ORIGINAL ARTICLE

# EEG-motion: a novel algorithm that detect restless legs syndrome using EEG signals on polysomnography

**Murat Kayabekir · Seda Kaya · Mete Yağanoğlu**

Received: 23 June 2025 / Accepted: 15 January 2026
© The Author(s) 2026

**Abstract**

Restless legs syndrome (RLS) is one of the most common sleep movement disorders diagnosed by detailed clinical and polysomnographic (PSG) evaluation. This study was conducted to facilitate the PSG diagnosis of RLS and to increase the physician's ability to interpret PSG analysis. The aim of this article is to develop a new diagnostic model that will assist PSG in detecting RLS from electroencephalogram (EEG) signals during sleep staging, without examining electromyography (EMG) recordings during PSG analysis. EEG signals of 60 volunteers with known RLS ($n=32$) and nonRLS ($n=28$) (Age; $38.2\pm5.31$ years and Body Mass Index; $34.1\pm3.47$) were analyzed by PSG measurement. These data were obtained directly from our own sleep laboratory records and do not contain any public datasets. Additionally, all EEG channels were filtered between 0.5–38 Hz and processed using a standardized methodology. A novel algorithm was developed for the EEG-motion model by training the EEG signals using machine learning methods to help determine whether a person has RLS. EEG-motion was compared with the classical method ('PSG-EMG-classical'; RLS diagnoses made by a doctor analyzing EMG recordings from PSG). A strong positive correlation was found between the results of the classical method and the novel model, and this correlation was statistically significant ($p<0.001$). Confusion matrix [accuracy (99%), sensitivity (98%), precision (100%), F1-Score (99%)] and ROC analysis (AUC: 99%) were performed to evaluate the EEG-motion model ($p=0.00$). These results demonstrate that the proposed EEG-only approach can reliably detect RLS without the need for EMG recordings, representing a significant methodological contribution by simplifying PSG analysis and reducing electrode usage. EEG-motion can be integrated into PSG measurements in sleep laboratories. The novel model will increase the interpretation power of physicians and researchers during the analysis by providing the input of the patient's periodic leg movement information from the EEG recording during sleep staging, which is the first stage of long PSG analysis.

**Keywords** Sleep · Polysomnography (PSG) · Electroencephalogram (EEG) · Machine learning · Restless legs syndrome (RLS)

## 1 Introduction

Sleep is a behavior in which the perception response to environmental stimuli gradually decreases but can return. It is an important physiological need in which the brain's motor and sensory networks are reorganized, and reflexes are reduced [1–3]. We can recognize sleep onset with three basic electrophysiological signal measurements: (1) EMG (electromyogram) shows a decrease in muscle tone. (2) EOG (electrooculogram) eye movements slow down. (3) EEG (electroencephalogram) low voltage, mixed frequency electrical waves occur [4, 5]. Today, Video-EEG-PSG (polysomnography) is the gold standard method for recording sleep: (a) REM (Rapid Eye Movement) with rapid eye movements and NREM (Non Rapid Eye Movement) without rapid eye movements during the night. (b) NREM voltage and frequency changes (N1, decreasing voltage compared to wakefulness, N2 sleep spindles and K complexes, N3 deep sleep, delta, slow wave). (c) Sawtooth EEG waves in REM sleep and EOG waves with rapid eye movements. The sleep pattern in healthy young adults averages at least four times 6 h per night with periods of 90 min (N1-N2-N3-N3-N2-REM). PSG diagnoses sleep physiology and diseases electrophysiologically with video-camera, EOG, EEG, chin-EMG, airflow, and leg EMG recordings [1, 4–8].

PLMS (periodic limb movements of sleep) and RLS (restless legs syndrome) are well-known sleep movement disorders and are diagnosed by PSG. Restless legs syndrome (RLS) is a common neurological disorder among sleep disorders. Clinically, the patient desires to move the legs, often accompanied by an uncomfortable and unpleasant sensation: "This desire and sensation increases during periods of inactivity (resting, sitting, lying down), decreases with movement, and is more severe at night than during the day. There is also a positive family history, positive response to dopaminergic treatment, and periodic leg movements during sleep." Therefore, it is thought that PLMS and RLS are the continuation of each other. RLS is diagnosed through clinical evaluation. PLMS is only diagnosed through PSG. The frequent coexistence of RLS and PLMS allows PSG to confirm the diagnosis in patients diagnosed with RLS through clinical evaluation. This necessitates investigation of the presence of PLMS in PSG recordings. In PSG, the average duration of leg movements in both sleep and wakefulness (PLMS/NREM duration, PLMS/REM duration and PLMS/wakefulness duration) is understood by scoring EMG (leg movements) and EEG (sleep stages) recordings separately [9–11]. However, this process requires manual scoring by trained sleep technologists, making it time-consuming and prone to inter-scorer variability. In this study, we aimed to develop a system that allows a physician performing PSG analysis to understand whether a person has RLS or not through EEG signals when he/she completes sleep staging on EEG without any EMG scoring and to transfer this information directly to the physician. Our aim is to facilitate the polysomnographic diagnosis of RLS and to increase the physician's ability to interpret PSG analysis. Solving this problem is clinically significant because it enables automated or semi-automated diagnostic systems and reduces the burden on sleep laboratories. In this context, this study is unique in that it uses EEG as the sole input modality and evaluates a wide range of classifiers. In this study, we created our own datasets from EEG data obtained from PSG recordings of 60 volunteers (32 RLS, 28 controls) and tried various models including K-Nearest Neighbor (KNN), Decision Trees (DT), Extra Tree Classifier (ETC), Gradient Boosting Classifier (GBC), Voting Classifier (VC) and Deep Neural Networks (DNN) to develop a RLS diagnostic support based solely on EEG. To the best of our knowledge, previous studies have not explored EEG-only RLS detection with such an extensive comparative analysis of machine learning and deep learning algorithms, making this approach both novel and clinically valuable. Focusing entirely on EEG patterns without the need for EMG scoring, this study offers an approach that simplifies the diagnostic process and can help clinicians detect RLS more easily.

## 2 Materials and methods

This study was carried out in Erzurum Sleep and Electrophysiology Laboratories (Ethical approval number: 8–25/25.11.2021/ Patent Project Number: 2023/13332. Date: 07.11.2023, Atatürk University) in accordance with the standards of the American Academy of Sleep Medicine (AASM).

### 2.1 Study participants

The average sleep duration of the participants of the study, in which the rules of the Declaration of Helsinki were taken into account, was 6 ± 8.56 h. A database was created by analyzing EEG signals from PSG recordings of 60 volunteers known to have RLS ($n = 32$) and non-RLS ($n = 28$) (Age; 38.2 ± 5.31 and Body Mass Index 34.1 ± 3.47) were analyzed. The diagnosis of the 32 RLS patients included in this study was confirmed through clinical assessments by experienced physiologist and neurologist according to the International Restless Legs Syndrome Study Group (IRLSSG) criteria. People diagnosed with a disease were considered in the patient class, and people not diagnosed with a disease were considered in the healthy class.

### 2.2 Experimental recordings

The electrophysiological signal recordings obtained from the Grass Technologies PSG system (TWin 4.5.3, USA) for this study are as follows: "Six channels electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), electrocardiogram (ECG), snoring, breathing, airflow, partial oxygen pressures, body position and real-time video." F3-M2, F4-M1, C3-M2, C4-M1 and O1-M2, O2-M1 sleep EEG channels; LAT, Left anterior tibialis; RAT, right anterior tibialis sleep EMG channels) [4, 7, 8, 12].

### 2.3 Experimental protocol

According to AASM scoring criteria, a limb movement (LM) is recorded when the anterior tibialis EMG activity increases by more than 8 microvolts from the resting level and lasts between 0.5 and 10 s. If more than four such movements occur, spaced 5 to 90 s apart, they are considered a periodic limb movement series (PLMS). Diagnoses of PLMS and restless legs syndrome (RLS) in the volunteers were made by a physiology specialist (M.D.) following AASM guidelines (Fig. 1). A novel algorithm was developed to train the EEG signals for the EEG-motion model using machine learning methods (Table 1).

### 2.4 Experimental setting

Can we understand the polysomnographic diagnosis of PLMS and RLS, which are common among sleep movement disorders, through EEG signals instead of EMG signals? After sleep staging, which is the first step in PSG analysis, can the physician learn whether the patient has RLS or not during the EEG examination phase? Applying artificial intelligence techniques to address these questions was a key milestone in the creation of the EEG-motion model. The EEG-motion model was created by training EEG signals from PSG recordings in which RLS was diagnosed (Table 1).

In this study, EEG signals were obtained from six channels of each participant's PSG recordings. The preprocessing stage included outlier removal using the box-plot method to ensure signal consistency and a band-pass filter (0.5–45 Hz) to eliminate high-frequency noise and baseline drift. Three complementary feature types were then extracted from each EEG channel: (i) Discrete Wavelet Transform (DWT) coefficients to capture time–frequency characteristics, (ii) Power Spectral Density (PSD) values to quantify energy distribution across frequency bands, and (iii) the Hurst exponent to assess signal complexity and self-similarity. All extracted features were concatenated to form a comprehensive dataset (Xn), which was divided into training and test subsets. Various machine learning algorithms were applied to classify RLS and non-RLS segments. The model's performance was evaluated using standard metrics including accuracy, precision, sensitivity, and F1-score.

