter-subject variability [9], the usefulness of EEG signals is limited. A low SNR signal is affected more by task-irrelevant sources than task-relevant ones. A non-stationary signal has a time-varying mean and variance. Consequently, a classifier trained on limited data may not generalize well on the data recorded at different times. The inter-subject variability arises due to physiological differences among individuals and subject-specific cognitive styles. In such a situation, the classifier across the subjects may poorly perform.

EEG-based classification generally follows two paradigms: event-related potentials (ERP), and continuous response. In the ERP paradigm, the individual responds to known and time-locked external visual, auditory, or other stimuli, e.g., brain-computer interface (BCI) [10]. In the continuous response paradigm, the demarcation of EEG relating to an event/episode (e.g., sleep) involves subjectivity, where the onset and offset of an event may not be precisely defined [5]. Consequently, the length, and numbers of the events of interest, like microsleeps and alert/responsive, vary across the subjects and sessions. On the other hand, labels used in the classification need to be discrete. Such discretized events are referred to as states [11], as shown in Fig. 1. The corresponding gold standard (labels) comprises all responsive and microsleep states. The detection and prediction of microsleeps (states or events) from the corresponding EEG epoch (W) refers to $\tau = 0$, and $\tau > 0$, respectively.

EEG can measure the changes in brain activity associated with various states of arousal, and subsequently, has widely been used in the detection of vigilance [12], alertness, mental fatigue [13], drowsiness [14], sleep [15], and microsleep [1], [16].

The bibliographical databases contain several published conference and journal articles on EEG-based microsleep detection/prediction but showed no review article. This study, therefore, presents a comprehensive review of EEG-based microsleep detection/prediction techniques published in conferences and journal articles from January 2005 to January 2023. The review specifically discusses the preprocessing and feature engineering techniques, machine learning algorithms, and overall performance metrics. In addition, the review presents challenges in EEG-based microsleep detection and future directions, which could help improve the overall EEG-based microsleep prediction systems.

# 2 RESEARCH METHODOLOGY

This review article includes English peer-reviewed journals and conference papers published between January 2005 and January 2023, which at least have used one machine learning approach to detect microsleeps from EEG signals. Multiple keywords were formulated to retrieve the relevant literature from high-quality and reliable databases, like Web of Science, IEEE Xplore, PubMed, and Scopus. The following group-wise search terms were used to query the databases, and are shown in Table 1. Group 1 consisted of machine learning-related keywords, i.e., Predict*, detect*, class*, deep learning, machine learning, ensemble learning, artificial neural network, ANN, and neural network. Group 2 consisted of signal-related keywords, i.e., EEG, electroencephalogram, electroencephalogram, electroencephalography, electroencephalographic, and electroencephalograph*. Group 3 consisted of main theme keywords, i.e., Microsleep*, micro-sleep, microsleep, and lapse.

The logical OR and logical AND operations were respectively performed to pair the keywords within and among the groups and to form a search query. The query was then applied to the article title, abstract, and keywords to find the relevant peer-reviewed journal and conference paper. MENDELEY (a citation manager software) was used to store the search records against each search query.

Duplicate studies and all those that: (1) analyzed/characterized EEG features under microsleeps and responsive events, and (2) were non-peer-reviewed papers, books, book chapters, theses, surveys, blogs, or webpages, were excluded.

# 3 MICROSLEEP DETECTION/PREDICTION

The overall microsleep detection/prediction pipelines or systems include several steps, shown in Fig. 2, followed by its details.

## 3.1 Data Sets

The literature related to EEG-based microsleep detection indicates that customized datasets, which publicly were not available at the time of writing this manuscript, have been used. Three datasets with varying characteristics (e.g., sampling rate, number of electrodes, task) have been used, and their description is given in Table 2.

TABLE 1: Selected keywords in different groups

| | |
|---|---|
| **Group – I** (machine learning-related keywords) | Predict*, detect*, class*, deep learning, machine learning, ensemble learning, artificial neural network, ANN, neural network |
| **Group – II** (signal-related keywords) | EEG, electroencephalogram, electro-encephalogram, electroencephalography, electroencephalographic, electroencephalograph* |
| **Group – III** (main theme keywords) | Microsleep*, micro-sleep, microsleep, and lapse |
| **Group – IV** (publication year) | January 2005 – January 2023 |
| **Group – V** (document type) | Peer-reviewed journals, conference articles |
| **Final search query** | (Group – I) AND (Group – II) AND (Group – III) AND (Group – IV) AND (Group – V) |

TABLE 2: Mostly used datasets and their characteristics

| **Description** | **Gold standard** | **Used by** |
|---|---|---|
| Dataset **A**: 8 subjects performed 1D pseudo-random target tracking for two 1-h sessions, one week apart. 16-channel EEG signals were acquired at 256 Hz. | The gold standard was comprised of responsive, microsleep, and uncertain classes. Coherent tracking was labeled as responsive. The microsleep was the video rating of deep drowsy or lapse AND (erroneous tracking OR unresponsive). Epochs that did not fall contextually into either microsleep or responsive were marked Uncertain and were discarded. The prediction frequency and time () were respectively 4 Hz and 0.25 s [17]. | [1], [17]–[22] |
| | Comprised microsleep and responsive states with a detection frequency of 1 Hz. | [16], [22]–[26] |
| | The gold standard comprised lapse and responsive events. The event of lapse was a logical OR video rating of deep drowsy and flat-spot in the tracking performance. Detection of lapse events. The detection frequency was 1 Hz [7]. | [3], [7], [27] |
| Dataset **B**: The maintenance of wakefulness test (MWT) for 40 minutes was performed on 76 excessive daytime sleepiness (EDS) patients. The EEG signals were acquired at 200 Hz from seven sites, and band-pass filtered at 0.3 – 70 Hz. However, only one EEG signal from the occipital region referenced to opposite mastoid electrodes, and two electrooculogram (EOG) signals from E1 and E2 (referenced to the M1 electrode) were used. | Comprised episodes of wakeful, microsleep, drowsy, and microsleep candidate with a detection frequency of 200 Hz (i.e., continuous/sample-wise detection). Microsleeps were scored based on EEG (O1-M2 and O2-M1 derivations), EOG, and videography. The frequency of detection was 200 Hz [2]. | [2], [28] |
| Dataset **C**: 16 subjects performed eight 40-min simulated driving sessions. 7 channel EEG signals were acquired at a sampling frequency of 256 Hz. | The gold standard was comprised of 1484 microsleep events and 1940 events of sustained attention (SA). An event of 0.3 – 6 s, based on behavioral clues of eye closure and nodding-off, driving performances like lane deviation, and EOG, was considered as microsleep. Events in which the car remained in the lane were labeled as SA [29]. | [29] |