 https://doi.org/10.1007/s00521-026-11929-z

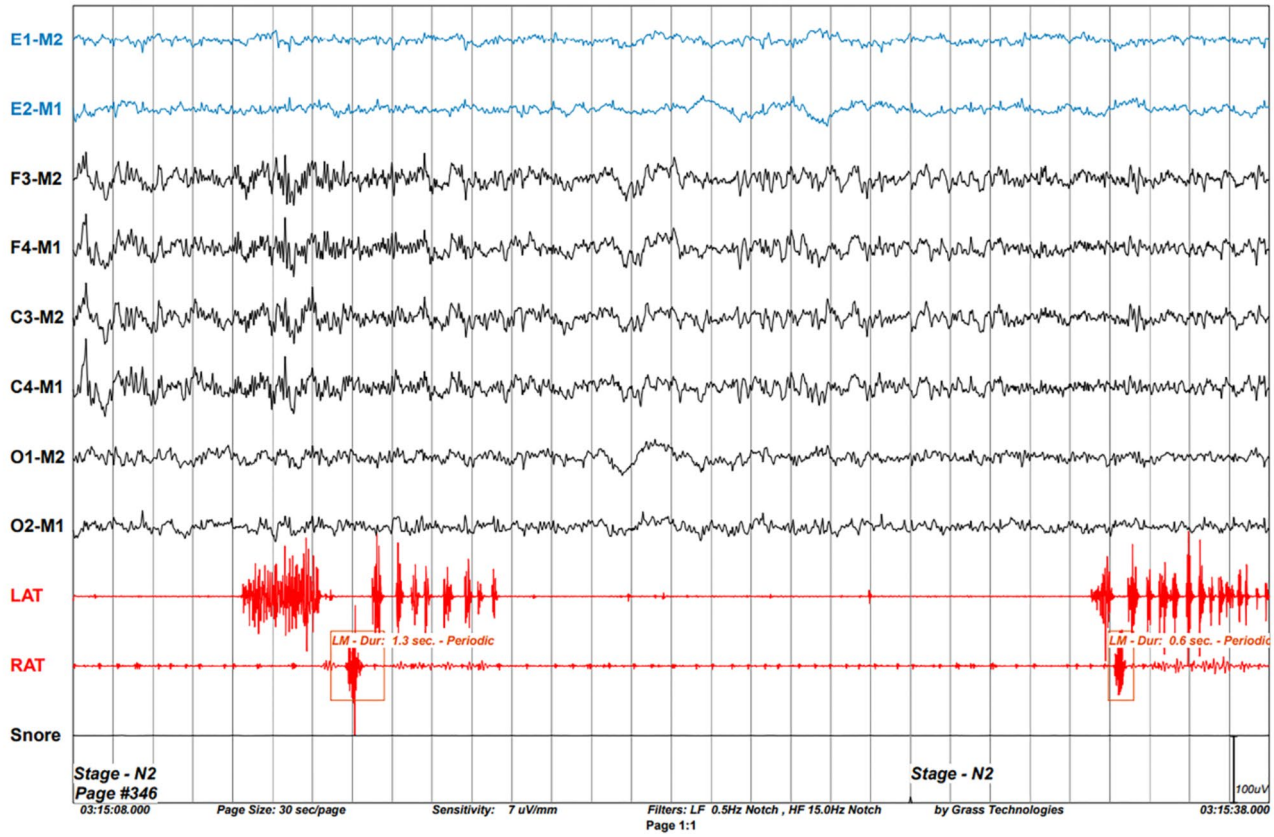


**Fig. 1** One epoch (30 s) of PSG recording sample showing EOG, EEG, EMG (LAT, RAT, LM Dur, PLMS & RLS) and Snore wave signals and NREM stage N2 sleep period. PSG, polysomnography; EOG, electrooculography "E1-M2, E2-M1"; EEG electroencephalography "Six EEG channels, frontal, F3-M2, F4-M1, centroparietal, C3-M2, C4-M1, occipital, O1-M2, O2-M1"; EMG, electromyography; LAT, Left anterior tibialis; RAT, right anterior tibialis; LM Dur, leg movement duration; PLMS & RLS; periodic limb movement of sleep & restless legs syndrome

**Table 1** Algorithm for EEG-motion

| **Algorithm EEG-motion** |
|---|
| 1: i person's PSG record (Xi) |
| 2: for all Xi |
| 3: Separate each person's 6 EEG channel signals (Xij) from PSG signals. |
| 4: for all Xij |
| 5: Outlier data cleaning with box plot method |
| 6: Apply band pass filter |
| 7: Calculated **Discrete Wavelet Transform Features (Xija)** |
| 8: Calculated **Power Spectral Density Features (Xijb)** |
| 9: Calculated **Hurst Exponent Analysis Feature (Xijc)** |
| 10: end for |
| 11: New data set (Xn = Xija+ Xijb+ Xijc ) |
| 12: Separate training/test data |
| 13: For all Xn |
| 14: Apply machine learning algorithms |
| 15: Performance evaluation |
| 16: end for |
| 17: Stop the collection of recordings from 6 EEG channels |

### 2.5 Algorithmic approach and steps to build the EEG-motion model

In our study, after data preprocessing and feature extraction steps on EEG data, a complete dataset containing all extracted features was created. Subsequently, the SMOTE method was employed to balance class distribution, producing a Post-SMOTE dataset. The splitting into training and test sets was then performed on this balanced dataset, strictly at the subject level, ensuring that each participant's feature data appeared exclusively in either the training or test set. This procedure aimed to ensure that the developed model would be generalized and applicable to different individuals.

(a) The EEG signals were first subjected to outlier removal and filtering (preprocessing). (b) Then, three different feature extraction methods (wavelet transform, spectral analysis and Hurst exponent analysis) were applied to the filtered data (feature extraction). (c) The features extracted from the EEG signal data were labeled as RLS or nonRLS classes and added to the new data set (new data set creation). (d) The new datasets were divided into two groups as training and testing, and the steps were finalized by i) applying classification algorithms to these groups and ii) performance evaluation for the obtained results (Fig. 2) GridSearchCV was used as a parameter selector for the classification algorithms to give the most accurate results. GridSearchCV is an efficient method provided by Scikit-learn, a Python library that combines different machine learning algorithms that estimate all necessary models and select the best parameters by calling the appropriate function for the data [13].

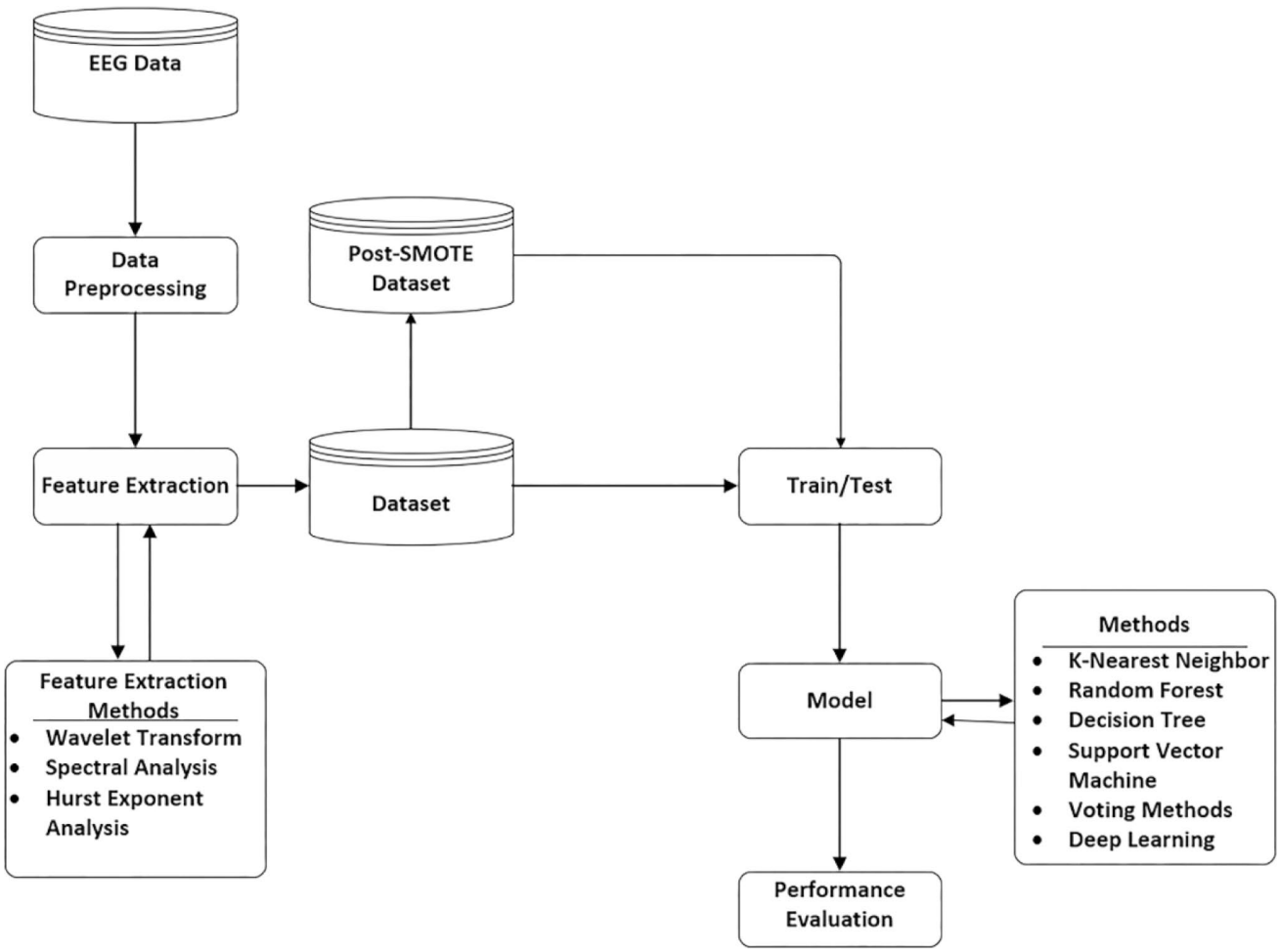


**Fig. 2** Summary flowchart for EEG-motion

## 2.6 Data editing and analysis

### 2.6.1 How was the data set for the EEG-motion model created?

We focused on the EEG wave signals of 60 volunteers with known Restless Legs Syndrome (RLS, $n=32$) and non-RLS ($n=28$), as identified by polysomnography (PSG) measurements performed at the Electrophysiology Laboratory, Sleep Disorders Center. The numerical amplitude values of EEG signals from six EEG channels—frontal (F3-M2, F4-M1), centroparietal (C3-M2, C4-M1), and occipital (O1-M2, O2-M1)—from each PSG recording comprised the raw datasets for each subject. A single PSG recording (mean duration: $6 \pm 8.56$ h) generates millions of digitized data points, with PSG signals digitized every five milliseconds. For instance, digitizing PSG signals from the longest recorded night yielded approximately 4,886,400 numerical data points. The values obtained by applying data pre-processing and feature extraction methods to these digitized data of each person constitute the data of the basic data set (Fig. 3).

Due to class imbalance arising from the relatively smaller number of RLS subjects compared to non-RLS subjects, the Synthetic Minority Oversampling Technique (SMOTE) was employed. SMOTE was selected because it generates synthetic samples by interpolating between existing minority class instances rather than merely replicating existing samples [14]. This approach improves model generalization and reduces the likelihood of overfitting, which can occur when simply duplicating minority samples. Alternative balancing methods, such as random oversampling, random undersampling, and hybrid methods, were considered during preliminary experiments. However, SMOTE consistently provided superior performance in terms of model accuracy and stability, especially when dealing with highly imbalanced and complex EEG datasets. After applying SMOTE, the dataset was balanced, resulting in an equal number of samples for RLS ($n=300$) and non-RLS ($n=300$), totaling $n=600$ subjects. The SMOTE method was used to address class imbalance by generating synthetic samples based on EEG features from the original dataset. This process does not increase the actual number of participants; rather,

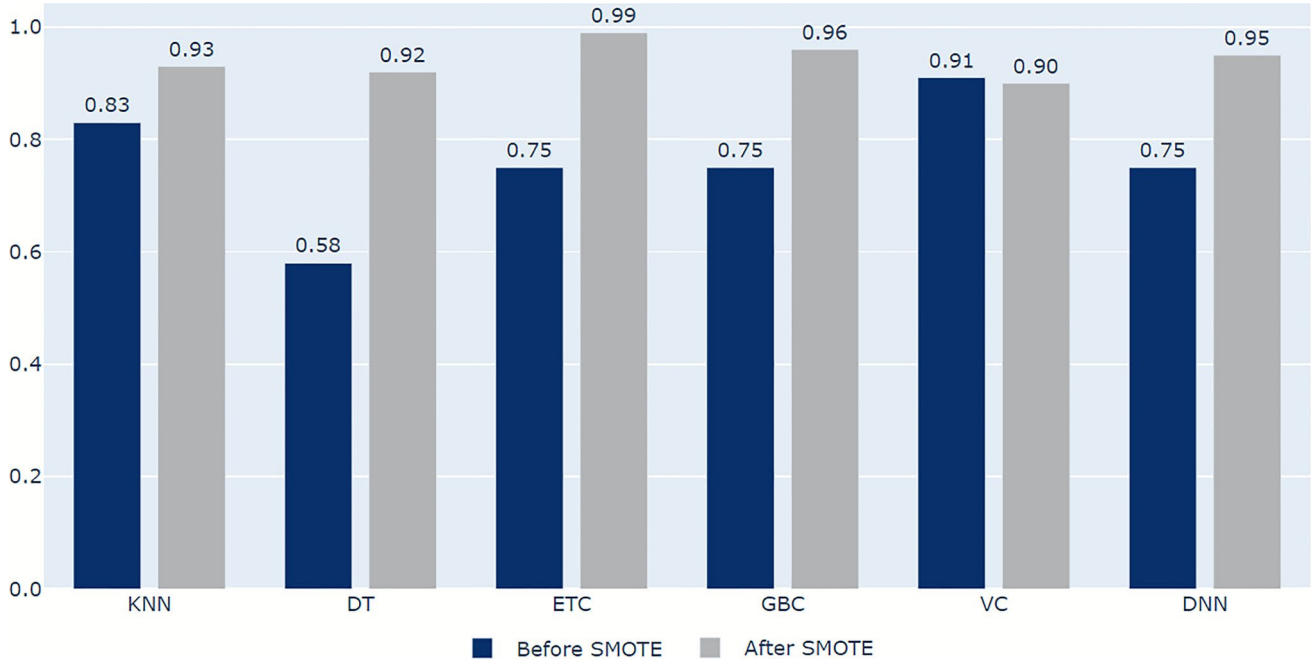


**Fig. 3** Comparison of the accuracy values of the classifiers (algorithms) used for the development of the EEG-motion model before and after SMOTE. The ETC algorithm is the highest accuracy (after SMOTE). KNN, K–Nearest Neighborhood; DT, Decision Trees; ETC, Extra Tree Classifier; GBC, Gradient Boosting Classifier; VC, Voting community learning method; DNN, Deep Learning

it balances classes by augmenting data derived from existing participants' EEG features. Thus, the total of 600 samples obtained after applying SMOTE does not correspond to 600 different subjects, but rather represents balanced synthetic samples derived from the original 60 participants.