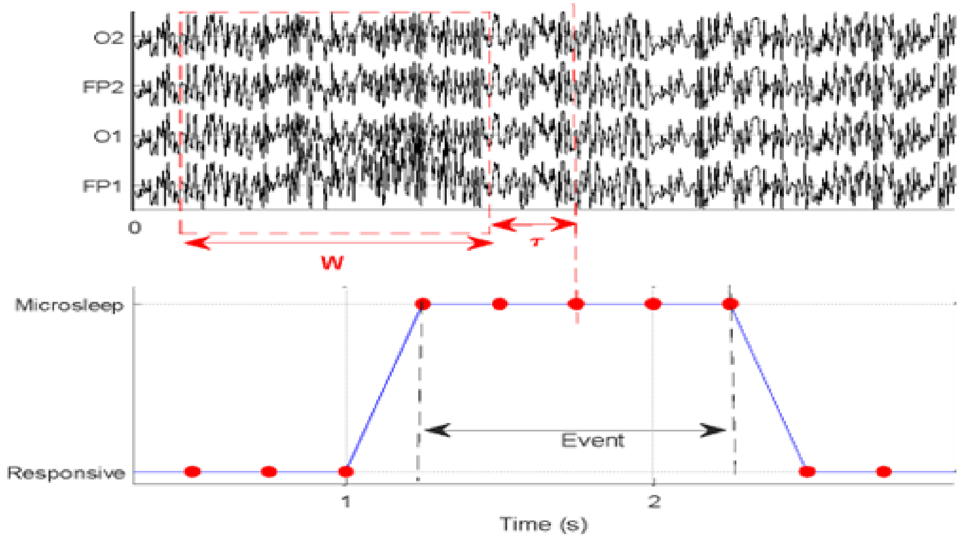


Fig. 1: Each red dot represents a state sampled at 4 Hz. and indicates a microsleep event of 1 s duration. $\tau$ and $W$ respectively indicate the prediction time and the window size of the EEG signal used to detect/predict an event (episode) or a state.

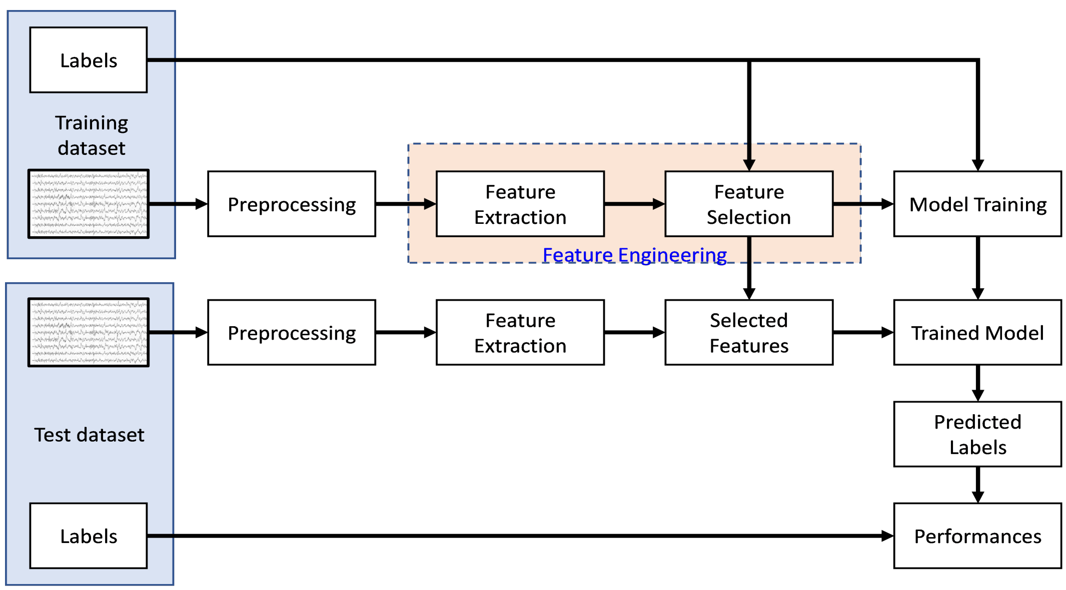


Fig. 2: Block diagram of overall EEG-based microsleep detection/prediction system. Feature extraction together with feature selection/dimensionality reduction/regularization is referred to as feature engineering [34]

### 3.2 EEG Data Acquisition

EEG signals have been acquired using different montages (combinations of electrodes) and per the international 10–20, and 10–10 systems. Poudel et al. [4], Golz et al. [29], and Golz et al [30] used 60, 9, and 7 electrodes respectively, whereas, Skorucak et al. [2], Malafeev et al. [28], and Peiris et al. [7] used 7, 6, and 16-channels respectively. Importantly, however, a higher number of EEG electrodes provides higher spatial resolution but at a cost of higher computations and the subject's comfort [31]. Similarly, EEG signals have been recorded at different sampling frequencies, like 128 Hz [30], 200 Hz [2], and 256 Hz [7], [28], [29].