To evaluate the model's performance, the dataset was initially divided into training and testing sets using an 80/20 split, establishing an independent test set. Within the training set, a fivefold cross-validation approach was applied to enhance the reliability and generalizability of the results. In this approach, the training data was partitioned into five equal subsets; in each iteration, four subsets were used for training, while the remaining subset served as the validation set. This procedure was repeated five times, ensuring each subset was used exactly once as validation data. Cross-validation was selected due to its capability to provide more consistent and reliable estimates of model performance, particularly useful for datasets with limited samples, significantly reducing the variance compared to a single training-test split. Finally, the model's performance was assessed on the previously separated independent test set.

#### 2.6.2 Pre-processing of EEG signal data for EEG-motion

Pre-processing steps involve preparing the data for analysis by addressing missing data, cleaning outlier data, and converting data into suitable formats. In this study, EEG data initially underwent outlier removal using the box plot method. Specifically, the amplitude distribution of EEG data was calculated, and values falling outside 1.5 times the interquartile range (IQR), determined by the first quartile (Q1) and third quartile (Q3), were identified as outliers and removed from the dataset. Subsequently, a band-pass filtering step was applied to reduce noise inherent in EEG recordings. EEG signals typically contain meaningful information within the 0.5–38 Hz frequency range, thus frequencies outside this range were regarded as irrelevant noise. Therefore, a band-pass filter with cut-off frequencies of 0.5–38 Hz was specifically employed to enhance signal quality by isolating and preserving essential EEG components while effectively suppressing unwanted noise and interference [15, 16].

### 2.7 Feature extraction in EEG signals dataset for EEG-motion

Feature extraction is a dimension reduction process. It reduces the dimensions of a complex data set into a simpler problem. The feature selection process is done to select the best features for optimized classifications according to various criteria. Feature extraction methods are based on the computation of statistical features or the generation of syntactic descriptions [17]. It is a critical step in EEG data analysis since EEG signals are non-stationary, complex, and noisy. The selection of appropriate feature extraction methods was driven by the nature of EEG data, as well as prior successful applications documented in relevant literature.

#### 2.7.1 Feature extraction methods used for the EEG-motion and its connection with EEG signal data

**2.7.1.1** Wavelet transform (WT) Wavelet Transform (WT) was selected because it effectively captures both temporal and frequency characteristics of EEG signals, which are non-stationary by nature. Traditional Fourier analysis lacks the flexibility of adaptive time–frequency localization, making WT particularly suitable for EEG analysis. By using variable-size windows, WT efficiently manages different frequency bands: shorter windows capture higher-frequency components accurately, and longer windows provide resolution for lower-frequency components. Thus, WT allows the extraction of detailed transient information crucial for accurate EEG interpretation and classification [18].

**2.7.1.2** Discrete wavelet transform (DWT) coefficient Discrete Wavelet Transform (DWT) coefficients were extracted to gain deeper insights into EEG signal characteristics at different resolutions and scales. The fourth-order Daubechies wavelet (db4) was chosen based on its proven capability to preserve signal integrity and effectively capture EEG transient behaviors as validated in prior EEG studies [19]. Five sets of coefficients (cA4, cD4, cD3, cD2, and cD1) were extracted, representing different frequency bands and scales. From these coefficients, statistical measures such as energy per wavelength, variance, wavelength, and standard deviation were calculated

for each EEG channel (F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, O2-M1), yielding a comprehensive feature set of 120 features.

**2.7.1.3** Power spectral density (PSD) PSD analysis was implemented to quantify the distribution of EEG signal power across frequency domains, a widely used technique for EEG data interpretation. Specifically, Welch's method was employed due to its robustness against noise and reliable estimation performance in EEG signal processing contexts [20, 21]. The PSD provided features reflecting overall signal power distribution, which are indicative of various physiological and cognitive states. Six PSD features were derived, one per EEG channel, providing essential information about the power distribution characteristics inherent to each EEG recording.

**2.7.1.4** Hurst exponent analysis The inclusion of Hurst exponent analysis was justified by its effectiveness in quantifying signal complexity and identifying long-memory processes in EEG time series data. This approach uniquely measures the self-similarity of EEG signals over successive time windows, distinguishing simpler, more predictable signals from complex, irregular ones [22, 23]. Extracting Hurst exponent values per EEG channel contributed six additional features that capture inherent complexity patterns of the EEG recordings.

The selection of these methods followed documented success in EEG signal analysis literature and their complementary nature to extract diverse yet relevant signal characteristics. Statistical moments and entropy measures were evaluated as alternative features but were excluded from the analysis because they either duplicated existing methods or showed weaker explanatory power in initial assessments. The selected methods established a strong foundation for machine learning tasks through their combination of theoretical justification and methodological diversity.

## 2.8 Classifiers are used for the EEG-motion and its connection with EEG signal data

Classification refers to identifying the class of an unknown pattern by using a classifier that takes the pattern's features as input [24]. Can near-accurate machine learning be achieved by classifying the EEG signal data of those with RLS? In other words, will these methods be able to reach the information 'RLS is present' from EEG signal data? During this study, EEG signal data from PSG recordings with or without RLS were classified using the most appropriate machine learning methods.

### 2.8.1 K–nearest neighborhood (KNN)

K-Nearest Neighbors (KNN) is a supervised machine learning algorithm known for its effectiveness in classifying data with multiple categories, such as EEG wave signals. Therefore, outputs were determined for the signal inputs of the EEG dataset. In this approach, a relationship between input and output variables was established using the labeled EEG dataset. For previously unseen data, the model used known input–output pairs to predict outcomes. Each input was assigned to a class based on the k nearest neighbors, identified by calculating the Euclidean distance between the input and all labeled data points. Once the distances were computed, the k closest samples were selected, and the input was classified based on its similarity to these neighbors [25]. In this study, the parameters metric = 'euclidean', N_neighbors = 5 for raw data and metric = 'chebyshev', N_neighbors = 1 for post-SMOTE data were used for classification with KNN (metric: distance calculation method between two neighbors; N_neighbors: how many nearest neighbors to look at).

### 2.8.2 Decision trees (DT)

Decision Trees (DT) are a type of supervised machine learning algorithm commonly used for classification tasks, as they separate data based on feature values [26]. n this study, the DT algorithm was employed to learn decision rules derived from the attributes of EEG wave signals and to construct a predictive model capable of identifying whether a case corresponds to Restless Legs Syndrome (RLS) or not. DT are trees obtained by sorting and classifying EEG signal sample data according to their feature values. The sample data were classified starting from the root node and ranked according to their feature values. The topmost tree is the root node, and the other nodes

are connected through branches. The process was repeated until there were no more links to connect to other nodes [27–29]. During the construction of the tree, each node was split based on the best split found within a randomly selected subset of features, rather than evaluating all available features [30]. In this study, the parameters criterion = 'log loss,' max-depth = 7 for raw data and criterion = 'gini,' max-depth = 10 for post-SMOTE data were used for classification with decision trees (Criterion is a function that measures the quality of a bin; max-dept is the depth of the tree).

#### 2.8.3 Extra tree classifier (ETC)

Extremely Randomized Trees Classifier (ETC) is an ensemble learning method that creates multiple unpruned decision or regression trees. Unlike traditional methods, ETC splits nodes using completely random thresholds and uses the entire training dataset instead of a random sample to build each tree. In this study, the full EEG wave signal dataset was used and classified using the ETC method. In this study, multiple trees were used to train the ETC ensemble and training data was obtained on the EEG signal samples of each tree. A subset of all available features was analyzed to find the best split at a node. Instead of searching for the best threshold value for each feature, we randomly selected threshold values for each feature. From the training data used in these random splits, the one with the highest score increase was selected. Introducing more randomness during training led to trees that were more independent from each other, which helped reduce variance. Therefore, ETC led to better results compared to random decision trees [31]. In this study, the parameters n_estimators = 20, criterion = gini', max-depth = 10 for raw data and n_estimators = 30, criterion = 'entropy,' max-depth = 10 for post-SMOTE data.

#### 2.8.4 Gradient boosting classifier (GBC)

Boosting algorithms work by repeatedly improving weak learners, which are models that perform only slightly better than random, until they become strong learners with high accuracy [32]. In our study, we aimed to transform weak learner EEG signal data into strong learner EEG signal data. In gradient boosting, decision trees were used as weak learners. To minimize the loss function, an ensemble model was built by summing the predictions of these trees. Trees were added one by one, and each new tree's output was combined with the previous trees' outputs to gradually improve the model's prediction. This process was continued until the loss function reached the desired value [33]. In this study, the parameters n_estimators = 100, learning_rate = 3, max-depth = 3 for raw data and n_estimators = 10, learning_rate = 1, max-depth = 7 for post-SMOTE data were used for classification with Gradient Boosting.

#### 2.8.5 Voting community learning method (VC)

VC is a method where two or more classifiers are used, and the dataset is given as input to these classifiers and the outputs are passed through a voting system for final classification. There are bagging, boosting, stacking and voting variants of VC. Voting was used in this study [34]**.** Considering that it will strengthen RLS predictions from EEG signal data, the training data set was first classified with at least two independent classifiers. With a voting classifier, these classifiers were fit into a single model, and the predictions of the sub-classifiers were averaged to make predictions for new data [35]. There are two approaches to the voting method: (a) hard (majority-based) and (b) soft (probability-based). In this study, the hard voting method was used: Each classifier was made to vote for each test dataset, and the one with the majority of votes was determined as the final output prediction.

Given the complex time–frequency structure of EEG data, it is difficult for a single algorithm to achieve overall high success. For this reason, we used the Voting Classifier, an ensemble learning method, to create a generalized classifier by integrating the strengths of different algorithms. In the literature, ensemble methods are known to improve generalization performance on complex and noisy data types such as EEG. In particular, they are recommended to be used in combination with deep learning methods to obtain more robust and consistent results

by compensating the errors of individual models. In our study, deep learning (DNN) methods are also tested and their performances are compared.

#### 2.8.6 Deep learning (DNN)

DNN is a branch of machine learning that mimics the human brain by forming complex and interconnected neural networks, and it can create a general model capable of processing different types of data [36, 37]. DNN is a neural network with many layers and parameters and generally uses neural network architectures as a learning method. For this reason, it is also called "deep neural networks." A deep neural network has an input layer, multiple hidden layers and an output layer. DNNs consist of multiple layers of nonlinear processing units that perform feature extraction and transformation. The layers closer to the input learn basic features, while the higher layers capture more complex patterns built on those simpler features [37]. Each layer contains weight parameters that progressively combine simple features into more complex representations. The goal of training DNN architectures is to optimize these weight parameters so that hierarchical designs can be optimally learned from the data. During optimization, the model first performs a forward pass to compute predictions, then calculates the error using a loss function. This error is backpropagated through the network to compute gradients, which are used to update the model's weights. The aim is to minimize training error while maintaining good generalization and avoiding overfitting [38]. In our study using an EEG signal dataset, a deep neural network with two hidden layers was designed. The first hidden layer included 32 neurons, and the second had 16 neurons. ReLU activation was applied in the hidden layers, while the output layer used a sigmoid function.

In this study, different ML algorithms were used considering the time series structure of EEG signals. K-Nearest Neighborhood (KNN) algorithm is preferred because it offers fast and efficient performance in classification based on the proximity of the samples. Decision Trees (DT) and Extra Tree Classifier (ETC) algorithms were chosen for their ability to reveal non-linear relationships in EEG data, their robustness to noisy data, and their ability to provide interpretable model outputs. In particular, ETC was used to reduce variance and increase generalization power by generating independent decision trees over random subsets. The Gradient Boosting Classifier (GBC) was chosen for its superior performance in reducing the classification error by combining successively weak classifiers. Finally, the Voting Classifier (VC) ensemble method was used because it combines the strengths of multiple models to develop more stable models with high generalization performance. The Deep Neural Network (DNN) model was included in the study due to its ability to automatically learn complex data patterns and perform well on high dimensional data.

GridSearchCV hyperparameter optimization method was used to determine the best model parameters for all algorithms used. For KNN (n_neighbors, metric), Decision Trees and Extra Trees (max_depth, min_samples_split, criterion), Gradient Boosting Classifier (learning_rate, n_estimators, max_depth) parameters were optimized. For Deep Neural Networks, parameters such as number of layers, number of neurons, activation function, epoch and batch size were optimized. With GridSearchCV, the best hyperparameter sets were determined using k-fold cross-validation.

### 2.9 Confusion matrix tables comparing EEG-motion and 'PSG-EMG-classical'

We constructed confusion matrices for the test data of EEG wave signals of PSG recordings that we evaluated in 5 ms time slices. The algorithm performance revealed through machine learning and statistical methods was evaluated using confusion matrix. When diagnosing RLS, two classes were created in this study, taking into account the rule in the AASM scoring criteria "if there is an increase of > 8 microvolts over resting EMG activity lasting 0.5–10 s": The first class indicates time periods of at least 0.5 s in which RLS is defined; the second class indicates time periods of at least 0.5 s in which RLS is not defined. Table 2 describes the properties of a matrix with a typical tabular layout. Table 3 shows the definitions of each numerical value in each box of the confusion matrix table comparing RLS diagnoses made by both methods (EEG-motion and 'PSG-EMG-classical').

**Table 2** 'PSG-EMG-classic' shows actual and EEG-motion predicted values

| | Predicted | | |
|---|---|---|---|
| | | Positive | Negative |
| Actual | Positive | True positive (TP) | False negative (FN) |
| | Negative | False positive (FP) | True negative (TN) |

**Table 3** Definitions of the numerical values in each box of the confusion matrix table comparing the learned EEG signal data (randomly selected EEG test data) of RLS identified or unidentified in time frames of at least 0.5 s for both methods ['PSG-EMG-classical' (actual) and EEG-motion (predicted)]

| | |
|---|---|
| TP | Test data set known to have RLS with 'PSG-EMG-classical' and also diagnosed with RLS with EEG-motion |
| FP | Test data set known to have RLS with 'PSG-EMG-classical' but not diagnosed with RLS with EEG-motion |
| TN | Test data set where were not diagnosed with RLS with 'PSG-EMG-classical 'and who could not be diagnosed with RLS with the EEG-motion |
| FN | Test data set where were not diagnosed with RLS by 'PSG-EMG-classical' but were diagnosed with RLS by EEG-motion |

#### 2.9.1 Use of the obtained characteristics and test data in the confusion matrix table

A two-way analysis was performed on the raw data and the data augmented with SMOTE. 20% of the data was used for testing and 80% for training. Using energy per wavelength, variance, wavelength, and standard deviation methods, we identified a total of 132 features: 120 through Discrete Wavelet Transform Coefficient, 6 through Power Spectral Density (PSD), and 6 through Hurst exponent analysis. Classifiers were applied to 132 features for each EEG signal data of n = 600 subjects after SMOTE (600 × 132). A confusion matrix table was generated from the randomly selected 600 × 20% test data ($n = 120$) (Fig. 4).

The EEG-motion algorithm demonstrated strong performance in identifying RLS, based on results from randomly selected test data. To evaluate the model, several performance metrics were used. Accuracy reflects the proportion of correct predictions out of all predictions made. Sensitivity, or recall, indicates how well the model identifies actual positive cases. Precision measures how many of the predicted positive cases are truly positive. The F1 score provides a balance between precision and recall by considering both false positives and false negatives [39].

#### 2.9.2 Comparison of EEG-motion and 'PSG-EMG-classical' methods with ROC analysis

This comparison between the two methods is important for our study because ROC analysis helps evaluate the accuracy of diagnostic tests and prediction models. It shows how well a test can distinguish between different conditions, compares the performance of multiple tests, and helps monitor their quality. The ROC curve displays the relationship between sensitivity and the false positive rate. By examining the shape of the curve, sensitivity and specificity levels can be understood. ROC analysis is also useful for understanding the balance between the benefits and costs of diagnostic decisions. The Area Under the Curve (AUC) shows how well the model separates the classes [39]. A higher AUC value means better distinction between classes. In our study, the degrees of discrimination between the classifier algorithms for the raw and post-smote data sets are shown by ROC curves (Figs. 5, 6).

#### 2.9.3 Statistical analysis

RLS detection results obtained from both the classical method and the EEG-motion model were compared using the 'SPSS 22 for Windows' software. The chi-squared test was applied for statistical analysis, and a p-value less

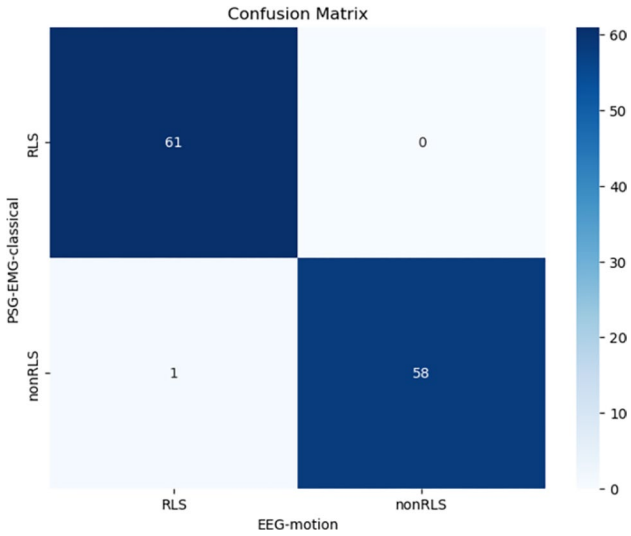


**Fig. 4** Shows actual (detected by 'PSG-EMG-classical') and predicted (detected by EEG-motion-ETC classifier) numerical values 'RLS/nonRLS' for 120 test data. As concerns the values detected 120 test data, when 5 milisecond time frames are taken into consideration, 'PSG-EMG-classical' method detected 59 nonRLS and EEG-motion detected 58 nonRLS (**TN**), 'PSG-EMG-classical' detected 61 RLS and EEG-motion detected 0 RLS (**FP**), 'PSG-EMG-classical' detected 61 RLS and EEG-motion detected 61 RLS (**TP**), 'PSG-EMG-classical' detected 59 nonRLS and EEG-motion detected 1 RLS and 58 nonRLS (**FN**) [According to this matrix, Accuracy: 0.99, Sensitivity: 0.98, Precision: 1.00, F1-Score: 0.99 values were obtained]

than 0.05 was considered statistically significant. The accuracy of the algorithm was evaluated using confusion matrix tables. Finally, the EEG-motion and PSG-EMG-classical methods were compared through ROC analysis.

## 3 Results

### 3.1 Results of the classifiers used for the development of the EEG-motion model

Using raw data, 0.91 Accuracy, 0.85 Sensitivity, 1.00 Precision, and 0.92 F1-scores were obtained with the VC algorithm (Table 4).

Using the post-SMOTE data, the ETC algorithm obtained 0.99 Accuracy, 0.98 Sensitivity, 1.00 Precision, and 0.99 F1-score. The algorithm with the highest sensitivity was the DNN classifier (Table 5). The ETC algorithm had the highest accuracy (Fig. 3).

The histogram comparing the accuracy values of the classifiers (algorithms) used in the development of the EEG-motion model before and after SMOTE is shown in Fig. 3.

### 3.2 Findings of confusion matrix tables comparing RLS/nonRLS number of people detected by both methods

The values detected by the methods were considered real for 'PSG-EMG-classical' and predicted for EEG-motion. If RLS is noticed within 5 ms, it is marked as 1; not as 0 (Fig. 4 shows the confusion matrix for 120 random test data). Among the results of the classifiers (algorithms) used to reveal the EEG-motion model with post-SMOTE data, ETC had the best performance. (ETC accuracy: 0.99, Fig. 3). Due to its high performance, the ETC classifier was proposed for the EEG-motion model. The complex matrix for EEG-motion using the ETC classifier is shown in Fig. 4 According to the matrix, 61 of the 120 test data were RLS and 59 were non-RLS. EEG-motion correctly predicted all 61 data sets with RLS, whereas it incorrectly predicted only one data set as RLS out of 59 known nonRLS data sets.