### 3.3 EEG Preprocessing Techniques

The raw EEG signals go through a preprocessing pipeline, which typically, includes bandpass filters to remove DC, power line interference, and noise [17], [24], [28]. In addition, EEG signals are referenced using different referencing techniques like common average reference (CAR) [32], and electrode standardization technique (REST) [33] to improve their overall SNR. CAR being insensitive to noise and the number of EEG electrodes has been the most used EEG referencing technique. Furthermore, CAR does not require prior head model information. Different artifact removal techniques like canonical correlation analysis blind source separation, subspace reconstruction (ASR), and independent component analysis (ICA) are then used to remove eye blinks (ocular), muscle, and electrocardiogram (EKG) artifacts from the EEG signals [2], [17], [24]. However, sometimes artifactual EEG signals/epochs are discarded [23], [24]. The clean EEG signals are also decomposed into delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (¿30 Hz) sub-bands [1], [3]. Long EEG signals are finally segmented/epoched to reduce the sample size and achieve discrete labels.

### 3.4 Feature EEG Extraction Techniques

Feature extraction maps an input space (signals) to another reduced space and can involve signal or statistical processing algorithms. Features, compared to original signals, simultaneously compress the data and retain the relevant information. Subsequently, features improve the generalized performance of overall machine learning pipelines and reduce computational and storage requirements. Good features have minimum intra- and maximum inter-class variability [34].

Power spectral features have generally been extracted using parametric and nonparametric approaches methods. These features, though extracted differently, have widely been used in EEG-based microsleep detection/prediction.

Davidsons et al. [3], [23] calculated power spectral densities from one-second non-overlapping EEG segments using a 40th-order covariance method-based autoregressive (AR) model. The spectral densities (features) were converted into z-scores concerning the first minute of EEG data, and then finally log-transformed, termed Log-power spectral features. Peiris et al. [24], [27] calculated Log-power spectral features from two seconds and 50% overlapping EEG segments using a 40th order Burg method-based order AR model. These features together with spectral power ratios and normalized spectral powers have been used in successive EEG-based microsleep detection studies [16], [25], [26]. Skorucak et al. [2], however, calculated power spectral features from one-second and 80% overlapping EEG segments via a 16th-order Burg method-based AR model.

Shoorangiz et al. [17], [20] calculated Log-power spectral features from a five-second sliding window with a step size of 0.25 seconds via Welch's method (also known as periodogram). Similarly, Golz et al. [29] calculated power spectral features via a Hanning windowed periodogram.

Nonlinear features, like fractal dimension, approximate entropy, and Lempel-Ziv complexity have also been used with spectral features for EEG-based microsleep detection [27]. Similarly, auto and cross Choi-Williams distributions have been used with spectral features [29].

Normalized and non-normalized spectral, temporal, and information-theoretic interchannel (also known as functional connectivity) features of coherence and cross-spectral power, correlation and covariance, and mutual information and joint entropy, computed nonparametrically, have also been used to predict microsleep states [1], [18], [19].

Furthermore, Spatio-temporal features extracted using regularized Spatio-temporal filtering and classification (RSTFC) have been used to predict microsleep states [20].

### 3.5 Feature Selection Techniques

The EEG signals in feature space can become high-dimensional datasets, and consequently, challenge the performance of the overall learning systems [25]. Therefore, feature selection or dimensionality reduction techniques become an integral part of the overall learning system. Feature selection techniques do not change the original features' representation and maintain their semantics. Whereas dimensionality reduction techniques project the original input data into a lower-dimensional feature space and don't require learning/training.