### 3.3 ROC analysis of the classifiers applied to the datasets of EEG signals for EEG-motion

ROC curves were used to statistically compare the performance of the classifiers and to clearly observe the sensitivity and specificity of the methods. Moreover, by demonstrating the AUC size, we tried to understand the

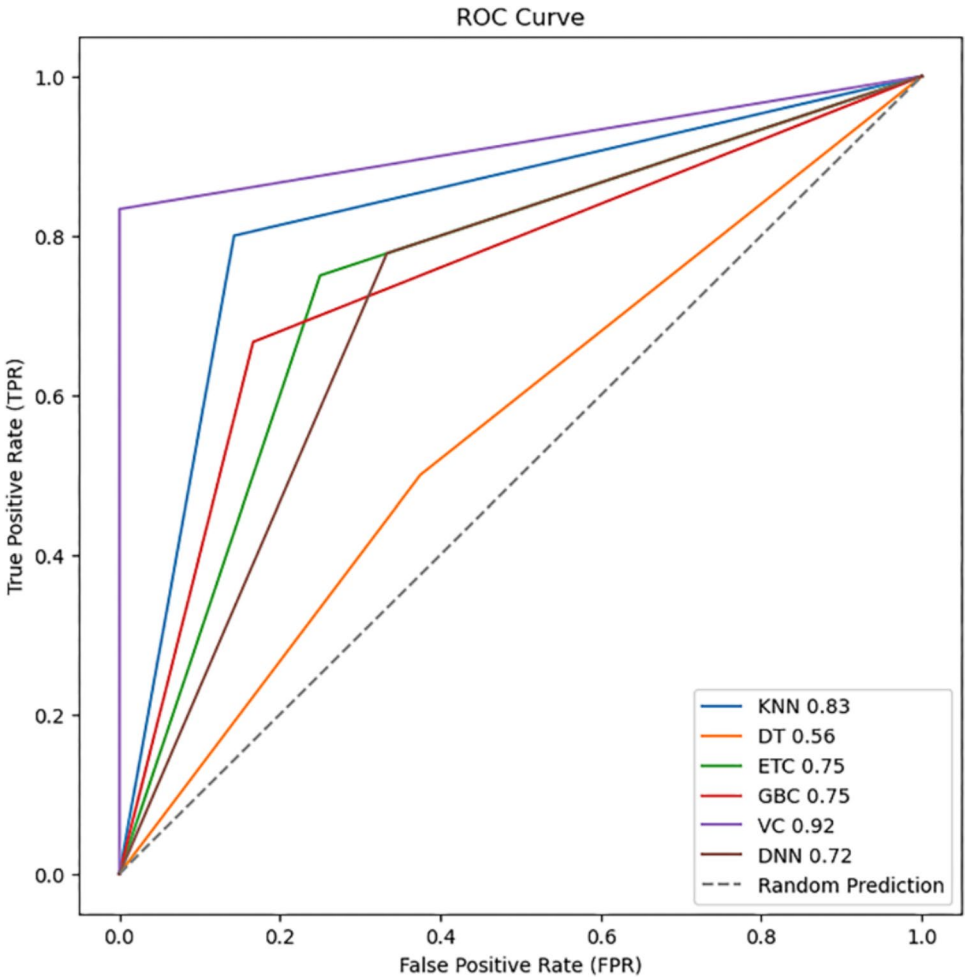


**Fig. 5** ROC curves plotted for the algorithms of the classifiers applied to the raw data sets.. The proposed purple plotted VC classifier for EEG-motion has the highest AUC values (AUC: 0.99; $p=0.00$). KNN, K–Nearest Neighborhood-*blue*; DT, Decision Trees-*orange*; ETC, Extra Tree Classifier-*green*; GBC, Gradient Boosting Classifier-*red*; VC, Voting community learning method-*purple*; DNN, Deep Learning-*brown*

distinctive performances of our proposed ETC classifier for EEG-motion in detecting RLS. The ROC curve illustrates the relationship between sensitivity and specificity for the 'PSG-EMG-classic' and EEG-motion test results. The dark blue dashed line represents a test with no discriminative ability, where the area under the curve is 0.5. For best test performance, this should be 1. Increasing slopes of the curves from the dark blue dashed line upwards indicate that the discriminatory capacity of the diagnostic test in question is increasing [39, 40]. Therefore, to indicate that a diagnostic test has high sensitivity and specificity, the area under the ROC curve is expected to fall between 0.5 and 1.0. ROC curves of the classification algorithms with raw (Fig. 5) and post-SMOTE (Fig. 6) data are plotted. In both graphs, the AUC values remained above 0.5. The classifier with the highest AUC value in the raw data was VC, while the ETC classifier had the highest AUC values in the post-SMOTE data (AUC: 0.99; $p=0.00$). In this study, the ETC algorithm was evaluated as the best classifier of the EEG wave signal dataset and a new model was proposed for EEG-motion.

## 4 Discussion

The aim of this study was to present a new model approach to PSG devices developed on the basis of sleep neurophysiology and to improve the interpretation ability of PSG analyzers by enabling them to recognize RLS patients early. Our hypothesis at the beginning of the study was that we could make a polysomnographic diagnosis of PLMS and RLS by analyzing EEG signals instead of EMG signals. In the literature, we did not come across

 https://doi.org/10.1007/s00521-026-11929-z

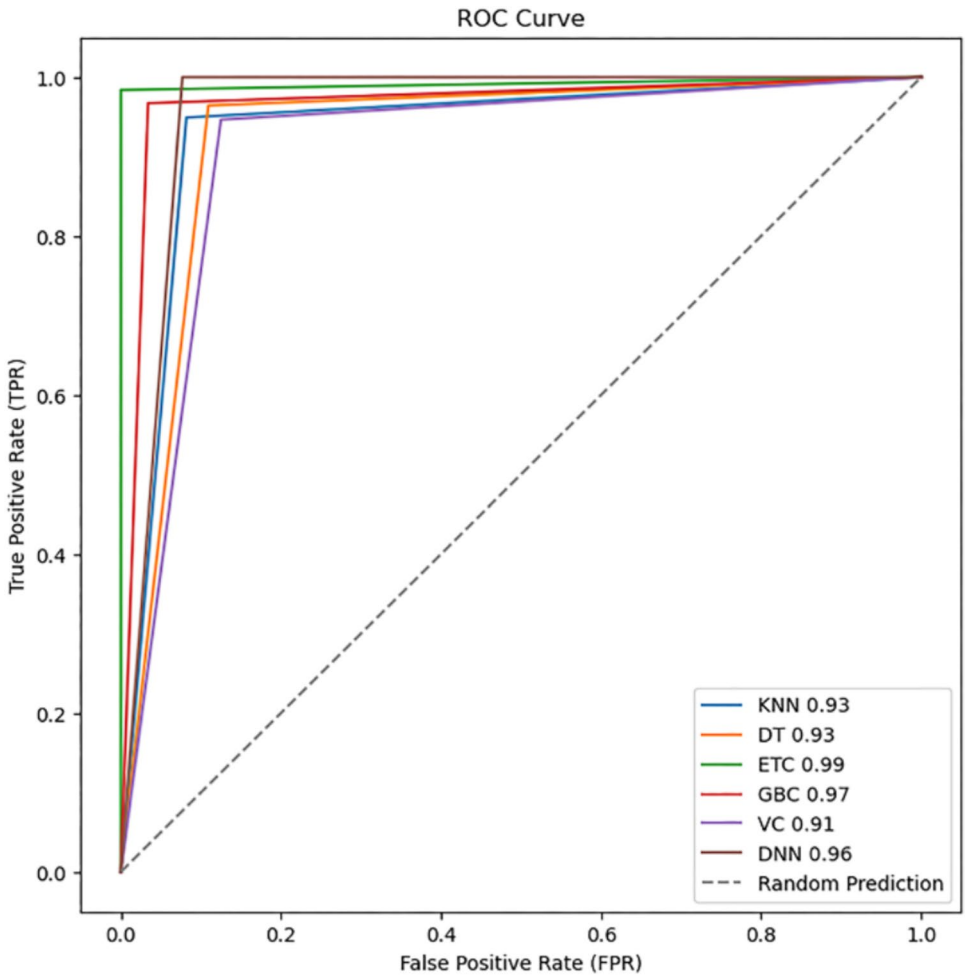


**Fig. 6** ROC curves plotted for the algorithms of the classifiers applied to the post-SMOTE data sets. The proposed green plotted ETC classifier for EEG-motion has the highest AUC values (AUC: 0.99; $p = 0.00$). KNN, K–Nearest Neighborhood-*blue*; DT, Decision Trees-*orange*; ETC, Extra Tree Classifier-*green*; GBC, Gradient Boosting Classifier-*red*; VC, Voting community learning method-*purple*; DNN, Deep Learning-*brown*

**Table 4** Results of classifiers (algorithms) using raw data to reveal the EEG-motion model

| Algorithm | Accuracy | Sensitivity | Precission | F1-score |
|---|---|---|---|---|
| KNN | 0.83 | 0.85 | 0.85 | 0.85 |
| DT | 0.58 | 0.71 | 0.62 | 0.66 |
| ETC | 0.75 | 0.85 | 0.75 | 0.79 |
| GBC | 0.75 | 0.71 | 0.83 | 0.76 |
| VC | 0.91 | 0.85 | 1.00 | 0.92 |
| DNN | 0.75 | 0.77 | 0.87 | 0.82 |

*KNN* K–nearest neighborhood, *DT* decision trees, *ETC* extra tree classifier, *GBC* gradient boosting classifier, *VC* voting community learning method, *DNN* deep learning

**Table 5** Results of classifiers (algorithms) using post-SMOTE data to reveal the EEG-motion model

| Algorithm | Accuracy | Sensitivity | Precission | F1-score |
|---|---|---|---|---|
| KNN | 0.93 | 0.94 | 0.91 | 0.93 |
| DT | 0.92 | 0.93 | 0.91 | 0.92 |
| ETC | 0.99 | 0.98 | 1.00 | 0.99 |
| GBC | 0.96 | 0.94 | 0.96 | 0.96 |
| VC | 0.90 | 0.85 | 0.87 | 0.79 |
| DNN | 0.95 | 1.00 | 0.92 | 0.96 |

*KNN* K–nearest neighborhood, *DT* decision trees, *ETC* extra tree classifier, *GBC* gradient boosting classifier, *VC*, voting community learning method, *DNN* deep learning

researchers who asked this specific question and sought an answer. The literature focused on the effects of RLS on EEG signals and/or its relationship with other electrophysiologic signals. While searching for an answer to this question, we developed a hypothetical approach: Can we teach the neurological events of PLMS and RLS, which are recognized by EMG signals, to EEG signals? We tested this hypothesis by using machine learning and artificial intelligence methods. Thus, we developed an algorithm that can teach the presence of RLS to EEG signals. Thanks to this study, we not only tested our hypothesis but also added a new functional feature to PSG systems in sleep laboratories. This novel algorithm, which we call EEG-motion, has been introduced as a new polysomnographic feature that allows a physician who examines PSG records to recognize the presence or absence of RLS early, immediately after completing the first stage of the analysis of sleep staging on EEG.

### 4.1 Clinical Neurophysiologic and historical importance of RLS & PLMS

RLS, Willis-Ekbom disease (1685 Thomas Willis, 1945 Karl-Axel Ekbom) "a hitherto overlooked disease of the legs," in 1953 Symonds called a series of motor phenomena occurring during sleep and wakefulness: “nocturnal myoclonus” and also Symonds thought that the jerks might be of epileptic origin [41, 42]. By the mid-1960s, Lugaresi et al. first mentioned RLS by correlating EEG/EMG recordings. By 1980, Coleman et al. defined the neurological phenomenon as "periodic leg movements in sleep" and differentiated it from myoclonus with long muscle potentials (at least 250 ms) [43–45]. Today, the International Classification of Sleep Disorders (ICSD-II) uses the term "periodic limb movements during sleep" (PLMS) since the legs and arms can be affected together. ICSD-II defined "periodic limb movement disorder" (PLMD) as patients who have more than five periodic limb movements per hour in children and more than 15 periodic limb movements per hour in adults (PLM Index, PLMI), which cannot be explained by another sleep disorder but have a clinical sleep disorder. Finally, PLMS and RLS diagnoses were developed according to AASM scoring criteria from standard PSG recordings [46, 47]. Our study contributed to this important historical development of RLS with machine learning methods. PLMS and RLS are quite common in the community as sleep-related movement disorders (prevalence 5–15%). They can pose significant health risks (sympathetic hyperactivity associated with PLMS has been hypothesized to lead to cardio and cerebrovascular comorbidities) [48–50]. Because of these clinical risks, it is very important to recognize it and to recognize it quickly. This study examined the PSG recordings of people diagnosed with PLMS and RLS according to the AASM scoring criteria in the sleep laboratory and facilitated the recognition of RLS with the results obtained. Similar to the relationship between EEG/EMG recordings first established by Lugaresi et al. 60 years later, we dreamed of giving a new performance task to EEG signal data by considering the EEG/EMG relationship of "RLS, Willis-Ekbom patients" in our study. We processed the EEG signal data of PLMS and RLS cases diagnosed by EMG in PSG with machine learning methods. Thus, we successfully taught the presence of RLS to EEG signal data. With the tests we conducted, we found that EEG signal data recognized RLS with high accuracy and sensitivity. Incorporating this result into PSG devices with a model called EEG-motion will quickly alert physicians performing PSG analysis about "RLS," leading to changes in the prevalence rates of the disease, and a clinical event with heart and brain risks will be quickly recognized.

### 4.2 Methods for recording and scoring RLS & PLMS

The best method to measure muscle activity during sleep is surface electromyography [51, 52]. Video polysomnography (PSG) is necessary to record movements and behaviors that occur during sleep. Actigraphy is generally accelerometer sensor systems worn on the wrist like a watch [53, 54]. Periodic leg movements are scored based on the amplitude and duration of EMG activity. The PLMS index is calculated by dividing the number of PLMS events by the total hours of sleep during which leg movements were recorded (PLMS/hour). The PLMS with arousal index (PLMA) is the number of leg movements associated with arousals divided by the hours of sleep in which both leg movements and arousals were observed (PLMA/hour). The PLMW index is calculated by dividing the number of leg movements during wakefulness by the total hours the person was awake (PLMW/

hour) [55–57]. RLS & PLMS is a sleep movement disorder, a phenomenon that needs to be diagnosed after a detailed evaluation of clinical complaints, electrophysiologic signal recordings, and calculations to help score. EEG-motion can recognize the presence of RLS from EEG signals in PSG. The EEG-motion model presented in this study helps in the easy diagnosis of this disorder, which is quite complex to recognize.

### 4.3 Are RLS & PLMS related to disturbed sleep?

PLMS most frequently occurs during N1 and N2 sleep stages, may also be seen in N3, and is rarely observed during REM sleep [58]. According to Culpepper et al., two distinct PLMS patterns have been identified throughout the night: one with a high PLMS index in the first half and another with a peak in the middle of the night [59]. PLMS can occur with or without EEG changes. EEG changes include K-complexes, K-alpha complexes, short bursts of alpha activity, or other cortical/subcortical arousals. LMS accompanied by microarousals is more frequent during the N1 and N2 sleep stages, while PLMS without microarousals is more commonly observed during slow-wave sleep [60]. "Karadeniz et al. examined the relationship between PLM and EEG arousals, finding that 49% of arousals occurred before leg movements, 30% occurred simultaneously, and 23% occurred immediately afterward. The higher rate of EEG arousals preceding leg movements suggests that these movements may not be a primary phenomenon, but rather a secondary response to an underlying arousal disturbance [61]. PLMS is linked to sleep fragmentation. Sforza et al. reported that microarousals were accompanied by autonomic activation, while PLMS episodes were associated with a notable increase in theta and delta EEG activity, as well as a significant reduction in the RR interval on the ECG. Both EEG activation and tachycardia were observed during PLMS events, regardless of the presence of microarousals [62, 63]. These limited number of valuable studies in the literature correlating EEG signals with other electrophysiological signal data have helped us to understand the importance of PLMS&RLS in the sleep and wakefulness mechanisms of the brain. These important studies on the factors affecting EEG signal data and the etiopathogenesis of PLMS&RLS have encouraged us to develop a simple, easy and fast model to diagnose PLMS&RLS using EEG signal data.

### 4.4 Interventional approaches regarding the diagnosis of RLS

Even if arousal associated with PLMS is not evident in the EEG, it does not mean that it is not there, and arousals that are invisible to the human eye are clearly recognized by fast Fourier transform. Visual arousal scoring in EEG correlates with PLMS through spectral analysis [62, 63]. EEG wave and heart rate (HR) changes associated/not associated with PLMS and RLS, microarousals have been studied: "Winkelman [64] did not find a statistical relationship between PLMS and arousal, but observed a relationship with HR in the absence of arousal. Lavoie et al. [65] observed that EEG and HR responses during PLMS differed between wakefulness and sleep stages and were less in wakefulness. They found an increase in delta and theta bands before the onset of PLMS in NREM sleep, and EEG activation in REM sleep started with PLMS. They found a characteristic cardiac response pattern in NREM and REM sleep [65]. Hornyak et al. [66] analyzed the spectral power differences of sleep EEG between patients with RLS and healthy subjects, examined the relationship with arousal events, and found no statistically significant difference between them. Ferri et al. [67] evaluated the changes in EEG spectra and heart rate accompanying periodic leg movements and non-periodic leg movements during sleep in patients with RLS. As a result of this evaluation, they observed that EEG activation preceded leg movements in NREM, but there was no activation in the REM phase during PLM and at any phase during NonPLM [67]. Lin et al. [68] developed an algorithm that successfully uses EMG signals by utilizing AASM criteria to detect PLMS automatically. Sezgin [69] proposed a hybrid model including wavelet packet transform (WPT) and extreme learning machine (ELM) with a 96.85% accuracy rate to classify EMG signals of obstructive sleep apnea syndrome (OSAS) and RLS, PLMS patients. He showed that there is a significant relationship between OSAS and PLMS and that OSAS and PLMS can be automatically diagnosed through this model [69]. Umut and Çentik [70] tried to detect periodic leg movements by analyzing PSG signals other than leg EMG with digital signal processing and machine

**Table 6** Accuracy (%) performance of other diagnostic methods and our (EEG-motion) proposed classifiers for recent PLMS&RLS diagnostic studies on different electrophysiological signal data sets

| Diagnostic method research studies | Physiological signal | Classifier | Accuracy |
|---|---|---|---|
| Sezgin [69] | EMG | ELM | 96.85% |
| Umut & Çentik [70] | EEG-ECG | KNN | 91.87% |
| Urtnasan et al. [78] | ECG | DNN | 91.50% |
| This study, 2025 | EEG | ETC | 99.00% |

learning methods (WEKA, KNN classification algorithm) for the diagnosis of RLS & PLMS. Machine learning methods for OSA detection from ECG signals have recently been studied by Yuxing Lin et al. [71]. Kye et al. [72] produced a coin-sized motion sensor (a wearable band) to detect PLMS and classify PLMS-related movements using machine learning algorithms within the system. Sieminski et al. [73] evaluated the temporal distribution of arousal-related measurements near PLMS from RLS patient data to investigate sympathetic activation and blood pressure increase events that occur during PLMS. In this study, the researchers found that arousal and sympathetic nervous system events followed the PLMS [73]. Atahavale et al. [74] proposed a device-independent approach to measure PLMS severity by analyzing actigraphy signals. They used a Naive Bayes learning model to classify PLMS and proposed this new device as a screening tool [74]. Zhou et al. [75] used hardware consisting of motion sensors other than PSG to detect RLS and classified the signals with deep learning according to seven types of movements during sleep (accuracy: 97.83%). Carvelli et al. [76] designed an end-to-end deep learning system for automatic scoring of leg movements and PLMS during sleep. Carvelli's system outperformed previous automatic detection systems and live physician scoring with an F1-Score value of 85% [76]. Jarchi et al. [77] used simultaneous analysis of ECG and EMG signals to diagnose respiratory and movement-related sleep disorders. The analyzed subjects were divided into four groups: healthy individuals, patients with obstructive sleep apnea, patients with RLS, and those with both conditions. Using Jarchi's algorithm, they proposed a set of markers extracted from high-noise electrophysiological data to help identify disease-related symptoms based on the analyzed signals [77]. Urtnasan et al. [78] developed a deep learning model for the automatic detection of PLMS using ECG signals. The model architecture included four one-dimensional convolutional layers, two long short-term memory (LSTM) units, and a fully connected layer. Their findings showed that PLMS can be automatically detected from ECG data using this deep learning approach. In this section of the paper, we review the limited number of studies in the literature for the diagnosis of PLMS&RLS [78]. In general, studies have focused on the relationship between PLMS&RLS and electrophysiological signals such as arousal, HR, ECG, EMG, and NREM or REM sleep periods, and as far as we have learned, these relationships have been tried to be understood using statistical methods, machine learning methods such as Fourier transform, spectral power, WPT, ELM. Our work is focused on EEG signals. A large number of feature extraction methods have been applied to EEG signal data, and high-performance classification methods have been used for EEG signal data, which have not been studied much in the literature. In particular, our study applied ensemble learning methods for complex EEG signal data. As a result, the EEG-motion model is presented to the reader as a simple diagnostic model developed by training EEG signal data with machine learning methods. An original idea similar to our research has not been found in the literature. Therefore, we cannot compare the performance values of the algorithm of our proposed EEG-motion model for PSG devices with similar models that process EEG signals diagnosing PLMS&RLS, but you can see Table 6 below, which compares the performance values of 3 different models that have recently developed diagnostic approaches with different electrophysiological signal data with the EEG-motion study. The obtained classification accuracy (99%) and precision (100%) rates are quite high. This may indicate a possible overfitting. To reduce this risk and assess the model's generalization ability, the data were randomly divided into 80% for training and 20% for testing, and fivefold cross-validation was performed. In addition, measures were taken to minimize the risk of overfitting by early stopping, regularization, data augmentation (SMOTE) and hyperparameter optimization.

Table 6 presents the performance results of four different models developed in the literature for the diagnosis of PLMS and RLS. Sezgin (2015) achieved 96.85% accuracy using Wavelet Packet Transform and Extreme Learning Machine (ELM) on EMG signals. This study demonstrated a significant relationship between OSAS and PLMS and the feasibility of automatic diagnosis based on EMG. Umut and Çentik (2016) obtained 91.87% accuracy using a KNN classifier on EEG and ECG signals, indicating that periodic leg movements can also be detected using signals other than EMG. Urtnasan et al. (2022) achieved 91.50% accuracy using a DNN on ECG data.

The proposed EEG-motion model in this study achieved 99% accuracy and 100% precision using EEG signals with an Ensemble Tree Classifier (ETC). This high performance is attributed to the effective feature extraction from EEG data and the ensemble learning approach.

The comparison of the results in the table indicates that the EEG-motion model demonstrates higher accuracy and precision compared to other approaches in the literature. Furthermore, performance differences among different signal types (EMG, ECG, EEG) and classifiers can be attributed to the type of data, feature extraction methods, and model architectures used. The use of EEG, in particular, represents a novel contribution, as EEG-based approaches for PLMS and RLS diagnosis are still limited in the literature. Although additional algorithms such as Random Forest were tested in preliminary analyses, they did not outperform the classifiers reported in this study. Therefore, we focused on the models that provided the most stable and reliable performance for EEG-based RLS detection.

### 4.5 Why innovation? "reasons for developing the EEG-motion"

Our working group follows human sleep and wake physiology/physiopathology processes by applying machine learning methods to electrophysiological wave signal data. In recent years, the speed of our studies on EEG (sleep/wake processes of the brain) signals in PSG (calibrated laboratory outputs in accordance with AASM rules) data has increased. With artificial intelligence methods, we are paving the way for innovative approaches to understand electrophysiological signals during sleep and to contribute to diagnosis and treatment in this field. In this study, we developed the EEG-motion model, which we think will have a simple but strong diagnostic effect, which provides easy and rapid recognition of a neurological event that is common in society, which is associated with important clinical outcomes, and whose diagnostic stages are difficult and long due to both the multiple applications of polysomnographic devices and the prolonged PSG analysis and interpretation for the physician. We hope that it will take its place in the literature as an innovative study contributing to the diagnosis of PLMS&RLS.