Principal component analysis (PCA) has been the most used dimensionality reduction technique in EEG-based microsleep detection/prediction [3], [16], [24], [26], [27]. Compared to nonlinear dimensionality reduction techniques of kernel PCA, classical multidimensional scaling, isometric mapping, nearest neighbor estimation, stochastic neighborhood embedding, autoencoder, stochastic proximity embedding, and Laplacian eigenmaps, PCA has also been reported as the best dimensionality reduction technique at detecting microsleeps from EEG signals [25]. Furthermore, Bayesian multi-subject factor analysis has also been used as a dimensionality reduction technique [21].

Features selection in EEG-based microsleep prediction has been performed through sequential forward selection [1], [18], [19], and greedy forward selection [17] methods. Golz et al. [29] used regularization parameter C to reduce the complexity, and subsequently, avoid the overfitting of the learning model.

The dimensionality of feature space is generally related to the number of EEG electrodes/channels. Subsequently, low-dimensional datasets, to avoid the underfitting of the machine model, do not require feature selection. Studies [2], and [23] have used all the available features and have not performed the feature selection step. Deep learning inherently extracts features and reduces dimensionality (known as feature engineering) [9], [35]. Therefore, studies [22], and [28] have not performed any feature engineering.

### 3.6 Machine Learning Models/Classifiers

Machine learning is about understanding and learning from observational data, where the predictive features are independent of the learning model. Broadly, multiple conventional machine learning, ensemble learning, and deep learning models have been used in EEG-based microsleep prediction systems.

From conventional machine learning models, linear discriminant analysis (LDA) has been the most used classifier, both in single and ensemble configurations, in EEG-based microsleep detection [1], [7], [17]–[20], [27]. Linear and nonlinear support vector machine (SVM) classifiers have also been used in some EEG-based microsleep detection studies [1], [2], [16], [29]. Furthermore, random forest (RF) – an ensemble of decision trees (DT) –[2], sparse Bayesian learning (SBL), and variational Bayesian logistic regression (VBLR) [20] have been used in detecting microsleeps from EEG signals.

Different authors have exploited convolutional neural networks (CNN), and different versions of recurrent neural networks (RNN) like long-short term memory (LSTM), echo state network (ESN), and liquid state machine (LSM), in single and ensemble configurations [2], [16], [22], [23], [26], [28]. In addition, optimized learning vector quantization (OLVQ) has been used in an EEG-based microsleep study [29].

### 3.7 Performance Metrics

Except for [2], and [28], all the reviewed articles have considered microsleep detection as a binary classification problem, where various performance metrics have been formulated from elements of a confusion matrix. For class-balanced datasets, accuracy alone is sufficient to describe the overall system performance. However, for class-imbalanced datasets, in addition to sensitivity, specificity, and precision, F-measure, geometric mean (GM), and Mathew's correlation coefficient have been the most used performance metrics [36].

In addition, two curve-based and threshold-independent metrics of the area under the curve of the receiver operating characteristic (AUC-ROC) and the area under the curve of precision-recall (AUC-PR) have also been used in class-balanced and class-imbalanced binary learning problems [37], [38].

## 4 CURRENT CHALLENGES

The detection performances on the continuous tracking task, reported in all the reviewed articles, are low for real-life microsleep detection applications. A variety of challenges ranging from data acquisition to performance metrics equally contribute to such low performances. The EEG-based microsleep detection systems generally have two parts: signal processing and machine learning.

EEG signals have low SNR and are largely affected by intrinsic and extrinsic artifacts. Physiological artifacts due to their complex nature and inference (overlapped) with the neural systems, are highly complicated to remove and misleadingly affect practical applications [39], [40]. Besides being non-stationary, EEG signals, due to physiological differences among individuals and subject-specific cognitive styles, vary within and across the subjects performing the same task. Such variations can result in covariate shifts. In addition, during microsleeps, the power spectra of EEG inconsistently change [3]. Therefore, EEG signals inherently impede the performance of the overall microsleep detection system.