### 4.6 Limitations of the study and future work for improving the EEG-motion model

This study has developed a system that understands whether the person has RLS through EEG signals when a physician performing PSG analysis completes sleep staging on EEG without any EMG scoring and transfers this information directly to the physician. This system, called EEG-motion, facilitates the polysomnographic diagnosis of RLS and increases the physician's ability to interpret PSG analysis. From another point of view, with its high success rates, EEG-motion facilitates the work of PSG systems, which are the gold standard in the diagnosis of sleep disorders, to diagnose RLS. What we think is lacking in the model is that it cannot provide information about the degree (severity, intensity and frequency) of PLMS&RLS from EEG signal data to the physician performing PSG analysis. In addition, the fact that it does not have an algorithm that can understand the characteristics of OSA+RLS EEG signal data for PLMS&RLS, which is very common with OSAS, is another deficiency of EEG- motion that needs to be improved. The EEG-motion model should be improved, or new models should be developed thanks to the development of machine learning methods. Our future innovations in this field will be based on micro-arousals on EEG wave signals during sleep that disrupts sleep quality. We will focus on the

relationship of micro-arousals that we frequently encounter in EEG recordings with clinically well-defined common sleep disorders.

The main research limitation involves the use of EEG data collected at a single sleep laboratory. The model's performance on EEG data from various centers cannot be directly applied due to this limitation. The model requires validation through multicenter studies, independent datasets, and different cohorts before it can be used extensively in clinical settings. Our future research will address this limitation by evaluating the external validity of our model through EEG data collection at multiple centers. The model's potential for clinical use will gain strength through evaluations of its performance across larger patient groups with different sleep disorders and various clinical conditions.

The SMOTE method is preferred because it generates synthetic samples by linear interpolation between the existing minority class samples, rather than simply repeating the existing samples. Thus, the risk of overfitting of the algorithm is reduced and the generalizability and stability of the model are increased. However, there are some important limitations to the use of the SMOTE technique. First, synthetic extension of existing data runs the risk of not fully capturing the complexity of real EEG signals. Synthetically generated data may not fully capture the time–frequency features and biological variation in real EEG patterns. This can lead to the risk of poor performance of the model when compared to real data. To address this concern, after generating the synthetic data, both the original dataset ($n=60$) and the SMOTE-enhanced dataset ($n=600$) were evaluated separately and their performance metrics were compared. As a result of this comparative analysis, it was observed that while the model accuracy was around 91% on average before SMOTE was applied, the accuracy increased to 99% after balancing with synthetic data. This performance improvement indicates that the model trained with synthetic data shows better generalization and lower variance. Nevertheless, considering the performance values of real data, it is possible that this high accuracy may be due to synthetic data.

## 5 Conclusion

This study has developed a new model called EEG-motion, which informs the physician about RLS information with a high success rate by using machine learning methods on EEG signal data. It proposes to integrate this novel model into PSG. In summary, the novel EEG-motion algorithm presents a promising alternative for the diagnosis of RLS during sleep staging. By leveraging EEG signals and advanced machine learning techniques, our model achieved performance metrics 99% accuracy, 98% sensitivity, 100% precision, and a 99% F1-score with a statistically significant correlation ($p<0.001$) to the conventional PSG-EMG method. These results demonstrate that EEG-motion can effectively detect periodic leg movements associated with RLS without the need for additional EMG recordings.

The integration of EEG-motion into routine polysomnographic analysis offers several potential advantages, including a simplified diagnostic process and enhanced interpretation power for clinicians and researchers in sleep electrophysiology. Moreover, the high performance of the algorithm indicates its potential for improving diagnostic efficiency and patient management in sleep laboratories. The proposed EEG-based method provides a practical solution for the clinical diagnosis of RLS. By relying solely on EEG signals, it eliminates the need for additional EMG recordings and simplifies the polysomnographic analysis process. This approach enables faster and more efficient detection of RLS during routine sleep studies, reduces the number of electrodes attached to the patient, increases patient comfort, and significantly decreases the time required for manual scoring.

Future studies with larger and more diverse cohorts are recommended to further validate the clinical applicability and robustness of the EEG-motion model. Overall, our findings suggest that incorporating EEG-motion into PSG protocols could substantially advance the early and accurate diagnosis of RLS, ultimately contributing to better treatment outcomes and patient care.

In order to evaluate the generalizability of the results obtained after training with synthetic data, the model should be tested on an external validation set that is independent and does not contain synthetic data. In our future

studies, we aim to test the real-world performance and clinical applicability of the model on a more robust basis by using independent EEG data sets obtained from different clinical centers. In this way, the potential bias caused by synthetic data will be minimized and the adaptation of the model to the clinical environment will be achieved more reliably.

**Funding** Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). Atatürk University Scientific Research Unit, Grant/Award Number: TFM-2023–13332.

**Data availability** The datasets analyzed during the current study are not publicly available due to the policy of the project agreement but are available from the corresponding author upon reasonable request.

## Declarations

**Conflict of interest** The authors declare no conflicts of interest.

**Ethics approval and consent to participate and consent for publication** Informed consent was obtained from all the participants included in the study. The study was approved by the Local Ethics Committee of Atatürk University Faculty of Medicine (8–25/25.11.2021) and was conducted in accordance with the latest version of the Helsinki Declaration.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

## References

1. Kayabekir M (2022) Sleep Medicine and the evolution of contemporary sleep pharmacotherapy. In: Larrivie D (ed) Neurophysiology of Basic Molecules Affecting Sleep and Wakefulness Mechanisms, Fundamentals of Sleep Pharmacology. 1st edn. in London United Kingdom: Intechopen, pp 17–40
2. Kandel ER, Schwartz JH, Jessell TM, Siegelbaum SA, Hudspeth AJ (2013) Principles of neural science. In: Sleep and Dreaming. 5th ed. London and New York: McGraw-Hill, pp. 1140–1146. ISBN 978–0–07–139011–8
3. Kryger MH, Roth T, William CD (2011) Principles and practice of sleep medicine. In: Kryger MH, Roth T, William CD (eds) Normal Sleep and its Variations: History of Sleep Physiology Medicine, 5th edn. St. Louis, Missouri, Elsevier Saunders, pp 3–16
4. Kayabekir M (2019) Updates in sleep neurology and obstructive sleep apnea. In: Fabian HR (ed) Sleep Physiology and Polysomnogram, Physiopathology and Symptomatology in Sleep Medicine, 1st edn. London Bridge Street, Intechopen, pp 5–12
5. Guyton AC, Hall JE (2019) Textbook of medical physiology. Hall JE Behavioral and Motivational Mechanisms of the Brain-the Limbic System and the Hypothalamus, 13th edn. Mississippi, Elsevier Saunders, pp 751–761
6. Kryger MH, Roth T, William CD (2011) Principles and practice of sleep medicine. In: Kryger MH, Roth T, William CD (eds) Normal Sleep and its Variations: Normal Human Sleep, 5th edn. St. Louis, Missouri, Elsevier Saunders, pp 16–26
7. Kayabekir M (2020) Updates in sleep neurology and obstructive sleep apnea. In: Fabian HR (ed) Diagnosis, 1st edn. London Bridge Street, Intechopen, pp 1–13
8. Kayabekir M, Yağanoğlu M (2022) The relationship between snoring sounds and EEG signals on polysomnography. Sleep Breath 26:1219–1226. https://doi.org/10.1007/s11325-021-02516-8
9. Allen RP, Picchietti D, Hening WA, Trenkwalder C, Walters AS, Montplaisi J (2003) Restless legs syndrome: diagnostic criteria, special considerations, and epidemiology. A report from the restless legs syndrome diagnosis and epidemiology workshop at the National Institutes of Health. Sleep Med 4(2):101–119. https://doi.org/10.1016/s1389-9457(03)00010-8
10. Wijemanne S, Ondo W (2017) Restless legs syndrome: clinical features, diagnosis and a practical approach to management. Pract Neurol 17(6):444–452. https://doi.org/10.1136/practneurol-2017-001762
11. Silber MH, Buchfuhrer MJ, Earley CJ, Koo BB, Manconi M, Winkelman JW, Scientific and Medical Advisory Board of the Restless Legs Syndrome Foundation (2021) The management of restless legs syndrome: an updated algorithm. Mayo Clin Proc 96(7):1921–1937. https://doi.org/10.1016/j.mayocp.2020.12.026

12. Iber C, Ancoli-Israel S, Chesson A, Quan SF (2007) The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications. American Academy of Sleep Medicine, Westchester
13. Shuai Y, Zheng Y, Huang H (2018) Hybrid software obsolescence evaluation model based on PCA-SVM-GridSearchCV. IEEE 9th International Conference on Software Engineering and Service Science (ICSESS), pp. 449–453
14. Elreedy D, Atiya AF, Kamalov F (2024) A theoretical distribution analysis of synthetic minority oversampling technique (SMOTE) for imbalanced learning. Mach Learn 113(7):4903–4923
15. Aboalayon KAI, Faezipour M, Almuhammadi WS, Moslehpour S (2016) Sleep stage classification using eeg signal analysis: a comprehensive survey and new ınvestigation. Entropy 18(9):272. https://doi.org/10.3390/e18090272
16. Phan H, Mikkelsen K (2022) Automatic sleep staging of EEG signals: recent development, challenges, and future directions. Physiol Meas. https://doi.org/10.1088/1361-6579/ac6049
17. Cvetkovic D, Übeyli ED, Cosic I (2008) Wavelet transform feature extraction from human PPG, ECG, and EEG signal responses to ELF PEMF exposures: a pilot study. Dig Signal Process. https://doi.org/10.1016/j.dsp.2007.05.009
18. Al-Fahoum AS, Al-Fraihat AA (2014) Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains. ISRN Neurosci. https://doi.org/10.1155/2014/730218
19. Rao TV, Vishwanath DD (2014) Detecting sleep disorders based on EEG signals by using discrete wavelet transform. Int Conf Green Comput Commun Electr Eng (ICGCCEE) 2014:1–5
20. Wang R, Wang J, Yu H, Wei X, Yang C, Deng B (2015) Power spectral density and coherence analysis of Alzheimer's EEG. Cogn Neurodyn 9(3):291–304. https://doi.org/10.1007/s11571-014-9325-x
21. Ong ZY, Saidatul A, Ibrahim Z (2018) power spectral density analysis for human EEG based biometric ıdentification. International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA)
22. Díaz MHA, Córdova F (2022) On the meaning of Hurst entropy applied to EEG data series. Procedia Comput Sci 199(4):1385–1392
23. Şimazu K, and Kurimoto I (2022) hurst exponent analysis for differenced time series of EEG signal at the metacognition occurrence during answer ınduced task. 61st Annual Conference of the Society of Instrument and Control Engineers (SICE).
24. Soofi AA (2017) Classification techniques in machine learning: applications and issues. J Basic Appl Sci 13:459–465
25. Hosseini MP, Hosseini A, Ahi K (2021) A review on machine learning for EEG signal processing in bioengineering. IEEE Rev Biomed Eng 14:204–218. https://doi.org/10.1109/RBME.2020.2969915
26. Devi RDH, Devi MI (2016) Outlier detection algorithm combined with decision tree classifier for early diagnosis of breast cancer. Int J Adv Eng Technol 7(2):93–98
27. Osisanwo FY (2017) Supervised machine learning algorithms: classification and comparison. Int J Comput Trends Technol (IJCTT) 48(3):128–138
28. Smith JR, Karacan I (1971) EEG sleep stage scoring by an automatic hybrid system. Electroencephalogr Clin Neurophysiol 31(3):231–237. https://doi.org/10.1016/0013-4694(71)90092-7
29. Rodríguez-Sotelo J, Osorio-Forero A, Jiménez-Rodríguez A, Cuesta-Frau D, Cirugeda-Roldán E, Peluffo D, MDPI AG (2014) Automatic sleep stages classification using EEG entropy features and unsupervised pattern analysis techniques. Entropy 16(12):6573–6589. https://doi.org/10.3390/e16126573
30. Dutta D, Paul D, Ghosh P (2018) Analysing feature ımportances for diabetes prediction using machine learning. 9th annual ınformation technology, Electronics and Mobile Communication Conference (IEMCON) pp 924–928
31. Geurts P, Ernst D, Wehenkel L (2006) Extremely randomized trees. Mach Learn 63:3–42
32. Bentéjac C, Csörgő A, Martínez-Muñoz G (2021) A comparative analysis of gradient boosting algorithms. J Artif Intell 54:1937–1967
33. Weldegebriel HT, Liu H, Haq AU, Bugingo E, Zhang D (2019) A new hybrid convolutional neural network and extreme gradient boosting classifier for recognizing handwritten Ethiopian characters. IEEE Access 8:17804–17818
34. Gemein LAW, Schirrmeister RT, Chrabąszcz P, Wilson D, Boedecker J, Schulze-Bonhage A, Hutter F, Ball T (2020) Machine-learning-based diagnostics of EEG pathology. Neuroimage 220:117021. https://doi.org/10.1016/j.neuroimage.2020.117021
35. Kumar UK, Nikhil MS, Sumangali K (2017) Prediction of breast cancer using voting classifier technique. In 2017 IEEE İnternational Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials ICSTM pp. 108–114
36. Al-Saegh A, Dawwd SA, Abdul-Jabbar JM (2021) Deep learning for motor imagery EEG-based classification: a review. Biomed Signal Process Control. https://doi.org/10.1016/j.bspc.2020.102172
37. Shinde PP and Shah S (2018) A review of machine learning and deep learning applications. In: 2018 Fourth İnternational Conference on Computing Communication Control and Automation (ICCUBEA) pp. 1–6
38. Min S, Lee B, Yoon S (2017) Deep learning in bioinformatics. Brief Bioinform 18(5):851–869
39. Kayabekir M, Yağanoğlu M, Köse C (2022) SNOROSALAB: a method facilitating the diagnosis of sleep breathing disorders before polysomnography. IRBM 43(4):259–271. https://doi.org/10.1016/j.irbm.2021.08.002
40. Sarker IH (2021) Machine learning: algorithms, real-world applications and research directions. SN Comput Sci 2(3):160. https://doi.org/10.1007/s42979-021-00592-x

41. Ekbom K (1945) Restless legs. Ivar Hoeggstroms, Stockholm, Sweden
42. Symonds CP (1953) Nocturnal myoclonus. J Neurol Neurosurg Psychiatry 16:166–171. https://doi.org/10.1136/jnnp.16.3.166
43. Lugaresi E, Tassinari CA, Coccagna G, Ambrosetto C (1965) Particularite's cliniques et polygraphiques du syndrome d'impatience des membres inferieurs. Rev Neurol 113:545–555
44. Kouri I, Junna MR, Lipford MC (2023) Restless legs syndrome and periodic limb movements of sleep: from neurophysiology to clinical practice. J Clin Neurophysiol 40(3):215–223. https://doi.org/10.1097/WNP.0000000000000934
45. Coleman RM, Pollak CP, Weitzman ED (1980) Periodic movements in sleep (nocturnal myoclonus): relation to sleep disorders. Ann Neurol 8:416–421. https://doi.org/10.1002/ana.410080413
46. Chabli A, Michaud M, Montplaisir J (2000) Periodic arm movements in patients with the restless legs syndrome. Eur Neurol 44:133–138. https://doi.org/10.1159/000008221
47. American Academy of Sleep Medicine (2005) International Classification of Sleep Disorders, Diagnostic & Coding Manual, 2nd edn. American Academy of Sleep Medicine, Westchester, IL
48. Yeh P, Walters AS, Tsuang JW (2012) Restless legs syndrome: a comprehensive overview on its epidemiology, risk factors, and treatment. Sleep Breath 16:987–1007
49. Ohayon MM, O'Hara R, Vitiello MV (2012) Epidemiology of restless legs syndrome: a synthesis of the literature. Sleep Med Rev 16:283–295
50. Walters AS, Rye DB (2009) Review of the relationship of restless legs syndrome and periodic limb movements in sleep to hypertension, heart disease, and stroke. Sleep 32(5):589–597
51. Berry R, Brooks R, Gamaldo C et al (2014) The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications, version 2.0.3. [Darien, Illinois: American Academy of Sleep Medicine; Available at] www.aasmnet.org.
52. Zucconi M, Ferri R, Allen R et al (2006) The official World Association of Sleep Medicine (WASM) standards for recording and scoring periodic leg movements in sleep (PLMS) and wakefulness (PLMW) developed in collaboration with a task force from the International Restless Legs Syndrome Study Group (IRLSSG). Sleep Med 7:175–183 (PMID: 16459136)
53. American Academy of Sleep Medicine (2014) International classification of sleep disorders. 3rd ed. American Academy of Sleep Medicine: Darien (Ill.) PMID: 25221449
54. Högl B, Zucconi M, Provini F (2007) RLS, PLM, and their differential diagnosis—a video guide. Mov Disord 22(18):414–419
55. Gossard TR, Trotti LM, Videnovic A, St Louis EK (2021) Restless legs syndrome: contemporary diagnosis and treatment. Neurotherapeutics 18(1):140–155. https://doi.org/10.1007/s13311-021-01019-4
56. Allen RP, Picchietti DL, Garcia-Borreguero D, Ondo WG, Walters AS, Winkelman JW, Zucconi M, Ferri R, Trenkwalder C, Lee HB, International Restless Legs Syndrome Study Group (2014) Restless legs syndrome/Willis-Ekbom disease diagnostic criteria: updated International Restless Legs Syndrome Study Group (IRLSSG) consensus criteria--history, rationale, description, and significance. Sleep Med 15(8):860–873. https://doi.org/10.1016/j.sleep.2014.03.025
57. Hertenstein E, Gabryelska A, Spiegelhalder K et al (2018) Reference data for polysomnography-measured and subjective sleep in healthy adults. J Clin Sleep Med 14:523–532
58. Pollmacher T, Schulz H (1993) Periodic leg movements (PLM): their relationship to sleep stages. Sleep 16:572–577
59. Culpepper WJ, Badia P, Shaffer JI (1992) Time-of-night patterns in PLMS activity. Sleep 15:306–311
60. Sforza E, Jouny C, Ibanez V (2003) Time course of arousal response during periodic leg movements in patients with periodic leg movements and restless legs syndrome. Clin Neurophysiol 114:1116–1124
61. Karadeniz D, Ondze B, Besset A, Billiard M (2000) EEG arousals and awakenings in relation with periodic leg movements during sleep. J Sleep Res 9:273–277
62. Sforza E, Nicolas A, Lavigne G, Gosselin A, Petit D, Montplaisir J (1999) EEG and cardiac activation during periodic leg movements in sleep: support for a hierarchy of arousal responses. Neurology 52:786–791
63. Sforza E, Juony C, Ibanez V (2002) Time-dependent variation in cerebral and autonomic activity during periodic leg movements in sleep: implications for arousal mechanisms. Clin Neurophysiol 113:883–891
64. Winkelman JW (1999) The evoked heart rate response to periodic leg movements of sleep. Sleep 22(5):575–580. https://doi.org/10.1093/sleep/22.5.575
65. Lavoie S, de Bilbao F, Haba-Rubio J, Ibanez V, Sforza E (2004) Influence of sleep stage and wakefulness on spectral EEG activity and heart rate variations around periodic leg movements. Clin Neurophysiol 115(10):2236–2246. https://doi.org/10.1016/j.clinph.2004.04.024
66. Hornyak M, Feige B, Voderholzer U, Riemann D (2005) Spectral analysis of sleep EEG in patients with restless legs syndrome. Clin Neurophysiol 116(6):1265–1272
67. Ferri R, Zucconi M, Rundo F, Spruyt K, Manconi M, Ferini-Strambi L (2007) Heart rate and spectral EEG changes accompanying periodic and non-periodic leg movements during sleep. Clin Neurophysiol 118(2):438–448. https://doi.org/10.1016/j.clinph.2006.10.007

68. Lin YU, Balzer B and Schäfer A (2013) An automatic algorithm for the detection of periodic leg movements. Biomed Engin/Biomed Techk 58(SI-1-Track-G), 000010151520134195
69. Sezgin N (2015) EMG classification in obstructive sleep apnea syndrome and periodic limb movement syndrome patients by using wavelet packet transform and extreme learning machine. Turk J Electr Eng 23(3):873–884
70. Umut İ, Çentik G (2016) Detection of periodic leg movements by machine learning methods using polysomnographic parameters other than leg electromyography. Comput Math Methods Med 2016:2041467. https://doi.org/10.1155/2016/2041467
71. Lin Y, Zhang H, Wu W, Gao X, Chao F, Lin J (2023) Wavelet transform and deep learning-based obstructive sleep apnea detection from single-lead ECG signals. Phys Eng Sci Med. https://doi.org/10.1007/s13246-023-01346-0
72. Kye S, Moon J, Lee T, Lee S, Lee K, Shin SC, Lee YS (2017) Detecting periodic limb movements in sleep using motion sensor embedded wearable band. In: 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC) pp. 1087–1092
73. Sieminski M, Pyrzowski J, Partinen M (2017) Periodic limb movements in sleep are followed by increases in EEG activity, blood pressure, and heart rate during sleep. Sleep Breath 21:497–503
74. Athavale Y, Krishnan S, Raissi A, Kirolos N, Jairam T, Murray BJ, Boulos MI (2019) Actigraphic detection of periodic limb movements: development and validation of a potential device-independent algorithm. A proof of concept study. Sleep. https://doi.org/10.1093/sleep/zsz117
75. Zhou P, Huang L, Zhao Q, Xiao W, Li S (2019) A domestic diagnosis system for early restless legs syndrome based on deep learning. Zhongguo yi Liao qi xie za zhi= Chinese J Med Instrum 43(2):79–82
76. Carvelli L, Olesen AN, Brink-Kjær A, Leary EB, Peppard PE, Mignot E, Jennum P (2020) Design of a deep learning model for automatic scoring of periodic and non-periodic leg movements during sleep validated against multiple human experts. Sleep Med 69:109–119
77. Jarchi D, Andreu-Perez J, Kiani M, Vysata O, Kuchynka J, Prochazka A, Sanei S (2020) Recognition of patient groups with sleep related disorders using bio-signal processing and deep learning. Sensors 20(9):2594
78. Urtnasan E, Park JU, Lee JH, Koh SB, Lee KJ (2022) Deep learning for automatic detection of periodic limb movement disorder based on electrocardiogram signals. Diagnostics 12(9):2149

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

## Authors and Affiliations

**Murat Kayabekir[1] · Seda Kaya[2] · Mete Yağanoğlu[3]**

✉ Mete Yağanoğlu
yaganoglu@atauni.edu.tr

[1] Department of Physiology, Medical School, Atatürk University, Erzurum, Turkey

[2] Computing Unit, Faculty of Open and Distance Education, Atatürk University, Erzurum, Turkey

[3] Department of Computer Engineering, Faculty of Engineering, Atatürk University, Erzurum, Turkey