The microsleeps are identified and measured from the performances (in terms of error or reaction time) on the task, and generally verified through video recordings. The performance on a continuous task decreases gradually, which results in a small transitional period between responsiveness and microsleep. Consequently, the demarcation of microsleeps becomes subjective and an expert can't faithfully discriminate between the two events of microsleep and responsiveness, referred to as label noise [17]. Furthermore, the corresponding EEG signals overlap each other and have been shown to deteriorate the overall detection performance [28].

Mental fatigue can be induced by prolonged engagement with cognitive tasks [13]. Both drowsiness and fatigue can respectively be relieved by sleep and rest [41]. The mental fatigue and drowsiness being tonic have been classified using the first and last few minutes of the experiment. Contrary, microsleeps can equally affect both sleep-deprived and non-sleep-deprived healthy individuals [4], [7], occur intermittently, and not be induced. Microsleeps being phasic need to be classified against every alert state.

Microsleep datasets are therefore generally large and highly class-imbalanced. Machine learning assumes independent and identically distributed (iid) data, whereas the EEG samples (like time series data) are interdependent and causal. The current value (effect) of a causal signal depends on current and past samples (cause) but not the future samples. Machine learning models are good at associations in the data but unskilled at causation. Machine learning models always consider information that animals use heavily like domain shift and temporal structures as noise. For example, head nodding and eye blinks (in the video) are considered the indication of microsleep. Such indications in the EEG used to predict the microsleeps are, however, considered noise/artifacts, and are subsequently removed. Furthermore, machine learning models can't generalize out-of-distribution samples (i.e., artifacts) [42], [43].

## 5 DISCUSSION

The development of an accurate, robust, and easy-to-use microsleep detection system can prevent catastrophic accidents and save lives. High temporal resolution (at millisecond scale), making the EEG the most used imaging technique to detect microsleeps. However, the reviewed articles mostly used unique steps in each part of the EEG-based microsleep detection system (shown in Fig. 2). In addition, all the reviewed articles used their customized datasets, which at the time of writing this manuscript, were not publically available. Therefore, benchmarking a particular EEG-based microsleep detection study becomes hard.

Wide use of band-wise spectral features (though extracted differently) shows their effectiveness at classifying microsleep and responsiveness. Though most used, PCA being unsupervised can perform inferior to supervised feature selection techniques when the direction of maximum variance is different from classification-related information. Having a simple and stable decision boundary, LDA is more robust and less susceptible to overfitting than nonlinear classifiers [1] and has therefore been the most used classifier.

Microsleeps being rarely occurring events, on continuous tasks, result in highly class-imbalanced datasets. For such datasets, threshold-dependent metrics of F-measure, GM, Mathew's correlation coefficient, and threshold-free metrics of AUC-ROC and AUC-PR have been used.

## 6 FUTURE DIRECTIONS

The development of microsleep prediction systems can consider the following two issues. The current EEG-based microsleep detection systems are considered binary or multiclass classification problems. Where the transition time between the events (e.g., responsiveness and microsleep), and their subjective demarcation result in label noise that lessens the overall detection performances. To mitigate the effect of label noise and to improve the overall detection performances, the EEG-based microsleep detection system can be considered a regression problem. In such a scenario, the user's performance on the task needs to be predicted. A threshold on the predictions can be set to alert the user.

Microsleeps are indicated by eye closure, droopy eyes, head nodding, and total loss of visuomotor responsiveness. EEG with fewer electrodes specifically from occipital and temporal can therefore suffice. These EEG signals combined, at the feature or decision level, with easily measurable and socially acceptable physiological signals, like EOG, fascial muscle contraction, and skin conductivity [44] are likely to improve the overall detection performances.

## 7 CONCLUSION

All the reviewed articles reported low detection performances that can be attributed to the overlapping events of microsleep and responsiveness, low SNR of the EEG signals, and subject-specific and skewed data distributions. Consideration of microsleep detection as a regression problem and fusion of multiple easily measurable signals can be experimented with to improve the overall detection performances of the microsleep detection systems.

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